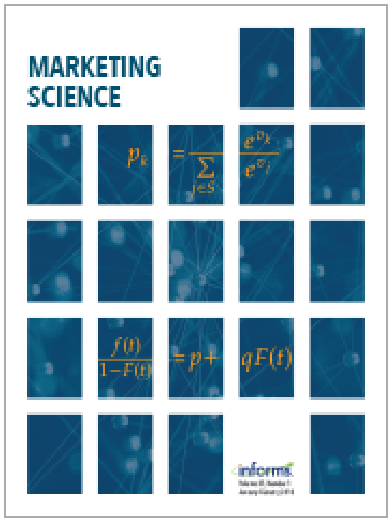

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Sensor Data and Behavioral Tracking: Does Usage-Based Auto Insurance Benefit Drivers?

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Abstract. Usage-based insurance (UBI) is a recent auto insurance innovation that enables insurers to collect individual-level driving data, provide feedback on driving performance, and offer individually targeted price discounts based on each consumer's driving behavior. Using individual driving behavior (from sensor data) and other information for UBI adopters, we estimate the relationship from being enrolled and monitored (for up to 26 weeks) in the UBI program and changes in the driving behavior of UBI customers. The key results of our analysis show that after UBI adoption, the UBI users improve the safety of their driving, providing a meaningful benefit for the individual driver, the insurer, and society as a whole. While UBI customers decrease their daily average hard-brake frequency by an average of 21% after six months, their mileage driven does not decrease comparing week 26 to week 1. We also find heterogeneous effects across different demographic groups. For example, younger drivers improve their UBI scores more than older drivers after UBI adoption, and females show more improvement than males. Furthermore, we find evidence that negative feedback and economic incentives correlate with greater improvement in driving behavior. Our results suggest that by sharing private consumer information with the insurer, UBI can benefit consumers who become better drivers, as well as the entire society from improved road safety.

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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. 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 communication devices continues to fall, and as the value of sensor-based information is more evident, usage-based insurance (UBI) is becoming a popular alternative to traditional automobile insurance. The basic idea of telematics-based 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, 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 set period of time, 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 with those who do not enroll in it. For consumers, enrollment in the UBI program is voluntary and they can drop out at any time. The drivers know they are being monitored by the insurance company. They receive an immediate signal in response to hard braking and they have an economic incentive to improve their driving behavior. UBI can offer many potential benefits for insurers, consumers, and society as a whole. Insurers benefit from the ability to differentiate their product offerings, improve 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 insurance premiums and receive ancillary benefits based on their own behavior. More importantly, society as a whole accrues benefits from improved road safety resulting from drivers' focus on vehicle usage and driving performance. Across the world, nearly 1,250,000 people die in road crashes each year.[1] Hard braking, a behavior that can be detected by the UBI program, is highly correlated with unsafe driving.[2] The company that we study in this paper defines a hard brake as occurring when the vehicle is traveling at more than 20 miles per hour (MPH) and its speed decreases by at least 8 MPH per second.

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 (Goldfarb and Tucker 2012). From the customer's perspective, although the privacy concern can limit the adoption rate of the UBI policy, we find that UBI can encourage adopters to improve their driving behavior and get a higher UBI discount,[3] possibly compensating for the cost of losing privacy. Although the potential benefits of UBI for customers and insurers are substantial, there is little knowledge about whether this strategy will actually 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 (i.e., 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 improve their driving performance while enrolled in the UBI program and receive permanent discounts averaging 12% below what they would have been charged had they not enrolled in the program.

In this paper, we use an internal database from a major U.S. 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 participants in this program changed 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 monitoring. 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. UBI participants living in urban areas exhibit a great change in UBI score than those living in rural areas. We also investigate the effect of immediate feedback and economic incentives on drivers' performance. We observe greater improvement for drivers who receive more negative feedback on hard brakes in the previous day than the day before. We look into the effect of economic incentives offered by UBI by dividing states into those offering No-Fault versus traditional insurance,[4] a policy decision that is exogenous to our research question. No-Fault states typically have higher average premiums than traditional states (Anderson et al. 2010). 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 be solely attributed to being monitored and receiving driving feedback in the UBI program, 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. For society as a whole, safer driving that is associated with fewer traffic accidents is a significant public health benefit. One caveat of our study is that, by the nature of the data that we have, we observe an individual's driving behavior only while he or she is enrolled in the UBI program; hence, the results apply only to the UBI drivers during the monitored time. It's noteworthy, however, that the 30% adoption rate is a large population (about 40,000 drivers in our sample), and we think the results are still important in assessing the economic and public safety impact of UBI.

The rest of this paper is organized as follows. After reviewing the literature related to usage-based insurance and establishing our research questions, we look at the industry background, focusing on the UBI policy, and 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 assess the empirical results for our models. Next, we discuss the role of immediate feedback and economic incentives and propose an approach to study 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—and to society more generally.

2. Literature Review

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

2.1. Usage-Based Pricing

UBI is one type of usage-based pricing (UBP) system that sets prices based on consumers' usage of a product. Some studies of UBP are in the telecommunication and software subscription industries. For example, Nevo et al. (2016) examine 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 has flexibility advantages for users whose data service needs vary over time. Altmann and Chu (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 with flat-rate plans. The UBP plan allows the internet provider to differentiate between those who want basic bandwidth or 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 cost for monitoring usage when it implements usage-based pricing. They show that offering different pricing schemes helps to differentiate the firms and relax price competition, particularly at higher monitoring costs, even when competing firms offer the same service quality. However, another stream of research shows that consumers would prefer flat-rate plans to usage-based plans. For example, Lambrecht and Skiera (2006) find that consumers tend to choose flat-rate plans even if these are more expensive than three-part tariff pricing schemes. Together with the literature on the benefit of usage-based pricing, one can argue that there is some tension in the question of whether usage-based pricing will be attractive to consumers.

Our research on UBI relates specifically to pay-as-you-drive (PAYD) auto insurance, in which the premium depends on the miles driven. The major distinctions between UBI and PAYD are, first, the premium for PAYD depends solely on mileage driven, but for UBI, a driver's premium also depends on how she drives; second, unlike PAYD, on which a driver's mileage affects only her current period's premium, UBI affects both the current and future insurance discount. Hultkrantz and Lindberg (2011) and Arvidsson (2011) 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 motorists' 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.

2.2. Information and Feedback

One key feature of the UBI program is that the consumers receive timely feedback about their driving behavior. For example, the drivers get immediate warnings when they exert a hard brake and also receive weekly emails about their driving performance. Our study is related to the behavioral and psychological literature on the effect of information and feedback on behavior change. For example, Taniguchi et al. (2003), in a study of prosocial 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. Fujii and Taniguchi (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) examine how sending dynamic alerts can help consumers better track their banking activities and change their behavior such that they 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.

2.3. Economic Incentives

Beyond information and feedback, other researchers examine the effect of economic incentives for behavior changes. This is particularly important, because authors such as Loewenstein[5] 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 drivers' 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, Angrist and Lavy (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 the UBI program.

3. Industry Background

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 United States, 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 U.S. private passenger auto insurance market (liability and physical damage) only grew 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 U.S. consumers had a UBI policy in force, compared with 4.5% in February 2013.[6] According to SMA Research,[7] approximately 36% of 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. According to a LexisNexis 2014 report, 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.[8]

Telematics-based UBI programs offer several potential consumer advantages. Consumers benefit most by having the ability to reduce their auto insurance costs. 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 (see Endnote 8), 78% of respondents cited discounts as an incentive to adopt telematics insurance programs, while 74% cited the ability to control their auto insurance costs as an incentive. Despite these substantial 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 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 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.

4. Data

4.1. Description of the UBI Policy

We study an individual's driving performance based on data from a major U.S. 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, and their participation in the UBI program cannot lead to a higher premium than under the traditional criteria. The UBI discount depends on a score based on a number of factors related to actual driving behavior. The actual formula is not disclosed, but the firm has provided data on the overall driving behavior score and two major components of the score-daily miles driven and number of hard brakes per day. A hard brake occurs when more force than normal is applied to the vehicle's brake. It is considered to be an indicator of aggressive or unsafe driving. The operational definition is technically specified by the company as an event in which the vehicle is traveling at more than 20 MPH and its speed decreases by at least 8 MPH per second. Several government studies show that these variables are highly correlated with the likelihood of an automobile accident.[10] A 2016 *Wall Street Journal* article reports that executives at Progressive Auto Insurance, which has more than 4 million drivers in their UBI program, indicate that hard brakes are the "most powerful predictor of accidents."[11]

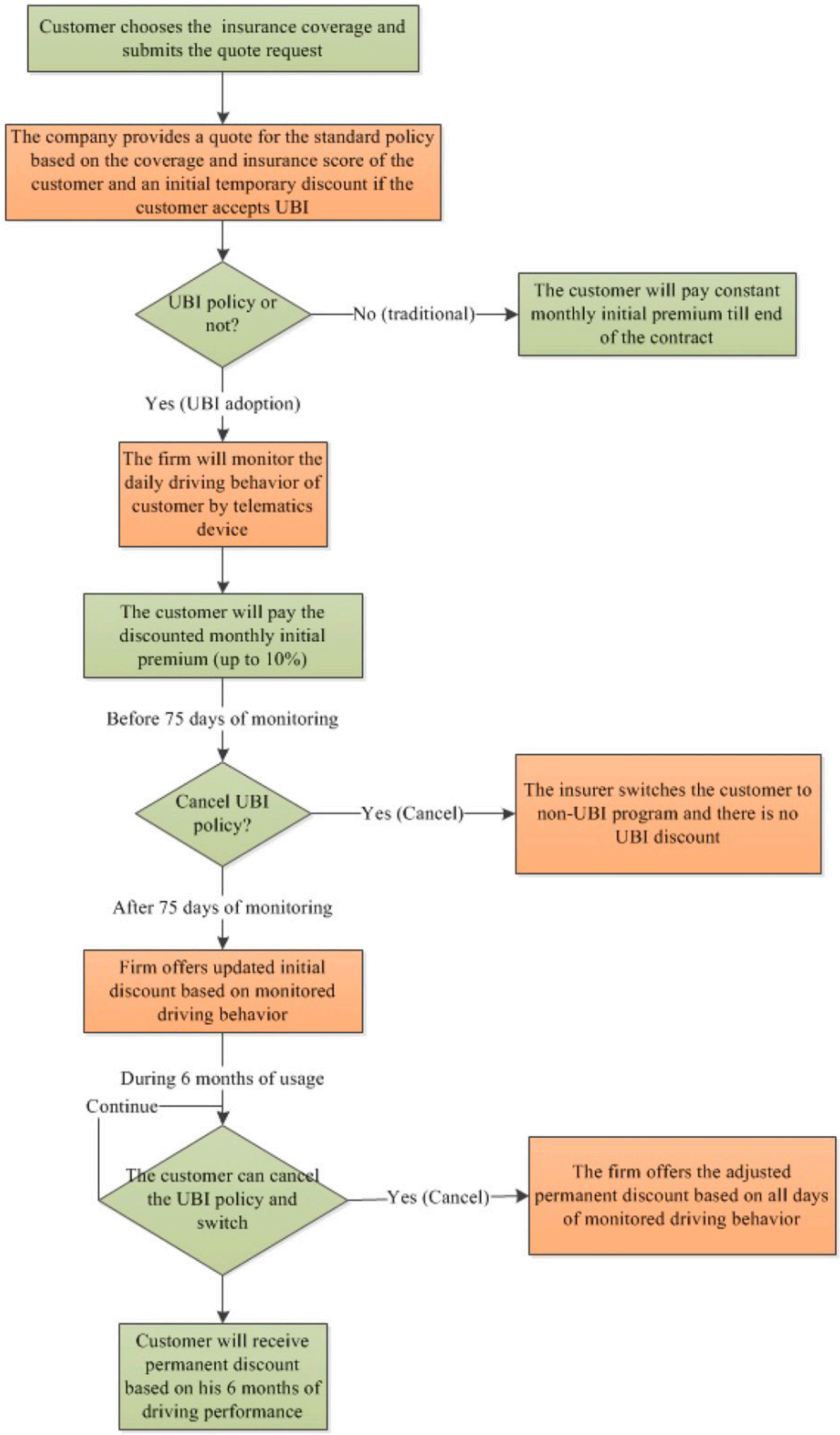
According to information in corporate annual reports, the insurance company started to offer usage-based insurance as a new policy to better target safer drivers and thus to increase their profit by attracting and keeping more profitable customers. Like almost all of the UBI policies in the United States, 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 new customers to sign up for a UBI policy by offering an initial (temporary) discount (typically 5%). The initial discount is given to customers as soon as they enroll in the UBI program, and they 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 she hard-brakes, the telematics device beeps—or monitor her performance on a daily basis via an app. The company also sends a weekly email to participants but does not have data on whether the emails are read or how often the app is consulted. After 75 days of using the monitoring device, the customer will receive an updated discount, which is based on her 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 a 25% permanent discount based on 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%. Before the consumers enroll in the UBI program, the drivers are informed of the firm's pricing policy including the initial discount, the maximum (25%) permanent discount, and the average (12%) permanent discount. 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.

In summary, UBI has the following features: (1) enrollment in the program is voluntary and consumers can drop out at any time; (2) the drivers know they are being monitored by the insurance company; (3) the drivers receive an immediate signal in response to hard braking; and (4) the drivers have an economic incentive to improve their UBI score and will receive a permanent discount if they remain in the program for at least 75 days.

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

Figure 1. (Color online) Flowchart of Customer and Firm Decisions in UBI Policy



auto insurance from March 2012 to November 2014. All of these customers had the option to choose between a traditional insurance policy and UBI. In this data set, we observe some of the customers' demographic information (including age, gender, and the state and zip code where the customer lives), the insurance score that the firm assigns to each customer, the insurance coverage, and the initial premium the customers would pay under their policies. There is also the UBI acceptance decision for all customers and the initial discount

Table 1. Summary Statistics of All Customers

	Total	Non-UBI	UBI
Number of customers	135,540	95,013	40,527
UBI acceptance rate	0.3		
Average age	45.8	48.7	39.3
Fraction male	0.53	0.53	0.52
Fraction of urban customers	0.78	0.77	0.82
Average initial monthly premium	109.1	107.6	112.4
Average initial insurance score	52.06	53.31	49.14
Average initial discount			0.05
Average permanent discount			0.12
First-year renewal rate	0.8	0.77	0.86
Average renewal insurance score	54.11	54.8	52.8
Average renewal premium (discount excluded)	104.85	104.12	106.5

for each UBI customer who adopts 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%. The fraction of urban customers variable shows the proportion of customers in each group that live in an urban versus rural area.[12] The percentage of males and females adopting is approximately the same, with drivers located in an urban area more likely to enroll than those in rural areas. In addition, the average age of the UBI policyholders (39.3 years) is much lower than that of the non-UBI customers (48.7 years), 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 young drivers because of 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 behavior, 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 compared with older or more 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. 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. 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. The average initial discount for UBI customers in our sample is 5% (standard deviation (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 of 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[13] than that for non-UBI customers ($108) 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. The renewal rate of UBI customers is 9% higher than for non-UBI customers.

To test the relationship between the UBI adoption and drivers' characteristics, we estimate a logit model in which the dependent variable is defined as whether a driver adopts the UBI policy. Urban is defined as a dummy variable that equals one if the driver lives in an urban area, and zero if he or she lives in a rural area. In addition, new driver is a dummy that shows whether the driver had previous driving experience or not. The estimation results are summarized in Table 2 after considering the fixed effects of states.

$$UBIacceptance_i = \text{logit}(age_i,\ premium_i,\ state_i,\ gender_i,\ urban_i,\ new\ driver_i).$$

Consistent with the summary statistics, the results show that the age coefficient is significantly negative, implying that the UBI policy is more attractive for younger drivers. The coefficient of initial premium is positive and significant, which means that customers with a higher initial premium are more likely to enroll in the UBI policy. In addition, the coefficients for urban dummy and the dummy for new drivers are significant, which means that the customers in urban areas and new drivers are more likely to adopt this policy. Finally, the coefficient for gender is not statistically

Table 2. Logit Regression Analysis Results for UBI Adoption

	Estimate (standard error)
Intercept	0.4652 (0.004)**
Age	−0.0053 (0.00004)**
Premium	0.0008 (0.00004)**
Gender (male)	−0.0014 (0.0013)
Dummy_urban	0.0137 (0.0028)**
New driver	0.0581 (0.0049)**
State dummies	Included

Note. Sample size = 135,540.
*$p < 0.05$; **$p < 0.01$.

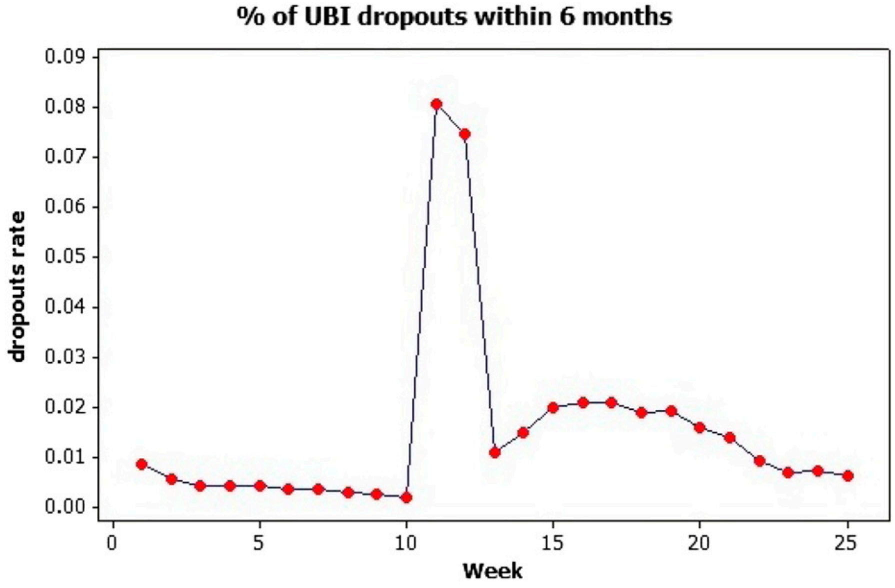
significant, suggesting that males and females are equally likely to adopt the UBI policy. The differences between the UBI adopters and the non-UBI users may be due to possible self-selection. Since we only observe the UBI adopters' driving behavior, our findings on driving performance changes only apply directly to UBI adopters.

The second data set contains several sensor-based measures of the UBI customers' daily driving behavior. The data are collected by the telematics device for up to six 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 the telematics device plugged into their automobile. In addition to mileage and hard brakes, we observe the driving score that all UBI customers can monitor each day. In other words, the daily UBI score represents the daily 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 data set, we show in Online Appendix Table A2 that daily hard brakes and mileage are two key components of the daily UBI score. These two factors explain about 57% of the variation in the observed daily UBI score. In summary, we have a panel data set 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.[14] Although we do not know the formula that the company uses to calculate the UBI score,[15] we have data on two direct driving behavior measures.

It is important to note that we do not observe the driving behavior of all UBI customers for the full 26 weeks, since about 35% of participants withdrew from the UBI program before six 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 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 people drop out after receiving the initial feedback.[16]

In the next section we look at the weekly changes in our driving performance measures (UBI score, hard

Figure 2. (Color online) Weekly Dropout Within UBI Program



brakes, and mileage). We aggregate our data to the weekly level to study the participants' overall driving patterns over time because there is large variation in daily driving, particularly between weekdays and weekend days. Nonetheless, in Section 5.1 we show that we obtain similar qualitative results for our main model when we use daily data.

4.2. Descriptive Evidence of Improvement in Driving Behavior

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.

4.2.1. The Weekly Average UBI Score. Figure 3(a) shows the weekly average UBI driving score of all UBI customers in our data set. 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 six months. 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 because of UBI policy dropouts during the 26 weeks. Figure 3(b) helps us better understand this issue; the plot shows the weekly average UBI driving score of customers who used the monitoring device for six 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.

4.2.2. 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.[17] Figure 4(a) shows the average daily number of hard brakes observed in 26 weeks of UBI usage for all UBI customers. We find that the daily number of hard brakes has a notable decreasing pattern during the 26 weeks of our data set. 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 data set, 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 cancel 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(b) 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. Comparison of 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 out of the UBI policy, the overall decline in hard braking holds for the sample of people who are monitored for all 26 weeks.

4.2.3. Average Changes in Daily Mileage. Daily mileage is one of the other elements tracked by the UBI telematics device. Average daily mileage per week of UBI customers is shown in Figure 5, panels (a) and (b).

Figure 3. (Color online) Weekly Average UBI Score

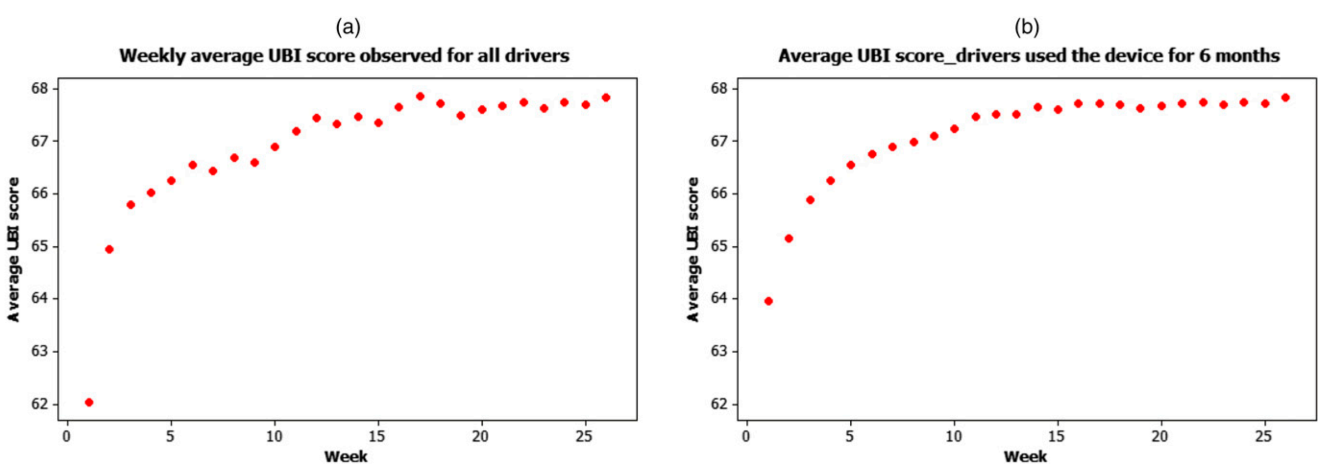
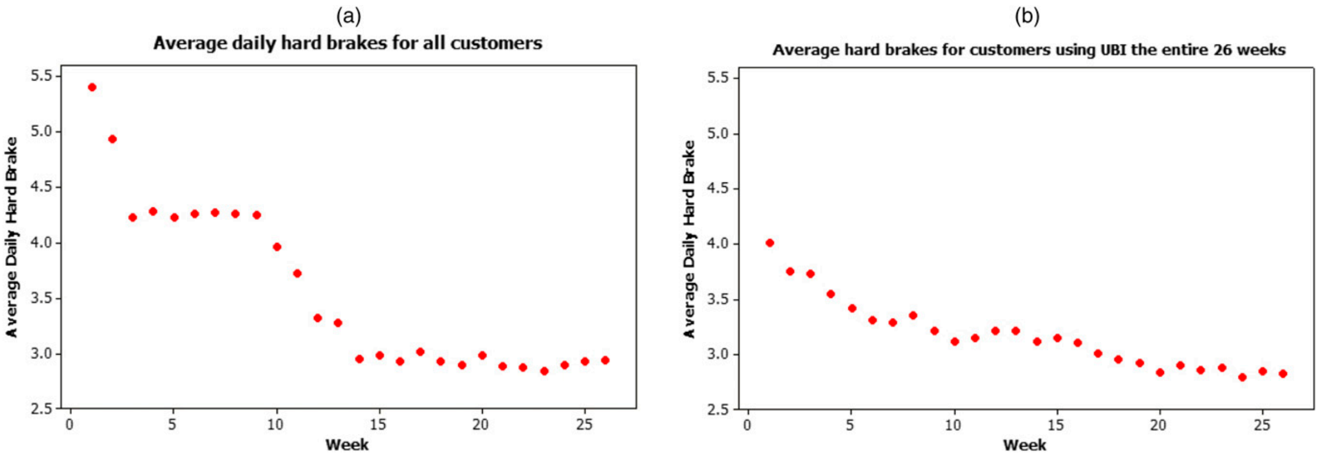


Figure 4. (Color online) Average Daily Number of Hard Brakes



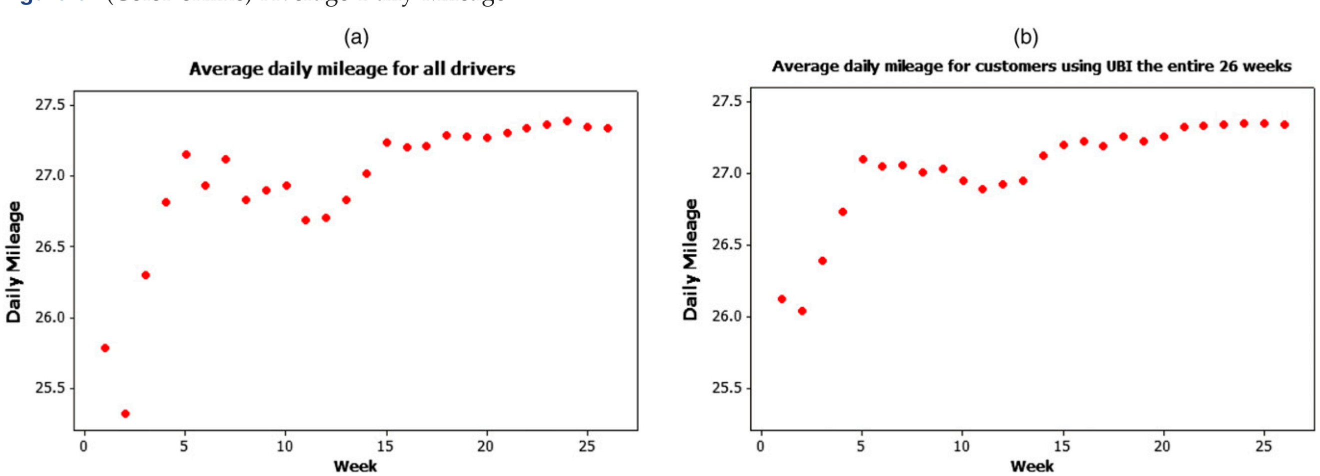
Interestingly, the weekly mileage driven first increases, although not uniformly, and then appears to be relatively constant (within ±0.5 miles compared with an overall average of 27 miles per day). The general pattern in this plot is different from that for the hard brakes and UBI scores shown above. 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, we use our panel data to propose a fixed-effects model to address these issues.

5. Empirical Analysis and Results

In this section, we analyze how customers have changed their driving behavior during their UBI adoption period. We first describe our empirical approach and the construction of our key explanatory variables. Our baseline specifications are regressions of observed UBI scores and measures of actual driver behaviors during the time period when motorists are enrolled in the UBI program, and control variables. We consider consumers' demographic characteristics 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,

Figure 5. (Color online) Average Daily Mileage



and daily mileage) for up to six 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 by using fixed-effects models.

5.1. Model Specification

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

$$S_{it} = \alpha_0 + \alpha_1 \times age_i + \alpha_2 \times age_i^2 + \alpha_3 \times gender_i + \alpha_{13} \times age_i \times gender_i + \alpha_4 \times single_i + \alpha_5 \times new\ driver_i + \alpha_6 \times insurance\ score_i + \alpha_7 \times urban_i + \beta' \times week\_dummies_{it} + StateDummies_i + \varepsilon_{it}, \quad (1)$$

where

$$S_{it}: \textit{the UBI score of driver } i \textit{ at week } t.\ t = 1, \ldots, 26,$$
$$age_i: \textit{the age of driver } i,$$
$$insurance\ score_i: \textit{the insurance score of driver } i \textit{ before starting UBI},$$
$$gender_i = \begin{cases} 1 & \textit{if the driver } i \textit{ is female} \\ 0 & \textit{else}, \end{cases}$$
$$single_i = \begin{cases} 1 & \textit{if the driver } i \textit{ is single} \\ 0 & \textit{else}, \end{cases}$$
$$new\ driver_i = \begin{cases} 1 & \textit{if driver } i \textit{ is applying for an insurance policy for the first time} \\ 0 & \textit{else}, \end{cases}$$
$$urban_i = \begin{cases} 1 & \textit{if the driver } i \textit{ lives in urban area} \\ 0 & \textit{else}, \end{cases}$$
$$dummy_{it} = \begin{cases} 1 & \textit{if the observation is in week } t \textit{ after UBI adoption} \\ 0 & \textit{else}, \end{cases}$$
$$\beta = [\beta_2, \ldots, \beta_{26}]',$$
$$week\_dummies_{it} = [dummy_{i2}, \ldots, dummy_{i26}]',$$
$$\varepsilon_{it}: \textit{identical and independent distributed across time } t \textit{ and individual } i.$$

In this specification, in addition to the age (at time of enrollment), gender, and interaction of age/gender of driver i in Equation (1), we consider other covariates to show the effect of insurance score, driving experience, state of residence, living in an urban area or not, and marriage status on UBI score. The coefficients of the week dummies in this specification capture the UBI score changes compared with the first-week UBI score.

Table 3 shows the estimation results of the cross-sectional regression analysis.[18] 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 2.79 points higher than males on average, suggesting that females on average have better driving behavior than males in the UBI program, but the interaction of age and gender shows no significant effect on average weekly UBI score, which means the effect of age on UBI score is not significantly different across genders. We find that insurance scores are positively correlated with the UBI scores. The negative and significant coefficient of the Single variable shows that the single drivers' average UBI score is lower than married drivers. Interestingly, the new drivers' average UBI score is significantly higher than experienced drivers. Urban drivers on average have significantly lower UBI score compare with rural area drivers. Considering all positive and significant coefficients of week dummy variables, the UBI customers achieve higher UBI scores over the total period of UBI

Table 3. Cross-Sectional Regression Analysis Results for UBI Score

	Estimate (standard error) Pr(> |t|)
Intercept	63.47 (0.08)**
Age	−0.15 (0.01)**
Age^2	0.02 (0.04)
Gender (female)	2.79 (0.03)**
Age × *gender*	0.06 (0.04)
Single	−0.42 (0.09)**
New driver	0.26 (0.13)*
Urban	−0.41 (0.19)*
Insurance score	0.18 (0.07)**
Week_dummy2	3.60 (0.09)**
Week_dummy3	3.95 (0.09)**
Week_dummy4	4.06 (0.09)**
Week_dummy5	4.18 (0.09)**
Week_dummy6	4.14 (0.09)**
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 (0.12)**
Week_dummy22	5.48 (0.12)**
Week_dummy23	5.60 (0.13)**
Week_dummy24	5.52 (0.13)**
Week_dummy25	5.64 (0.13)**
Week_dummy26	5.68 (0.14)**
State fixed effects	Included
Multiple R^2: 0.208	
Adjusted R^2: 0.198	

Note. Sample size = 705,752.
$^*p < 0.05$; $^{**}p < 0.01$.

usage in comparison with 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 driving ability, willingness to remain in the UBI program, and other idiosyncratic factors. Consequently, we estimate a regression model (Equation (2)) with driver individual fixed effects. The approach identifies β using variation within each individual driver.

$$S_{it} = \beta' \times week\_dummies_{it} + driver_i + \varepsilon_{it}, \qquad (2)$$

where $driver_i$ is the fixed-effects parameter of a driver.

Table 4 is the estimation result of the fixed-effects regression model for the three measures as dependent variables (*UBI score*, *Hard brakes*, *Mileage*). Based on column (a) of Table 4, all 25 weekly coefficients are significantly positive, implying that customers have better UBI scores on average compared with those from the first week. We did further analysis to indicate whether the weekly change in UBI score in week t is significant in comparison with the previous week (week $t - 1$). We find that in the first 11 weeks, customers have a significantly (0.05 level) higher UBI score than in the previous week for every week, and after that these changes lessen and drivers have more consistent UBI scores. This suggests that UBI customers drive more safely (higher UBI score) while using monitoring devices and receiving feedback in the first three months of usage, and their behavior is relatively consistent afterward. In addition, by comparing Tables 3 and 4 (column (a)), we observe the differences that arise when comparing the coefficient estimates of the week dummy variables in the fixed-effects model with the cross-sectional regression analysis. This comparison suggests that the cross-sectional regression results are positively biased because of selection issues.

Furthermore, we 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.

Column (b) of Table 4 shows the result of fixed-effects model estimation for the number of daily hard brakes. We observe that this number decreases significantly when compared with the first week in our fixed-effects model. In addition, similar to UBI score, we find that during the first six weeks the UBI customers improve their driving performance weekly by reducing the number of hard brakes. Column (b) of

Table 4. Fixed-Effects Regression Analysis Results for Three Measures of Driving Behavior

Variables	Estimate (standard error)		
	(a) Dependent variable: *UBI score*	(b) Dependent variable: *Hard brakes*	(c) Dependent variable: *Mileage*
Week_dummy2	2.57 (0.01)**	−0.26 (0.02)**	−0.06 (0.05)
Week_dummy3	2.93 (0.01)**	−0.28 (0.02)**	0.13 (0.07)′
Week_dummy4	3.06 (0.01)**	−0.41 (0.02)**	0.10 (0.09)
Week_dummy5	3.14 (0.01)**	−0.45 (0.02)**	0.26 (0.12)*
Week_dummy6	3.28 (0.01)**	−0.48 (0.02)**	0.19 (0.13)
Week_dummy7	3.40 (0.01)**	−0.47 (0.02)**	0.16 (0.13)
Week_dummy8	3.41 (0.01)**	−0.43 (0.02)**	0.07 (0.14)
Week_dummy9	3.49 (0.01)**	−0.48 (0.02)**	0.10 (0.15)
Week_dummy10	3.77 (0.01)**	−0.51 (0.02)**	0.06 (0.15)
Week_dummy11	4.34 (0.01)**	−0.48 (0.02)**	0.04 (0.20)
Week_dummy12	4.42 (0.01)**	−0.48 (0.02)**	0.17 (0.21)
Week_dummy13	4.27 (0.01)**	−0.47 (0.02)**	0.15 (0.23)
Week_dummy14	4.33 (0.01)**	−0.49 (0.02)**	0.35 (0.24)
Week_dummy15	4.29 (0.01)**	−0.48 (0.02)**	0.46 (0.24)′
Week_dummy16	4.24 (0.02)**	−0.50 (0.02)**	0.45 (0.26)′
Week_dummy17	4.29 (0.02)**	−0.51 (0.02)**	0.48 (0.26)′
Week_dummy18	4.37 (0.02)**	−0.53 (0.02)**	0.54 (0.28)′
Week_dummy19	4.36 (0.02)**	−0.57 (0.02)**	0.53 (0.29)′
Week_dummy20	4.40 (0.02)**	−0.61 (0.02)**	0.53 (0.30)′
Week_dummy21	4.44 (0.02)**	−0.59 (0.03)**	0.55 (0.31)′
Week_dummy22	4.47 (0.02)**	−0.59 (0.03)**	0.57 (0.31)′
Week_dummy23	4.50 (0.02)**	−0.60 (0.03)**	0.60 (0.32)′
Week_dummy24	4.54 (0.02)**	−0.62 (0.03)**	0.61 (0.35)′
Week_dummy25	4.57 (0.02)**	−0.60 (0.03)**	0.60 (0.34)′
Week_dummy26	4.59 (0.02)**	−0.61 (0.03)**	0.59 (0.36)
Multiple R^2	0.419	0.386	0.285

Note. Sample size = 705,752.
′$p < 0.1$; *$p < 0.05$; **$p < 0.01$.

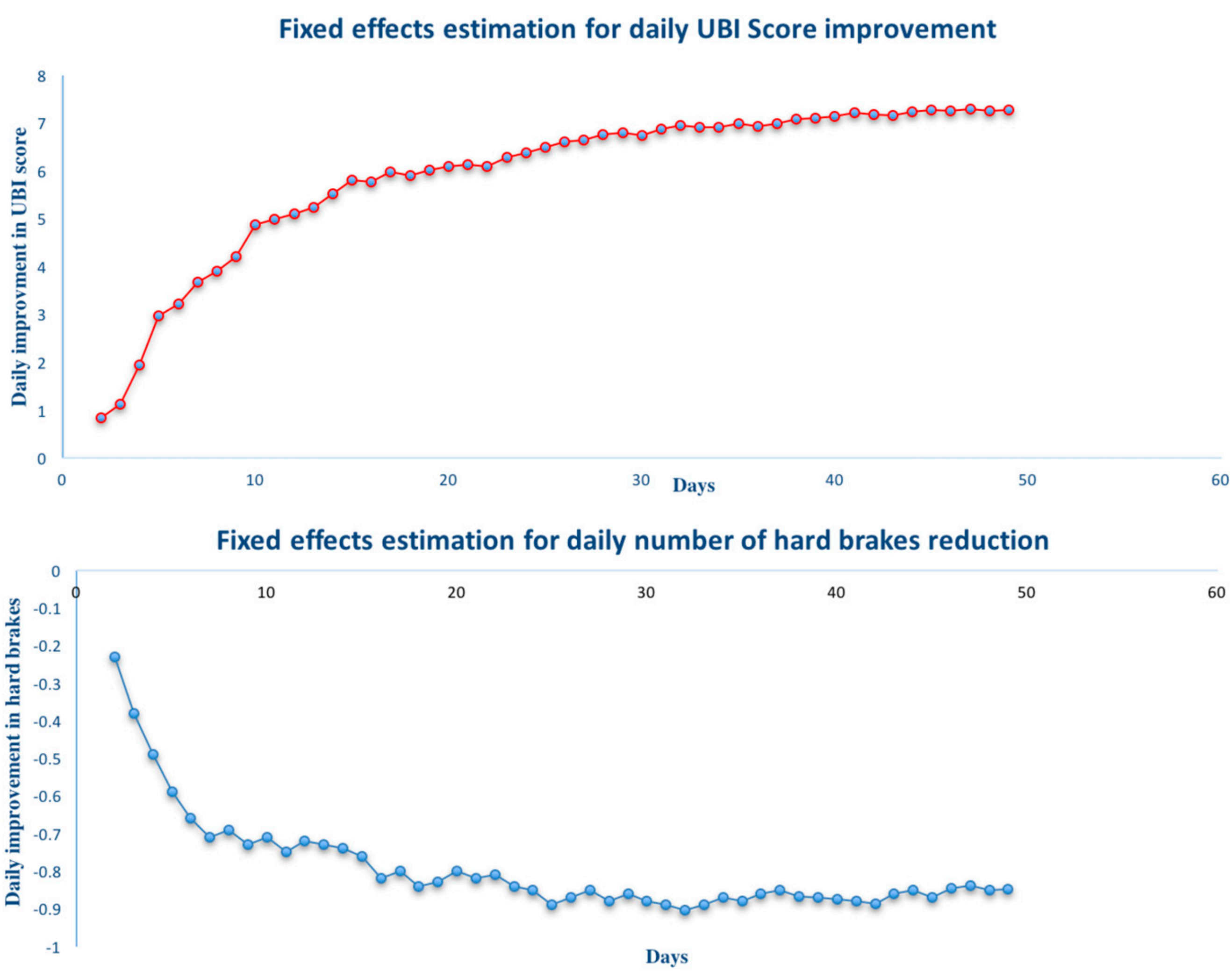
Table 4 shows evidence that UBI customers can significantly reduce their daily hard brakes and maintain that reduced rate over the monitoring period.

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 six months. As column (c) of Table 4 shows, the coefficient estimates for the weekly dummies are not statistically significant, suggesting that the UBI customers do not change the mileage per day after using telematics devices for 26 weeks (except for only one significant mileage increase compared with first-week mileage at the 0.05 level in week 5).

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 the UBI program. We find that unlike UBI score and hard brakes, the mileage driven by UBI customers does not change significantly during 26 weeks of UBI usage.[19] One possible explanation for the different patterns between hard-brake 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 to improve their driving safety level than to reduce their automobile usage (mileage). Another interesting observation 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 suggests that drivers in the UBI program sustain for at least 26 weeks the driving behavior changes they make in the first three months of UBI usage.

As mentioned above, we aggregated the daily data into weekly-level data for all measures of driving performance, because the weekly data are less noisy, and it is easier to detect the time trend. To check the robustness of the results, we can also consider the daily driving data to capture the daily change in driving

Figure 6. (Color online) Fixed-Effects Estimation of Daily Changes in Driving Behavior of UBI Customers



behavior. We use the daily data and run a fixed-effects model by considering the day dummies and six weekdays' dummies to capture the difference between weekday and weekend driving performance of UBI customers. The results of this analysis are consistent with our results for the weekly data approach, and we find a gradual improvement in driving performance over time (for UBI score and hard brakes). Figure 6 shows the estimated daily improvement in the fixed-effects model for the first seven weeks with 48-day dummies of UBI usage. Figure 6 indicates the estimated coefficients in our fixed-effects model of UBI score and hard brakes.

5.2. Heterogeneity Across Different Groups of Customers

In this section, we investigate possible heterogeneity in driving behavior changes across different age groups, genders, and living in an urban or rural area. As in Section 5.1, we consider fixed-effects models to capture the weekly changes in driving behavior for different customer groups.

5.2.1. Age Groups. 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

$$\begin{aligned} S_{it} = \beta' \times week\_dummies_{it} + \gamma_2' \times age\_group2_i \\ \times week\_dummies_{it} + \gamma_3' \times age\_group3_i \\ \times week\_dummies_{it} + \gamma_4' \times age\_group4_i \\ \times week\_dummies_{it} + driver_i + \varepsilon_{it}, \end{aligned} \tag{3}$$

where

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

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

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

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

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

In the above setting, we consider four age groups that are commonly employed in the auto insurance industry.[20] The youngest group consists of all drivers 35 years old or younger (millennials), while the digital natives (36–50), baby boomers (51–65), and seniors (above 65) are the other groups of customers in our setting. The sample sizes of the four age groups are 15,561, 11,238, 9,763, and 3,962 UBI customers, respectively. The millennial group is considered as the baseline in our fixed-effects model; therefore, the β represents the changes in UBI score for the youngest age group of customers, and γ_k represents the difference between the weekly changes in UBI score of the age group k and the youngest group of drivers.

Since there are multiple parameters to estimate in the fixed-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 Online Appendix B.

Figure 7 shows the estimate of weekly changes in three measures of driving behavior (UBI score, hard brakes, and mileage) 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 7(a), the change patterns in UBI score are different for the four age groups. For example, the senior drivers show limited, but significant, improvement in UBI scores; however, the young drivers, who start with relatively low UBI scores, increase their UBI scores to achieve the highest UBI score among all age groups by the end of the program.[21]

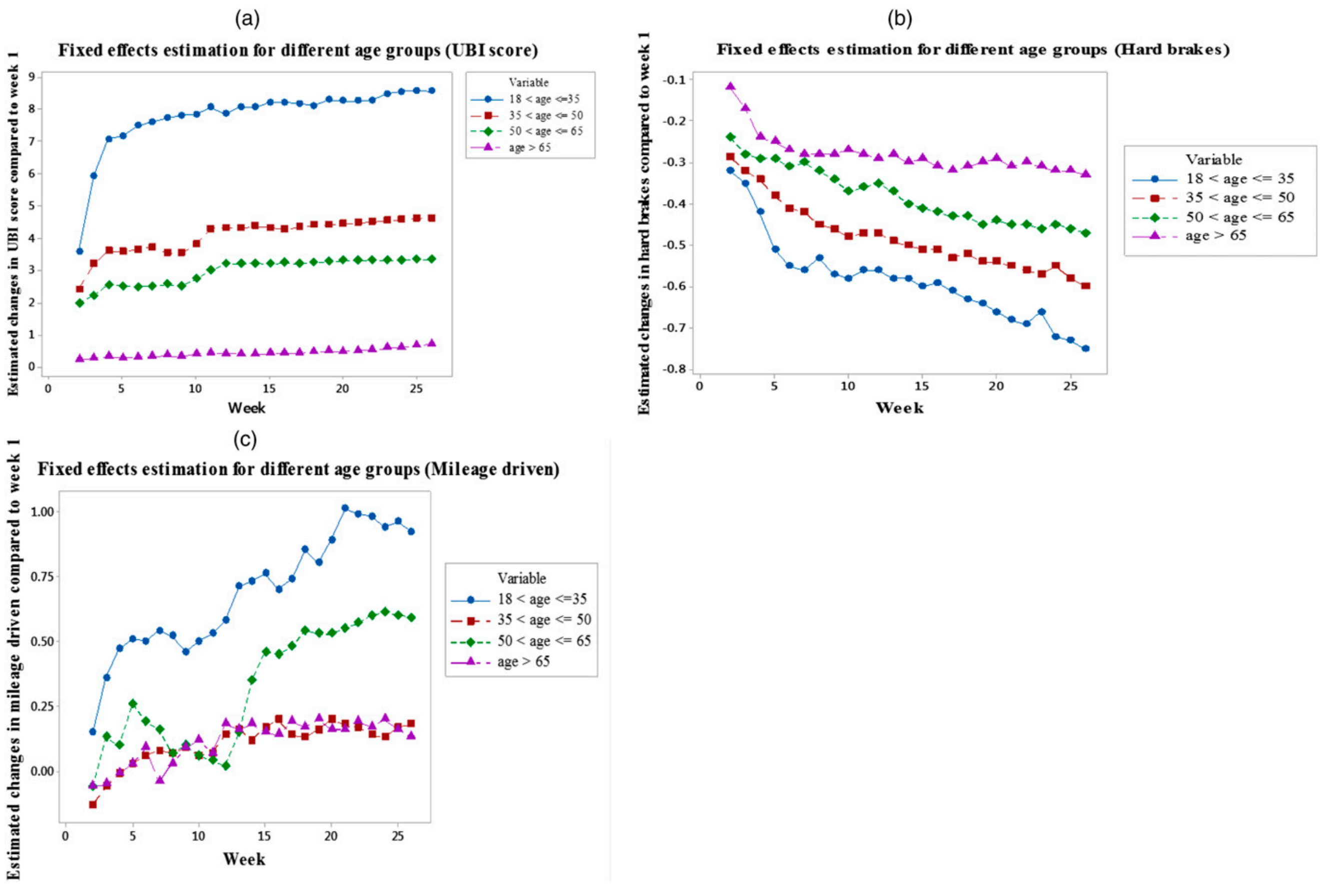
Each point in Figure 7(a) represents the change in UBI score in week t compared with the first week. For instance, the initial point of the black line shows that the average UBI score of the youngest group of drivers in the second week is 3.6 points higher than their UBI scores in the first week. The 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 with younger drivers leads to a lower average UBI score after 26 weeks of UBI usage for senior drivers. 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 compared with younger ones.

As shown in Figure 7(b) and similar to the UBI score results, the reduction from week 1 to week 26 in the daily number of hard brakes for the youngest drivers is greater 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.

Using the same fixed-effects model, but with mileage driven as the dependent variable, we find no significant interaction effect of age groups and weekly dummies on mileage driven (see Figure 7(c)), except for one, perhaps surprising, result. Namely, the mileage driven by young drivers in week 26 is significantly ($p < 0.05$) higher (by 3.6%) than in the first week,[22] which, if anything, would limit their improvement in UBI score.

We find that the driving behavior changes of UBI customers, in terms of UBI score and number of hard

Figure 7. (Color online) Weekly Changes Estimation in Driving Behavior for Different Age Groups



Notes. Panel (a) shows weekly changes in UBI score estimation. The average UBI score in the first week: millennials (≤35), 61.68; digital natives (36–50), 61.65; baby boomers (51–65), 63.14; seniors (>65), 65.73. Panel (b) shows weekly changes in hard brakes estimation. The average daily number of hard brakes in the first week: millennials (≤35), 4.14; digital natives (36–50), 4.08; baby boomers (51–65), 3.95; seniors (>65), 3.93. Panel (c) shows weekly changes in mileage estimation. The average daily mileage driven in the first week: millennials, 25.73; digital natives (36–50), 31.45; baby boomers (51–65), 30.54; seniors (>65), 24.96.

brakes, differ across customer age groups, and that the youngest drivers appear to be 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.

5.2.2. 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

$$S_{it} = \beta' \times week\_dummies_{it} + \delta' \times Gender_i \times week\_dummies_{it} + driver_i + \varepsilon_{it}, \quad (4)$$

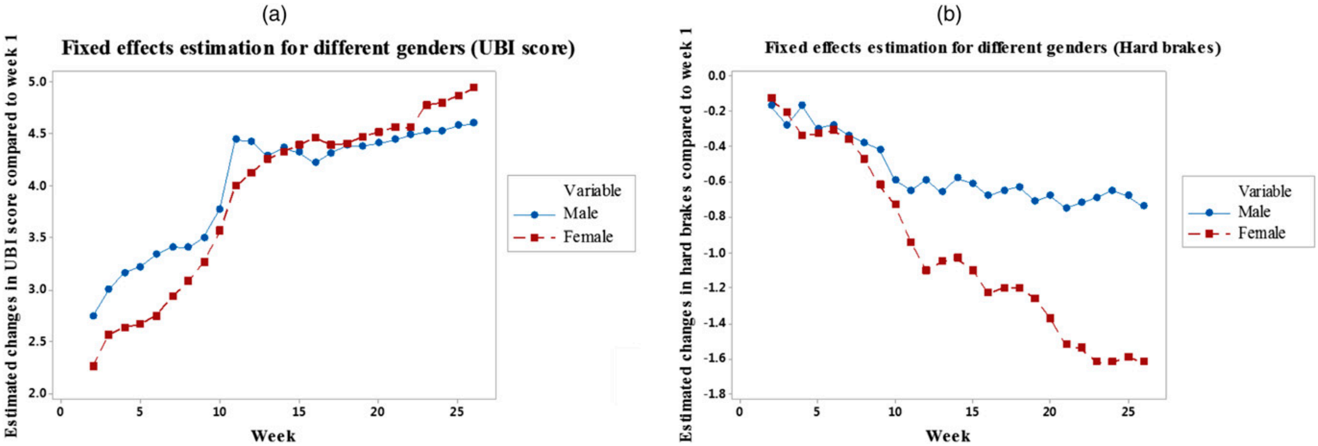
where

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

Figure 8 shows the result of the fixed-effects model for two measures of driving behavior (UBI score and hard brakes) when we add the interactions of gender and week variables. There are no significant effects by gender for mileage driven, so those results are not reported to save space. In Figure 8(a), although in the first few weeks of monitoring males show a greater improvement in their UBI scores as compared with the first week, by the end of the monitoring period, females show a higher overall improvement in UBI scorers. This result is consistent with Dweck (1986), who finds that learning patterns for males and females differ, with females showing a greater overall improvement. 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 versus 60.92) and the end (68.24 versus 65.31) of the monitoring period than males.

We carried out a similar analysis for changes in number of hard brakes by gender. Figure 8(b) shows

Figure 8. (Color online) Weekly Changes Estimation in Driving Behavior for Different Genders



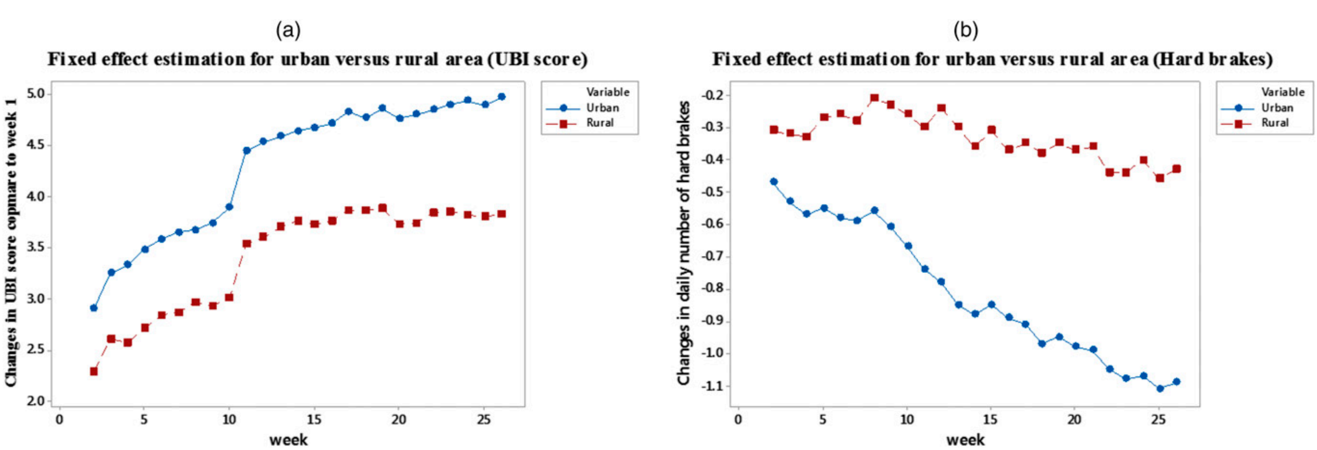
Notes. Panel (a) shows weekly changes in UBI score estimation. Average UBI score in the first week for each group of drivers: males, 60.92; females, 63.34. Panel (b) shows weekly changes in daily hard brakes estimation. Average daily number of hard brakes in the first week for each group of drivers: males, 3.64; females, 5.55.

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 with 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). Presumably, factors other than hard brakes account for females having a higher UBI score despite a higher hard-brake frequency at the end of 26 weeks.

5.2.3. Other Factors. We can also categorize the customers into groups based on other interesting factors to evaluate the heterogeneity across groups. For example, we can subdivide our sample into customers living in urban as compared with rural areas based on their zip code. We found significant improvement in overall driving behavior and number of hard brakes for both subsamples, with a stronger effect for those living in urban areas. There were no significant effects for miles driven. We show the detailed results for urban/rural area UBI score and hard brakes analysis in Figure 9. Urban drivers have lower initial UBI scores, lower initial insurance scores, and higher premiums than rural users. Thus, it would seem plausible that they have more to gain by improving their driving behavior. They may also have more opportunities of doing so as traffic in cities is denser and thus the benefits of careful driving may be higher despite lower mileage. Our results are consistent with this prediction that urban drivers improved more in their driving performance during the UBI program.

Figure 9. (Color online) Weekly Changes Estimation in Driving Behavior for Urban vs. Rural Drivers



Notes. Panel (a) shows weekly changes in UBI score estimation. Average UBI score in the first week for each group of drivers: urban, 61.82; rural, 63.24. Panel (b) shows weekly changes in daily hard brakes reduction estimation. Average daily number of hard brakes in the first week for each group of drivers: urban, 5.48; rural, 4.20.

In addition, we also 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 (but after receiving their revised discount at 75 days) of usage. The results (Online Appendix Table B12) show that the loyal customers change their driving behaviors more than the customers who drop out early, but there still is a significant improvement in driving performance for those who stay in the program only until they receive their revised permanent discount at 75 days. This result holds for both UBI score and for number of hard brakes.

6. Possible Factors Associated with Improvement in Driving

In the previous section, we found that the customers who adopted the UBI program improved their driving behavior while being monitored by the telematics device. One could argue that the improvement of driving performance could be driven merely by natural learning over time, even without UBI enrollment. However, natural maturation and improvement would usually happen only for younger or inexperienced drivers, and since our data set, as described above, includes more experienced and older drivers with many years of driving experience, we can test for that possibility. As shown in Figure 7, we find significant improvement for drivers over the age of 35. We ran our analysis separately for new and for experienced drivers and found significant improvement in each of these groups of customers. The detailed analysis can be found in Online Appendix Table B6. Hence, the improvement after UBI usage does not seem to be limited to just younger or inexperienced drivers.

One possible mechanism is a mere monitoring effect. That is, the installation of the telematics device increases the salience of unsafe driving behaviors being monitors. Hence, we would expect the effect to be highest at the time of the installation of the device and later possibly decline or stay constant. Although we cannot observe the instantaneous monitoring effect because we do not observe the drivers' performance before their UBI adoption, we find that the improvement of driving performance is significantly higher in early weeks than in later weeks. However, returning to the daily data in Figure 6 for both UBI score and hard brakes, we see that the improvement in performance increases for quite a while after the initial improvement and never reverts back to the initial performance level for UBI score and number of daily hard brakes. Thus, while monitoring may affect performance, it is unlikely that merely being monitored fully explains our results.

There are at least two other motivations for the improvement in behavior under UBI policy beyond the mere monitoring effects: first, improvement occurs because consumers respond to feedback from the telematics device. That is, drivers will learn and improve their driving performance by getting immediate or 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 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. A second source for driving-behavior improvement is its economic incentives: the benefit of discount and net premium reduction from the UBI policy may contribute to the customer's improvement in driving performance. Both effects are likely present in the empirical results we report above.

6.1. Immediate Negative Feedback and Drivers' Performance

To look into the impact of feedback on driver performance, we ran an analysis to show the effect of immediate negative feedback on the level of improvement. We expect that if a driver experienced a decline in performance between days and received negative feedback, it would lead to improved performance in the following day.[23] Since a consumer gets immediate warnings when he or she has a hard brake, in this analysis we consider the lagged variable for the feedback on the hard brakes and examine the effect of receiving increased negative feedback at day t on the next day's performance. The following model captures this negative feedback effect by considering the fixed-effects model:

$$Hardbrakes_{it} = \gamma' \times week\_dummies_{it} + \alpha' \times weekdays_{it} + \beta \times Negativefeedback_{it} + driver_i + \varepsilon_{it}, \quad (5)$$

$$Negativefeedback_{it} = \begin{cases} 1 & hardbrakes_{it-1} - hardbrakes_{it-2} > 0 \\ 0 & else, \end{cases}$$

where $Negativefeedback_{it}$ is defined as a dummy variable that equals one if a driver's last day driving performance (the number of hard brakes) is worse than the day before.

The results in Table 5 show that in addition to a reduction in the number of daily hard brakes compared with the first week of UBI usage, receiving negative feedback in day t is significantly associated with greater reduction in the number of hard brakes in the following day. As a robustness check, we ran a Poisson regression on these data and obtained similar results for the effect of negative feedback (see Online Appendix Table B19.)

6.2. Economic Incentives and Drivers' Performance

In the following analysis, we test the effects of economic incentives (lower premium as a result of the UBI discount) on improving the UBI driver performance. In

Table 5. Fixed-Effects Regression Results for Number of Daily Hard Brakes to Capture the Effect of Negative Signal on Performance

	Estimate (standard error) Pr(>|t|)
Negativefeedback	–0.174 (0.05)**
Monday	0.226 (0.08)**
Tuesday	0.168 (0.08)*
Wednesday	–0.091 (0.07)
Thursday	0.132 (0.07)′
Friday	0.203 (0.08)**
Saturday	0.105 (0.06)
Week_dummy2	–0.32 (0.03)**
Week_dummy3	–0.39 (0.03)**
Week_dummy4	–0.36 (0.03)**
Week_dummy5	–0.45 (0.04)**
Week_dummy6	–0.47 (0.04)**
Week_dummy7	–0.46 (0.04)**
Week_dummy8	–0.42 (0.04)**
Week_dummy9	–0.49 (0.04)**
Week_dummy10	–0.47 (0.04)**
Week_dummy11	–0.53 (0.05)**
Week_dummy12	–0.58 (0.05)**
Week_dummy13	–0.55 (0.05)**
Week_dummy14	–0.53 (0.05)**
Week_dummy15	–0.57 (0.06)**
Week_dummy16	–0.54 (0.06)**
Week_dummy17	–0.58 (0.06)**
Week_dummy18	–0.55 (0.06)**
Week_dummy19	–0.60 (0.06)**
Week_dummy20	–0.62 (0.06)**
Week_dummy21	–0.64 (0.07)**
Week_dummy22	–0.61 (0.07)**
Week_dummy23	–0.64 (0.07)**
Week_dummy24	–0.60 (0.07)**
Week_dummy25	–0.64 (0.07)**
Week_dummy26	–0.62 (0.07)**
Multiple R^2: 0.222	
Adjusted R^2: 0.219	

Note. Sample size = 4,936,264.
′$p < 0.1$; *$p < 0.05$; **$p < 0.01$.

other words, we want to see how the opportunity to lower the premium in the UBI policy can encourage drivers to be safer and better drivers while using the UBI device. To study the effect of economic incentives, we look for some exogenous differences in the premium that UBI customers pay, 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 is 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 selection issues in our identification.

The customers in our data set are from 15 states, allowing us to explore the regulatory differences in auto insurance markets across states. These regulations affect the insurance companies' costs 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 test the effect of economic incentives 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.

6.2.1. 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.)

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. 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, and UBI was first introduced in the United States in 2011. Therefore, there is no system change during our sample period.

In 2015, 13 states in the United States mandated the use of a No-Fault auto insurance policy. (Some states, but none in our data set, 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 induces higher premiums, which helps us to test the effect of economic incentives on changing driving behaviors in a UBI program.

As explained in the data section of this paper, the customers in our data set are from 15 different states, and four of them (Minnesota, Michigan, Pennsylvania, and New Jersey) have the No-Fault insurance system by regulation. To control for the differences in geography, we select four Fault states in the Midwest and eastern United States—namely, Wisconsin, Connecticut, Maryland, and Virginia—to compare with the No-Fault states. In Online Appendix Table B13, we provide a brief comparison of the Fault and No-Fault states. The key differences between the two groups of states are that the average monthly premium, UBI acceptance rate, and average age in No-Fault states are significantly higher than in traditional Fault states.[24] Since the premium is higher in No-Fault states, the UBI policy seems to be more attractive in these states, and this is reflected in a significantly higher UBI acceptance rate ($p < 0.05$) in No-Fault states. If anything, this would mean that the

UBI program is less selective in No-Fault states, so that we are likely to see a smaller effect, ceteris paribus, in No-Fault states. Similarly, the higher average age of enrollees in the No-Fault states would also limit the effect of the UBI policy in these states, as our main study indicates a greater improvement in UBI score for younger as compared with older drivers.

As the UBI discount is a percentage applied to the total premium, the economic incentives for better driving are higher in No-Fault insurance states because of the greater saving that UBI customers can gain from better performance. Consequently, comparing the changes in driving behavior of UBI customers in these two types of states after controlling for other factors (age, gender) can help us to detect the economic incentive's effect on driving behavior improvement in the UBI program.

We employ a fixed-effects model to test for changes in driving behaviors across the two types of states by considering the interaction of the state-type variable (Fault and No-Fault) and week dummy variables (see Table 6). We find that the average UBI score in No-Fault insurance states in the first week is marginally higher ($p < 0.08$) than in Fault states. More interestingly, the estimated changes in the weekly UBI score of No-Fault insurance states (mean = 5.77) is significantly higher ($p < 0.05$) than in Fault states (mean = 4.88). We find similar results for the number of hard brakes. 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.[25]

We also checked to see if the results reported in Table 6 also held if we controlled for gender and for age. As reported in Online Appendix Table B18, the results in Table 6 hold if we do the analysis separately for males and for females—that is, the No-Fault states show a greater improvement in UBI scores than the Fault states for males and females separately. For age, we find that No-Fault states show a greater gain in UBI score than in Fault states for each of the four age groups except for the senior drivers, and that the youngest drivers show the greatest gain. To provide tighter geographic control we compare Wisconsin (Fault) to two adjacent (No-Fault) states: Michigan (No-Fault), with the highest average premium cost in our sample, and Minnesota (No-Fault). In both pairwise comparisons there is a greater change in UBI score and number of hard brakes for Michigan and for Minnesota as compared with Wisconsin. Note also that Michigan has a lower average income than Wisconsin and Minnesota

Table 6. Weekly Changes in UBI Score Estimation for Customers in Fault vs. No-Fault States (8 States)

	Coefficients estimation	
	Fault states (standard error)	No-Fault × *week_dummies* (standard error)
Week_dummy2	1.84 (0.06)**	0.43 (0.14)**
Week_dummy3	2.37 (0.06)**	0.21 (0.14)
Week_dummy4	2.94 (0.06)**	0.18 (0.14)
Week_dummy5	3.39 (0.06)**	0.12 (0.14)
Week_dummy6	3.47 (0.06)**	0.24 (0.15)
Week_dummy7	3.62 (0.06)**	0.28 (0.15)*
Week_dummy8	3.69 (0.06)**	0.31 (0.15)*
Week_dummy9	3.75 (0.06)**	0.46 (0.15)**
Week_dummy10	3.91 (0.07)**	0.42 (0.16)**
Week_dummy11	4.24 (0.07)**	0.65 (0.16)**
Week_dummy12	4.46 (0.07)**	0.46 (0.16)**
Week_dummy13	4.52 (0.07)**	0.40 (0.16)**
Week_dummy14	4.54 (0.07)**	0.39 (0.16)**
Week_dummy15	4.58 (0.07)**	0.45 (0.16)**
Week_dummy16	4.51 (0.08)**	0.53 (0.16)**
Week_dummy17	4.57 (0.08)**	0.56 (0.17)**
Week_dummy18	4.61 (0.08)**	0.60 (0.17)**
Week_dummy19	4.59 (0.08)**	0.64 (0.17)**
Week_dummy20	4.65 (0.08)**	0.68 (0.17)**
Week_dummy21	4.68 (0.09)**	0.64 (0.17)**
Week_dummy22	4.74 (0.09)**	0.73 (0.18)**
Week_dummy23	4.76 (0.09)**	0.78 (0.18)**
Week_dummy24	4.73 (0.09)**	0.84 (0.18)**
Week_dummy25	4.81 (0.09)**	0.87 (0.18)**
Week_dummy26	4.88 (0.09)**	0.89 (0.18)**
Multiple R^2: 0.522		
Adjusted R^2: 0.517		

Note. Sample size = 383,829.
$*p < 0.05$; $**p < 0.01$.

a higher average income than Wisconsin (Online Appendix Tables B15 and B16).

7. Possible Long-term Effect

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. One way to assess the long-term impact of improved UBI performance of participants in the program would be to have direct measures of long-term driving performance. While we do not have data on accidents, we do have data on the insurance score for the next two years for those participants who continue with the company. While insurance scores depend on a number of factors, one important factor is whether a driver has had an accident. We examine the insurance score for the first renewal (six months after the monitoring ends) and second renewal (18 months after the monitoring ends); we study both, but the latter time point provides a better measure of long-term impact than would be available with the first renewal. Using a simple linear model (see Equation (6)) where the dependent variable is change in insurance score at the one-year point and two-year point (as compared with the initial insurance score), and considering the changes in UBI score as a covariate and controlling for age and gender, we find that the change in UBI score from week 1 to week 26 is positively ($p < 0.05$) related to the change in insurance score.

$$\begin{aligned}
&\Delta IS_i = \alpha + state_i + \beta_1 \times age_i + \beta_2 \times male_i + \beta_3 \times \Delta UBI_i + \varepsilon_{it},\\
&\Delta IS_i : Changes\ in\ insurance\ score\ of\ customer\ i\ after\\
&\qquad 1\ (or\ 2)\ year,\\
&\Delta UBI_i : Changes\ in\ UBI\ score\ of\ customer\ i\ after\ 26\ weeks.
\end{aligned} \tag{6}$$

The detailed results are in Table 7. This provides suggestive evidence that the improvement in driving behavior during the monitoring period has a long-term effect on driving behavior.[26]

Table 7. Long-term Effect of Changes in UBI Score on Changing the Insurance Score

	Estimate (standard error)	
	First renewal	Second renewal
Intercept	4.73 (0.15)**	9.04 (0.14)**
Age	−0.06 (0.005)**	−0.09 (0.02)**
Gender (male)	−0.14 (0.06)*	−0.32 (0.17)′
Δ UBI	0.07 (0.03)*	0.09 (0.04)*
Multiple R^2	0.48	0.45

Note. Sample size of first renewal observations = 20,754; sample size of second renewal observations = 7,178.
′$p < 0.1$; *$p < 0.05$; **$p < 0.01$.

8. Discussion

UBI auto insurance was introduced in the United States 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. If such improvement occurs, then the benefits would go beyond the company's profitability and lower prices for better drivers, to a meaningful societal and public health benefit from having fewer car accidents. To test for possible improvement in driving improvement among UBI customers, we use a unique sensor-based data set, which allows us to observe the individual-level customer data from a major auto insurance company and to track the driving behavior of customers who enrolled in the UBI program for up to six months. The challenge is that we are unable to compare driving behavior of users who signed up for UBI relative to those who did not because of the nature of the data collection. Therefore, our results directly apply only to those drivers who self-select into UBI during the time they are being monitored. 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.[27] However, drivers do not generally reduce the daily number of miles driven, another factor related to the likelihood of an accident. Changing such behaviors as the number of hard brakes may be easier for drivers than mileage reduction, which typically involves finding alternative 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.

Importantly, behavior changes occur immediately after a consumer adopts the UBI program and continue throughout the observation period. For both the overall UBI score and number of hard brakes, we observe improvement, as compared with the first week, as soon as the second week. After 11 weeks of improvement for the UBI score and six weeks of improvement for the number of hard brakes, the average driving behavior remains at that level without declining for the rest of the observation period. Because of the limitation of the technology, we cannot observe the drivers' behavior after the removal of the UBI device. However, our analysis on the drivers' renewal insurance scores after the device was removed in one year and two years after enrolling in the program provide some evidences on the long-term effect of their UBI usage.

In addition, we find that the improvements in driving behavior vary across age groups and by gender. All age groups improve their UBI score during the program, but members of the youngest group (those less than or including 35 years of age) improve the most and have the highest UBI score after six months of UBI usage over all age groups, despite starting with the lowest UBI score. Higher economic incentives and different learning patterns for younger, less experienced drivers compared with other drivers 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 may make a 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. However, it is important to note that older, more experienced drivers also have higher UBI scores at the end of the 26-week monitoring period, suggesting that more is occurring than just maturation or learning by young, relatively inexperienced drivers. In this paper, we do not separately identify these key factors underlying the differences in driving-behavior changes across age groups, leaving 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 because of 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 Angrist and Lavy (2009).

We also find that UBI customers who receive increased negative feedback in a day—that is, their number of hard brakes increased in the past day compared with the previous day—reduce their number of hard brakes more than the UBI customers who do not receive increased negative feedback. These results suggest that the customers are paying attention to the feedback that they receive and are able to change their behavior in response to such feedback.

Merely being monitored could also account for some of the effects we observe, but if that was the sole driver of our results, we would expect that the improvement observed would likely remain constant after an initial improvement or decline over time. However, we do not observe such a pattern and, moreover, the significant results for negative feedback and economic incentives, discussed next, would be unlikely to occur if monitoring were the primary factor associated with improved driving behavior.

To further understand the potential underlying mechanisms driving the behavior changes, we explore the different regulations across states in our data set. 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, since UBI customers in No-Fault states (higher-premium states) can save more than in the other states, our results showing that these customers may try to improve their driving behaviors more to get a higher discount rate on their initial premium suggest that economic incentives are important in the level of driving improvement that occurs.

8.1. 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 concerned about the privacy of their information and may be reluctant to share their information.

Importantly, in this study we show that there are direct benefits to the individuals from agreeing to have their behavior monitored. We observe two main benefits: (1) driving performance improves (as measured by the overall UBI score and the number of hard brakes), and (2) participants (who remain in the program for at least 75 days) receive a discount on the auto insurance premium that they would otherwise have been charged if they had not been in the UBI program. This discount is permanent for as long as the person remains with the company. Participants in the UBI program have higher renewal rates than nonparticipants, suggesting that these benefits are of value to individuals who enrolled in the program, and consequently the cost of allowing private information to be monitored (at least for a limited time) and other costs of enrolling in a new program are outweighed by the benefits received. These results showing a direct personal benefit of revealing private information in a large-scale setting are novel, to the best of our knowledge; however, further detailed examination of the impact of privacy concerns on participation in monitoring programs is clearly warranted.

8.2. 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 with 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 participants 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. In addition, the current UBI programs are mostly positioned as cost-saving options for consumers. Our results demonstrate that the benefits of UBI for consumers extend beyond lower price to encompass safer driving. The insurance company could emphasize the benefit of UBI on driving improvement, which is particularly attractive for younger and less experienced drivers.

The heterogeneous effect of the UBI policy on changing driving behavior across age groups is another interesting managerial result. Younger drivers appear to be an attractive target market for companies offering UBI programs, particularly if our results that younger drivers who enroll in the program have the greatest change in their driving behavior holds for a wider sample of young drivers who would be the specific targets of a marketing campaign. If so, then retaining these younger drivers over the long term would likely be an additional benefit to the company.

8.3. Social Benefits

If the UBI program, in fact, leads to safer driving behavior, then society as a whole gains, as there will be fewer accidents. The most important result would be that fewer people are injured or killed in motor vehicle accidents, a clear societal benefit. The magnitude of motor vehicle accidents is substantial: in 2015 in the United States, there were more than 11 million traffic accidents and 22,000 fatalities from such accidents (https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812413), so that improved driving behavior could have a significant impact on the country's welfare. Public policy officials would be well advised to take note of these potential benefits from UBI programs and other alternatives that monitor, provide feedback, and offer incentives for safer driving. And, of course, the decrease in property damage would be a substantial welfare benefit as well. A full analysis of the magnitude of these benefits is beyond the scope of this research, but safer driving would clearly be in the best interests of society.

8.4. 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. Our results for insurance scores suggest that the results hold for an extended period of time, but to fully 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 Google Maps and Waze.

There are 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 his or her 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. Finally, but more speculative, our findings have implications for helping consumers to engage in safe and healthy behaviors. For example, in the healthcare sector, Patel et al. (2016) 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.

Acknowledgments

The authors are listed alphabetically.

Endnotes

[1] Source: World Health Organization, Global status report on road safety 2015, http://www.who.int/violence_injury_prevention/road_safety_status/2015/en.

[2] https://progressive.mediaroom.com/2015-05-14-Lead-Foot-Report-from-Progressive-R-Insurance-Busts-Industry-Braking-Standards.

[3] Rainie and Duggan (2016), Privacy and Information Sharing, Pew Research Center.

[4] That is, states using a tort (Fault) auto insurance system where the driver who is at fault for causing a traffic crash is responsible for paying the victim's medical and other expenses including property damages.

[5] 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.)

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

[7] Strategy Meets Action (SMA) is a leading strategic advisory services firm in the insurance industry.

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

[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.

[10] "Comparing Real-World Behaviors of Drivers with High vs. Low Rates of Crashes and Near-Crashes" (U.S. Department of Transportation,

National Highway Traffic Safety Administration, February 2009) is another source of information on this issue.

[11] Scism 2016, https://www.wsj.com/articles/car-insurers-find-tracking-devices-are-a-tough-sell-1452476714.

[12] We use census data to classify the customers into urban or rural areas based on ZIP code (http://mcdc.missouri.edu/websas/geocorr2k.html).

[13] $p = 0.06$.

[14] 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 data set.

[15] Although the UBI formula used by the company we study is confidential, The Co-operators (a major Canadian auto insurance company that offers UBI insurance in the province of Ontario) discloses such information on its website. The Co-operators puts the following weights on these four elements: sudden braking has the highest weight (0.35) followed by distance travelled (0.25), late night driving (0.20), and rapid acceleration (0.20) (https://enroute.cooperators.ca).

[16] Sixty-three percent of UBI customers remain in this program for the entire 26 weeks. As shown in Online Appendix Table A1, withdrawing early decreases the level of permanent discount that customer receive, but they still receive a discount.

[17] The Lead Foot Report, Progressive Insurance Company, November 2015, https://www.progressive.com/newsroom/article/2015/may/lead-foot-report-from-progressive.

[18] In addition, we run another cross-sectional analysis by considering just the first-week UBI score as the dependent variable. The results are in Online Appendix Table A4. The senior drivers tend to have higher UBI score in the first week, and females drive significantly better than males in the first week of monitoring. In addition, the customers who live in rural area have higher initial UBI scores compared with urban customers.

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

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

[21] 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.

[22] For millennials, the mileage in week 26 is 0.92 miles higher than in the first week, when the average miles driven totaled 25.73.

[23] We also conduct this analysis at the weekly level and find similar results that consumers improved more after they receive more negative feedback in the previous week.

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

[25] Our results for UBI score and hard brakes also hold if we include all of the Fault states in our analysis instead of just the four Fault system states (Online Appendix Table B14).

[26] We also test the long-term effect of UBI adoption on changes in insurance score in Online Appendix Table A3.

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

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