MONITORING, SENSOR DATA, PRIVACY, AND CONSUMER BEHAVIOR: THE
CASE OF USAGE-BASED AUTOMOBILE INSURANCE

by

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Abstract

The Internet of Things (IoT)-powered services can deliver incredible monitoring capabilities to businesses and their customers. The IoT continues to evolve and reshape the businesses in different industries by collecting individuals’ sensor-based data. In the insurance industry, Usage-Based Insurance (UBI) is a recent auto insurance innovation that enables insurance companies to collect individual-level driving data, provide feedback on driving performance, and offer individually targeted price discounts based on each consumer’s driving behavior. In this thesis, we study consumer behavior from different perspectives in the presence of UBI program that relies on using consumers’ private data in three independent essays.

In the first essay, we examine and estimate the effect of the UBI policy on changing the customers’ driving behavior. By considering a fixed-effect model of drivers, we find that motorists improve their driving behavior, resulting in being safer drivers, providing a meaningful benefit for both the driver and the insurance company. We also find heterogeneous effects across different demographic groups. For example, younger drivers are more likely to adopt UBI and they also improve their UBI performance faster than older drivers.

To examine the tradeoffs consumer makes between costs (including privacy) and economic benefits of UBI, we study consumers’ adoption and usage of UBI by developing a dynamic structural model in the second essay. Our results suggest that the costs of being monitored (including privacy concerns) are significant, and they vary across demographic characteristics. Using a natural experiment resulting from a major (exogenous) data breach to examine the effect
of changing privacy perception, we also find that the data breach is associated with a decrease in retention rates among currently monitored customers.

In the third essay, we evaluate the effect of the UBI policy on changing the insurance coverage choice at the renewal time compared to the initial purchase. The results suggest that the UBI customers are significantly more likely to change their coverage choice than non-UBI customers at the renewal time. We capture price discount and information effects as two major sources of difference between UBI and non-UBI customers that could affect the different pattern of insurance coverage choice.
Lay Summary

Usage-Based Insurance (UBI) is a recent auto insurance innovation that enables insurance companies to collect driving data, provide feedback on driving performance, and offer individually targeted price discounts based on each consumer’s driving behavior. This thesis studies the effects of the UBI policy on consumer behavior from different aspects to better understand the costs and benefits of UBI policy in consumer and firm’s perspectives.

Our results suggest that by sharing private consumer information with the insurance company, UBI is not only beneficial to the company, but also to consumers who become better drivers. In addition, the customers who adopt and use the UBI policy are more likely to change their initial insurance coverage choice because of the price discount and information effects. We also capture and quantify the tradeoffs consumers make between costs (including privacy concern) and economic benefits of UBI by studying consumers’ adoption and usage of UBI.
Preface

I was the primary author of the work presented in this PhD thesis. I was responsible for identifying the research questions, conducting the literature review, collecting and managing supplementary data, analyzing the data, modeling and coding the estimation procedures, and preparing the manuscript. Specific contributions for each chapter are described below.

Chapter 1: Introduction.

I am the primary author of this chapter with intellectual contributions from Charles Weinberg and Ting Zhu.

Chapter 2 (Essay 1): Sensor Data and Behavioral Tracking: Does Usage-Based Auto Insurance Benefit Drivers?

I was primarily responsible for identifying the research question, preparing the literature, developing the model and estimation strategy, implementing data cleanup, and carrying out the estimations, as well as preparing the manuscript. Charles Weinberg and Ting Zhu contributed by editing the manuscript, identifying and positioning the research question. A major insurance company in US provided the dataset.


Chapter 3 (Essay 2): Threats to Privacy versus Saving Money: A Study of Consumers’ Adoption and Usage of Usage-Based Insurance
I identified the research question, reviewed the literature, developed the model, carried out the counterfactuals and prepared the manuscript. Charles Weinberg and Ting Zhu contributed to the model development, editing the manuscript, identifying and positioning the research question. A major insurance company in US provided the dataset.

Chapter 4 (Essay 3): The Effect of Lower Prices and Better Information on Insurance Coverage Choices: Insights from Usage-based Auto Insurance

I was primarily responsible for identifying the research question, preparing the literature, developing the model, as well as preparing the manuscript. Charles Weinberg and Ting Zhu contributed by editing the manuscript, identifying and positioning the research question. A major insurance company in US provided the dataset.

Chapter 4: Conclusion

I was the author of this chapter with intellectual contributions from Charles Weinberg and Ting Zhu.
Table of Contents

Abstract ................................................................................................................................. iii
Lay Summary .......................................................................................................................... v
Preface ....................................................................................................................................... vi
Table of Contents .................................................................................................................... viii
List of Tables ........................................................................................................................... xii
List of Figures .......................................................................................................................... xv
Acknowledgements ................................................................................................................ xvii
Dedication ............................................................................................................................... xviii

Chapter 1: Introduction ......................................................................................................... 1

Chapter 2: Sensor Data and Behavioral Tracking: Does Usage-Based Auto Insurance
Benefit Drivers? ....................................................................................................................... 9

2.1 Introduction ..................................................................................................................... 9

2.2 Literature Review ............................................................................................................ 14

2.2.1 Usage-Based Pricing .................................................................................................. 14

2.2.2 Information and Feedback .......................................................................................... 17

2.2.3 Economic Incentives .................................................................................................. 18

2.3 Industry background ....................................................................................................... 19

2.4 Data .................................................................................................................................... 21

2.4.1 Description of the UBI policy ..................................................................................... 21

2.4.2 Descriptive Evidence of Improvement in Driving Behavior ...................................... 29

2.4.2.1 The Weekly Average UBI Score ............................................................................ 29
Chapter 2: Possible Factors Associated with Improvement in Driving

2.4.2.2 Average Changes in Number of Hard Brakes ................................................. 30
2.4.2.3 Average Changes in Daily Mileage ................................................................. 30

2.5 Empirical Analysis and Results ........................................................................... 31

2.5.1 Model Specification ......................................................................................... 32

2.5.2 Heterogeneity Across Different Groups of Customers .................................... 37

2.5.2.1 Age groups ..................................................................................................... 38

2.5.2.2 Gender ........................................................................................................... 41

2.5.2.3 Other Factors ................................................................................................. 42

2.6 Possible Factors Associated with Improvement in Driving ............................... 43

2.6.1 Immediate Negative Feedback and Driver’s Performance .............................. 44

2.6.2 Economic Incentives and Drivers’ Performance ............................................. 45

2.6.2.1 No-Fault Auto Insurance ............................................................................... 46

2.7 Possible Long-term Effect ................................................................................... 49

2.8 Discussion ........................................................................................................... 51

2.8.1 Privacy Issues and Consumer Benefits .......................................................... 54

2.8.2 Managerial Implications ................................................................................ 55

2.8.3 Social Benefits ................................................................................................ 56

2.8.4 Limitations and Future Research ...................................................................... 57

2.9 Tables and Figures .............................................................................................. 59

Chapter 3: Threats to Privacy versus Saving Money: A Study of Consumers’ Adoption and Usage of Usage-Based Insurance ................................................................................. 70

3.1 Introduction ......................................................................................................... 70

3.2 Literature Review ............................................................................................... 76
3.3 Data ................................................................................................................................. 84

3.3.1 Data Breach and Consumer Adoption and Termination .............................................. 88
3.3.2 Model-free and Reduced-form Analysis Results .......................................................... 90

3.4 Model Setup ................................................................................................................... 93

3.4.1 Dynamic Structural Model ....................................................................................... 93
3.4.2 Discount Function ...................................................................................................... 100
3.4.3 State Space and Transition Probabilities .................................................................... 102
3.4.4 Structural Modeling to Capture the Effect of Data Breach ........................................ 104

3.5 Estimation and Empirical Results .................................................................................. 105

3.5.1 Transition Probabilities’ Estimation ......................................................................... 105
3.5.2 Discount Function Estimation .................................................................................... 109
3.5.3 Second – and Third – Year Premiums ....................................................................... 110
3.5.4 Dynamic Structural Model Parameters’ Estimation ................................................... 111
3.5.5 Observed Heterogeneity across Age and Gender Groups ......................................... 114
3.5.6 Unobserved Heterogeneity within Age Groups ........................................................ 116
3.5.7 Effect of Data Breach ................................................................................................. 117
  3.5.7.1 Heterogeneous Effect of Data Breach ................................................................. 118

3.6 Counterfactual Analysis .................................................................................................. 120

3.7 Discussion ....................................................................................................................... 122

3.7.1 Implications ............................................................................................................... 125
3.7.2 Limitations and Future Research .............................................................................. 128

3.8 Tables and Figures ........................................................................................................ 131
List of Tables

Table 2.1 The Summary Statistics of All Customers................................................................. 59
Table 2.2 Logit Regression Analysis Results for UBI Adoption.............................................. 59
Table 2.3 Cross-Sectional Regression Analysis Results for UBI Score.................................. 60
Table 2.4 Fixed-Effects Regression Analysis Results for Three Measures of Driving Behavior 61
Table 2.5 Fixed-Effects Regression Results for Number of Daily Hard Brakes to Capture the
Effect of Negative Signal on Performance .......................................................................... 62
Table 2.6 Weekly Changes in UBI Score Estimation for Customers in Fault vs. No-Fault States
(8 States) ............................................................................................................................... 63
Table 2.7 Long-term Effect of Changes in UBI Score on Changing the Insurance Score .......... 63
Table 3.1 Summary Statistics of UBI Adoption .......................................................................... 131
Table 3.2 Summary Statistics of “Loyal” and “Dropout” UBI Customers................................. 131
Table 3.3 Estimated Effect of Data Breach on UBI Adoption Rate ......................................... 132
Table 3.4 Estimated Effect of Data Breach on UBI “informed dropout” Rate......................... 132
Table 3.5 Estimated Coefficients of Power Function for Conditional Distribution of UBI Score
.................................................................................................................................................. 133
Table 3.6 Nonparametric Estimation of UBI Adoption Rate .................................................... 133
Table 3.7 Generalized Additive Regression Model Estimation for First-period UBI Score ..... 133
Table 3.8 Estimation of Insurance Premiums at Second and Third Years ............................... 134
Table 3.9 Estimated Coefficients of Structural Model (3-year time horizon).......................... 134
Table 3.10 UBI Adoption and Dropout Rate among Different Age and Gender Groups of
Customers ............................................................................................................................... 134

xii
Table 3.11 Structural Model Parameter Estimation for Two Age Groups ........................................... 135
Table 3.12 Structural Model Parameter Estimation for Two Gender Groups ................................. 135
Table 3.13 Structural Model Parameter Estimation for Two Age Groups with Unobserved Heterogeneity .......................................................................................................................... 135
Table 3.14 Extended Structural Model Parameter Estimation Considering Data-Breach Event 136
Table 3.15 Extended Structural Model Parameter Estimation Considering Data-Breach Event (Heterogeneity across Genders) .......................................................................................................................... 136
Table 3.16 Extended Structural Model Parameter Estimation Considering Data-Breach Event (Heterogeneity across Age Groups) .......................................................................................................................... 137
Table 4.1 The Summary Statistics of Customers .................................................................................. 176
Table 4.2 Logit Regression Analysis Results for Initial Coverage Choice ........................................... 177
Table 4.3 Upgrading and Downgrading Percentages for UBI and Non-UBI Customers .............. 177
Table 4.4 Multinomial Regression Analysis Results for Changing the Coverage Choice ............ 177
Table 4.5 Multinomial Regression Analysis Results for Changing the Coverage Choice at Second Renewal .......................................................................................................................... 178
Table 4.6 Estimation Changes in Insurance Coverage Choice Using Propensity Score Matching .......................................................................................................................... 178
Table 4.7 Logit Regression Analysis Results within UBI Customers for Upgrading Decision in First Renewal .......................................................................................................................... 179
Table 4.8 Comparing UBI and Non-UBI Customers in Adding the Comprehensive Coverage at Renewal .......................................................................................................................... 179
Table 4.9 Logit Regression Results for Comprehensive Decision within UBI Customers ............ 179
Table 4.10 Heterogeneous Effects of UBI Usage on Changing the Coverage Choice ............... 180
Table A.1 Regression analysis results for daily UBI score. ...................................................... 196
Table A.2 Regression analysis results for long term effect of UBI adoption. ......................... 197
Table A.3 Data summary of Fault and No-Fault states (UBI customers)................................. 197
Table A.4 Fixed effects regression analysis results for UBI Score for Wisconsin vs. Michigan.
.............................................................................................................................................. 198
Table A.5 Fixed effects regression analysis results for UBI Score for Wisconsin vs. Minnesota.
.................................................................................................................................................... 199
Table A.6 Logit regression analysis results for UBI adoption.................................................. 200
Table A.7 Logit regression analysis results for UBI “informed dropout” decision............... 202
# List of Figures

Figure 2.1 Flowchart of Customer and Firm Decisions in UBI Policy ................................................. 64
Figure 2.2 Weekly Dropout Within UBI Program .................................................................................. 65
Figure 2.3 Weekly Average UBI Score .................................................................................................. 65
Figure 2.4 Average Daily Number of Hard Brakes ............................................................................... 66
Figure 2.5 Average Daily Mileage ...................................................................................................... 66
Figure 2.6 Fixed-Effects Estimation of Daily Changes in Driving Behavior of UBI Customers 67
Figure 2.7 Weekly Changes Estimation in Driving Behavior for Different Age Groups .......... 68
Figure 2.8 Weekly Changes Estimation in Driving Behavior for Different Genders .................. 69
Figure 2.9 Weekly Changes Estimation in Driving Behavior for Urban vs. Rural Drivers .... 69
Figure 3.1 UBI Policy Timeline for Adoption and Dropouts ............................................................... 138
Figure 3.2 “Data Breach” Searched Keyword in US ........................................................................... 138
Figure 3.1 Data-Breach Event .............................................................................................................. 138
Figure 3.4 UBI Adoption and Informed Dropout Rate across 4 Periods ............................................ 139
Figure 3.5 Timeline of Decision Process in the Model ....................................................................... 139
Figure 3.6 Decision-Making Process at t = 0,1 .................................................................................... 139
Figure 3.7 UBI Monitoring and Remaining Periods in 3-year Time Horizon ...................................... 140
Figure 3.8 Estimated Adjusted Permanent Discount Functions ......................................................... 140
Figure 3.9 Simulated Adoption Rate in Counterfactual Analysis by Reducing the Costs ............ 140
Figure 3.10 Simulated Adoption Rate in Counterfactual Analysis by Increasing the Costs ...... 141
Figure 3.11 Counterfactual Estimation of Dropout Rates after Reduction in Costs .................... 141
Figure 3.12 Counterfactual Estimation of Dropout Rates after Increase in Costs ....................... 142
Figure 4.1 Events and Decisions’ Flow in our Setting ................................................................. 181

Figure 4.2 Coverage Choice Distributions for UBI and Non-UBI Customers............................. 181
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Dedication

This thesis is dedicated to my parents, Soheila and Seyedabbas, and my beloved wife, Mona.
Chapter 1: Introduction

The Internet of Things (IoT) has reshaped many industries over the last few years and led to significant transformation in business models. According to Gartner\(^1\) the IoT is likely to grow to 20 billion installed units by 2020, each equipped with sensors collecting data from a vast array of physical objects. In addition to the technology itself and the data it gathers, the new digital business models the technology creates will cause great disruption across a wide range of industries\(^2\). The initial benefit of IoT technologies has been on the operations side, where collecting sensor-based data from smart machines can be leveraged to increase their efficiency and effectiveness. Beyond operations, IoT technologies are also creating new ways to monetize smart machine data that underlie digital business services. On the consumer side, there is also a shift to digital business services based on collecting sensor data that create new business opportunities and new revenue models. For example, automobile insurance companies can collect and analyze sensor-based data about the actual driving behavior of their customers to offer personalized coverage options and premiums. In this situation, the insurance rate of drivers reflects their actual driving performance rather than paying premiums based on general statistics. Understanding the importance of these new technologies and innovations can help companies to survive and increase their profits. Although the potential benefits of IoT and innovations that rely on collecting private data are mentioned in different industry white papers and articles, there are


\(^2\) https://www.forbes.com/sites/delltechnologies/2017/08/23/sensing-disruption-how-smart-machines-are-creating-new-business-models/#54e0891d37e0
many puzzling aspects of these new technologies on both the consumer and firm sides. The current thesis is mainly motivated as an attempt to better understand the consumer decision making and reaction in the domain of IoT industries that rely on collecting their private sensor data. In general, we explore the effects of using the new technologies and innovations on customers’ behavior by considering the case of usage-based auto insurance (UBI), one of the innovative IoT solutions in the insurance industry. This technology is becoming increasingly popular to generate insights for marketers and policy makers in this important context.

This thesis adopts a quantitative approach to conduct three sets of empirical studies in three independent essays. To this purpose we use a unique dataset from a major US auto insurance company that offers usage-based insurance as an optional policy. We observe the individual level sensor-based data on consumers’ decisions on insurance coverage choice, demographic information, adoption of the UBI policy, and the consumer panel on actual driving behavior when using the telematics device in UBI policy. Our dataset covers more than 130,000 customers, of which 30% enrolled in the UBI program. The first essay studies the effect of adopting and using the UBI policy on changing and improving the driving behavior of enrolled customers. The core question is whether the UBI optional policy could help the insurance customers to improve their driving behavior and what are the sources of potential improvement in actual driving performance. The second essay is an empirical research study to investigate how customers trade off the benefits and costs of being monitored, including privacy issues, to adopt and keep a new usage-based pricing system that relies on using private data (UBI). The central research question is, how do consumers trade off the cost saving in insurance premium both while they are being monitored and in the long run with the cost of installing, using and
being monitored by the telematics device required for participation in the UBI program? We capture and identify the individual cost of adopting and using a new technology that relies on sharing private data, including the cost of privacy concern by developing and estimating the parameters of a dynamic structural model. The third essay looks at another potential benefit of offering UBI program for the firms which is the possibility of upselling the higher insurance coverage at the time of renewal. In this study, we examine and evaluate the effect of adopting and using the UBI policy on consumers’ decision to upgrade and buy add-on products (higher insurance coverage over the basic coverage) or to decrease coverage at the renewal time. We conduct regression analysis to study the customers’ decision to keep or change their insurance coverage at the renewal time compared to their initial purchases. Comparing the coverage choice pattern of insurance policyholders who used UBI with non-UBI customers at the individual level could help in understanding the effect of offering usage-based insurance policies on upselling the insurance coverage. The findings of the three essays contribute to the relevant literature, have implications for consumers and insurance companies in the context of new technologies that rely on using sensor private data, and generate practical insight for managers and policymakers.

In the first essay, using detailed information on insurance premium, retention rates of customers and individual driving behavior (from sensor data) for the UBI adopters, we examine and estimate the effect of the UBI policy on changing the customers driving behavior, which is a

3 The non-UBI customers purchased the traditional insurance policy.
potential source of profit improvement for the insurance company beyond better selection among customers and higher retention rates. Usage-Based Insurance (UBI) is a recent auto insurance innovation that enables insurance companies to collect individual-level driving data, provide feedback on driving performance, and offer individually targeted price discounts based on each consumer’s driving behavior. The key results of our analysis show that after UBI adoption, motorists improve their driving behavior, resulting in being safer drivers, providing a meaningful benefit for both the driver and the insurance company. We find that not all components of the UBI measure appear to change over time. In particular, we find that customers decrease their daily average hard brake frequency by an average of 21% after using UBI for six months, but we cannot find any significant effects on the mileage driven by customers after UBI adoption. We also find heterogeneous effects across different demographic groups. For example, younger drivers are more likely to adopt UBI and they also improve their UBI scores faster than older drivers after UBI adoption; and females show more improvement than males. We also find that economic incentives lead to higher adoption rates of UBI and greater improvements in driving behavior. Our results suggest that by sharing private consumer information with the insurance company, UBI is not only beneficial to the company, but also to consumers who become better drivers.

The second essay empirically examines consumers’ tradeoffs between privacy and economic and social benefits by studying consumers’ adoption and usage of UBI by developing a finite-time horizon dynamic structural model. In UBI programs, consumers make trade-offs between their concern for privacy and the premium savings gained by allowing their driving behavior to be monitored for up to 6 months. Once enrolled, customers can drop out at any time,
but receive a lesser discount the earlier they do so. UBI is an excellent setting for studying the economic significance of privacy for several reasons. First, UBI is an option that the customer can choose to enroll in or not. In other words, the customer can obtain the same auto insurance policy with or without agreeing to be monitored. This is unlike many innovations, such as Google Maps, where disclosing private information is not optional if the full benefit of the service is to be realized. Second, the consumer knows what information is being monitored, as compared to many apps in which it is unclear what behaviors are actually being tracked. Third, the consumer receives a direct economic benefit, so that the cost of adopting and being monitored can be compared to the monetary value to each individual consumer. Importantly, a major, but exogeneous data breach, allows us to employ a quasi-experimental design to examine the effect of changing privacy perception on consumers’ decision to adopt or drop the UBI monitoring program. The estimated parameters of the dynamic structural model indicate the crucial role of both initial and ongoing costs on the customers’ adoption and dropout decisions and their heterogeneity across demographic characteristics. In a natural experiment design, we find that a major data breach that occurred during our data collection period is associated with a decrease in retention rates among customers who are currently being monitored, consistent with the view that consumers trade off privacy costs against economic benefits.

The third essay focuses on the possibility of insurance companies to upsell the insurance coverages at the customers’ renewal time in the presence of UBI policy. In this study, we examine and evaluate the effect of adopting and using the UBI policy on the consumers’ changes in their insurance coverage choice at the renewal time compared to their initial purchases. The results suggest that UBI and non-UBI customers have different patterns in changing insurance
coverage choices at renewal time. The UBI customers are significantly more likely to change their coverage choice than non-UBI customers. Changing price and information are two major sources of difference between UBI and non-UBI customers that could affect the different pattern of insurance coverage choice between these two groups. The discounted premium and lower price for UBI customers could encourage them to upgrade their insurance coverage. On the other hand, receiving feedback and information about actual driving behavior with a telematics device in UBI program could help customers to better understand their actual driving abilities and update (upgrade or downgrade) their coverage choice at renewal time. The results presented in Chapter 4 indicate that UBI customers are more likely to upgrade or downgrade their insurance coverage at the renewal time after controlling other factors as compared to non-UBI customers. Additionally, within UBI customers we find the customers who show better driving behavior (higher UBI score) and get a higher discount are more likely to upgrade their insurance coverage to more inclusive coverages. We also examine separately the price effect by studying the comprehensive coverage (e.g., theft and fire) which is not directly related to driving behavior and covering the accidents’ costs, but the coverage is more expensive. The results suggest that the UBI customers are significantly more likely to add just the comprehensive coverage to their current insurance coverage at the renewal time compared to non-UBI customers.

The chapters proceed as follows: First, we discuss the “Sensor Data and Behavioral Tracking: Does Usage-Based Auto Insurance Benefit Drivers?” in nine sections in Chapter 2; a version of this essay has been published as Soleymanian, Weinberg, Zhu, Marketing Science (2019). We provide the research problem and overview of the project in Section 2.1, and discuss the literature and industry background in Sections 2.2 and 2.3 respectively. We then describe the
datasets and the variables included in the analysis along with the model free results (Section 2.4).

We provide the empirical setting, analysis and the results in Section 2.5 followed by discussion on different factors associated with improvement in driving behavior and long-term effect of UBI in Sections 2.6 and 2.7. We close the chapter with limitations, suggestions for future work, and managerial and policy implications (Section 2.8). Tables and figures are provided at the end of chapter 2 (Section 2.9), but the appendix (Appendix A) is located at the end of the thesis.

Second, we structure the “Threats to Privacy versus Saving Money: A Study of Consumers’ Adoption and Usage of Usage-Based Insurance” essay (Chapter 3) in 8 sections. Section 3.1 introduces the research questions and provide a brief background on the usage-based insurance and the trade-off between costs and benefits of using new technologies. It also discusses an overview of the project and its contribution. Next, we review the literature and describe the dataset, descriptive statistics and reduced-form analysis results in Sections 3.2 and 3.3 respectively. We detail the dynamic structural model development in Section 3.4. The estimation and empirical results of our dynamic structural models discussed in Section 3.5 followed by counterfactual analysis in Section 3.6. Discussions on managerial and policy implications are provided in Section 3.7. Tables and figures are provided at the end of chapter 3 (Section 3.8), but appendix (Appendix B) is located at the end of the thesis.

In chapter 4 we discuss the “The Effect of Lower Prices and Better Information on Insurance Coverage Choices: Insights from Usage-based Auto Insurance” essay in 6 sections. First, we introduce the research questions and upselling opportunities in auto insurance industry in Section 4.1. We then review the relevant literature in Section 4.2 related to our research
questions in this study. Section 4.3 covers the dataset description for our empirical study and the
model-free results which support our hypotheses. The results of an empirical model to capture
the effect of UBI policy on changing the insurance coverage choice are presented in Section 4.4
followed by discussion and managerial implications in Section 4.5. Tables and figures are
provided at the end of chapter 4 (Section 4.6).

Finally, Chapter 5 provides a brief overview of the thesis and opportunities for future
research.
Chapter 2: Sensor Data and Behavioral Tracking: Does Usage-Based Auto Insurance Benefit Drivers?

2.1 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. Hard braking, a behavior that can be detected by the UBI program, is highly correlated with unsafe driving. The company that we study in this research 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.

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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, 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.

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6 Rainie and Duggan (2016), Privacy and Information Sharing, Pew Research Center.
In this essay, 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 essay 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, 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.

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7 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.
The rest of this essay 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.

2.2 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 study 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.

2.2.1 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 study, 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 study, 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.
2.2.2 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.
2.2.3 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\(^8\) 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

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\(^8\) 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.)
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.

2.3 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. According to SMA Research, 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

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10 Strategy Meets Action (SMA) is a leading strategic advisory services firm in the insurance industry.
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.\textsuperscript{11}

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 11), 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 essay, 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.

2.4 Data

2.4.1 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 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.13 A 2016 Wall

12 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.
13 "Comparing Real-World Behaviors of Drivers with High vs. Low Rates of Crashes andNear-Crashes" (U.S. Department of Transportation, National Highway Traffic Safety Administration, February 2009) is another source of information on this issue.
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.”

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) maybe offered no discount, a surcharge is never imposed. Figure 2.1 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 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 for each UBI customer who adopts this program. Table 2.1 reports some summary statistics of the customers in our sample.

The first column of Table 2.1 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. 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.

15 We use census data to classify the customers into urban or rural areas based on ZIP code (http://mcdc.missouri.edu/websas/geocorr2k.html).
Therefore, the incentive for younger drivers seems to be higher to adopt the UBI program compared with older or more experienced drivers.

Table 2.1 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 2.1, 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 2.1 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\textsuperscript{16} than that for non-UBI customers ($108) due to the lower insurance score; however, the

\textsuperscript{16} p = 0.06.
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 2.2 after considering the fixed effects of states.

\[ \text{UBI acceptance}_i = \text{logit}(\text{age}_i, \text{premium}_i, \text{state}_i, \text{gender}_i, \text{urban}_i, \text{new driver}_i). \]  \( (2.1) \)

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 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 Appendix Table A.1 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.\textsuperscript{17} Although we do not know the formula that the company uses to calculate the UBI score,\textsuperscript{18} we have data on two direct driving behavior measures.

\textsuperscript{17} 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.

\textsuperscript{18} 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) (\url{https://enroute.cooperators.ca}).
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 2.2, 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.¹⁹

In the next section we look at the weekly changes in our driving performance measures (UBI score, hard 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 2.5.1 we show that we obtain similar qualitative results for our main model when we use daily data.

¹⁹ Sixty-three percent of UBI customers remain in this program for the entire 26 weeks.
2.4.2 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.

2.4.2.1 The Weekly Average UBI Score

Figure 2.3(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 2.3(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 essay when we employ a more fully developed (fixed effects with panel data) econometric model of driving performance.
2.4.2.2 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. Figure 2.4(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 2.4(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.

2.4.2.3 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 2.5, panels (a) and (b). 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 2.3 and 2.4, 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.

2.5 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, 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.

### 2.5.1 Model Specification

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

\[
S_{it} = \alpha_0 + \alpha_1 \cdot age_i + \alpha_2 \cdot age_i^2 + \alpha_3 \cdot gender_i + \alpha_{13} \cdot age_i \cdot gender_i + \alpha_4 \cdot single_i + \\
\alpha_5 \cdot new\ driver_i + \alpha_6 \cdot insurance\ score_i + \alpha_7 \cdot urban_i + \beta' \cdot weekdummies_{it} + Statedummies_{i} + \epsilon_{it},
\]  

(2.2)

Where

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

\[age_i: the\ age\ of\ driver\ i,\]

\[insurance\ score_i: the\ insurance\ score\ of\ driver\ i\ before\ starting\ UBI,\]

\[gender_i = \begin{cases} 
  1 & \text{if the driver } i \text{ is female} \\
  0 & \text{else,} 
\end{cases}\]

\[single_i = \begin{cases} 
  1 & \text{if the driver } i \text{ is single} \\
  0 & \text{else,} 
\end{cases}\]
\[
new\ driver_i = \begin{cases}
1 & \text{if the driver } i \text{ is applying for an insurance policy for the first time} \\
0 & \text{else,}
\end{cases}
\]

\[
urban_i = \begin{cases}
1 & \text{if the driver } i \text{ lives in urban area} \\
0 & \text{else,}
\end{cases}
\]

\[
dummy_{it} = \begin{cases}
1 & \text{if the observation is in week } t \text{ after UBI adoption} \\
0 & \text{else},
\end{cases}
\]

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

\[
\text{weekdummies}_{it} = [dummy_{i2}, ..., dummy_{i26}]',
\]

\[
\epsilon_{it}: \text{identical and independent distributed across time } t \text{ and individual } i.
\]

In this specification, in addition to the age (at time of enrollment), gender, and interaction of age/gender of driver \( i \) in Equation (2.2), 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 2.3 shows the estimation results of the cross-sectional regression analysis.\(^{20}\) 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

\(^{20}\) In addition, we run another cross-sectional analysis by considering just the first-week UBI score as the dependent variable. 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.
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 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 (2.3)) with driver individual fixed effects. The approach identifies $\beta$ using variation within each individual driver.

$$S_{it} = \beta' \ast \text{weekdummies}_{it} + \text{driver}_i + \epsilon_{it}, \quad (2.3)$$

Where $\text{driver}_i$ is the fixed-effects parameter of a driver.

Table 2.4 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 2.4, 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 2.3 and 2.4 (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 (2.3) 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 2.4 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 2.4 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 2.4 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.\textsuperscript{21} 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

\textsuperscript{21} 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).
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 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 2.6 shows the estimated daily improvement in the fixed effects model for the first seven weeks with 48-day dummies of UBI usage. Figure 2.6 indicates the estimated coefficients in our fixed-effects model of UBI score and hard brakes.

2.5.2 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 2.5.1, we consider fixed-effects models to capture the weekly changes in driving behavior for different customer groups.
2.5.2.1 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 (2.3). Therefore, the fixed-effects model to capture heterogeneity across different age groups can be specified as

\[ S_{it} = \beta' \ast \text{weekdummies}_{it} + \gamma_2' \ast \text{agegroup2}_{i} \ast \text{weekdummies}_{it} + \gamma_3' \ast \text{agegroup3}_{i} \ast \text{weekdummies}_{it} + \gamma_4' \ast \text{agegroup4}_{i} \ast \text{weekdummies}_{it} + \text{driver}_i + \epsilon_{it}, \] (2.4)

\[
\begin{align*}
\text{agegroup1}_i &= \begin{cases} 
1 & \text{age of driver } i \leq 35 \\
0 & \text{else},
\end{cases} \\
\text{agegroup2}_i &= \begin{cases} 
1 & 35 < \text{age of driver } i \leq 50 \\
0 & \text{else},
\end{cases} \\
\text{agegroup3}_i &= \begin{cases} 
1 & 50 < \text{age of driver } i \leq 65 \\
0 & \text{else},
\end{cases} \\
\text{agegroup4}_i &= \begin{cases} 
1 & 65 < \text{age of driver } i \\
0 & \text{else},
\end{cases}
\]

In the above setting, we consider four age groups that are commonly employed in the auto insurance industry. 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

\[\text{http://www.datamentors.com/blog/insurance-generations-marketing-boomers-and-millennials.}\]
considered as the baseline in our fixed-effects model; therefore, the $\beta$ represents the changes in UBI score for the youngest age group of customers, and $\gamma_k$ 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.

Figure 2.7 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 2.7(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.

Each point in Figure 2.7(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;

\footnote{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.}
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 2.7(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 2.7(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, which, if anything, would limit their improvement in UBI score.

\textsuperscript{24} 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.
We find that the driving behavior changes of UBI customers, in terms of UBI score and number of hard brakes, differ across customer age groups, and that the youngest drivers 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.

2.5.2.2 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 (2.3) to capture the heterogeneity across males and females. So, we will have

$$S_{it} = \beta' \ast weekdummies_{it} + \delta' \ast Gender_i \ast weekdummies_{it} + driver_i + \epsilon_{it}, \quad (2.5)$$

where

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

Figure 2.8 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 28(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 2.8(b) shows the results of estimation for both males and females. Each plot point represents the weekly changes in daily number of hard brakes for males and females compared 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.

2.5.2.3 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 2.9. 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.

2.6 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 2.7, 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. 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 2.6 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.

2.6.1 Immediate Negative Feedback and Driver’s 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. 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:

$$
Hardbrakes_{it} = \gamma' \cdot \text{weekdummies}_{it} + \alpha' \cdot \text{weekdays}_{it} + \beta \cdot Negativefeedback_{it} + driver_i + \epsilon_{it},
$$

(2.6)

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 2.5 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.

### 2.6.2 Economic Incentives and Drivers’ Performance

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25 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.
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 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.

2.6.2.1 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 essay, 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 Appendix A Table A.3, 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. 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

\[\text{26 This is consistent with the RAND study, which shows that the premium in No-Fault states is higher.}\]
week dummy variables (see Table 2.6). 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.  

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 a higher average income than Wisconsin (Appendix A Tables A.4 and A.5).

2.7 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

27 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.
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 (2.7)) 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.

\[
\Delta IS_i = \alpha + state_i + \beta_1 * age_i + \beta_2 * male_i + \beta_3 * \Delta UBI_i + \epsilon_{it}, \quad (2.7)
\]

$\Delta IS_i$: Changes in insurance score of customer $i$ after 1 (or 2) year,

$\Delta UBI_i$: Changes in UBI score of customer $i$ after 26 weeks.
The detailed results are in Table 2.7. This provides suggestive evidence that the improvement in driving behavior during the monitoring period has a long-term effect on driving behavior.\textsuperscript{28}

\subsection*{2.8 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 essay 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

\textsuperscript{28} We also test the long-term effect of UBI adoption on changes in insurance score in Appendix A Table A.2.
occurrence of accidents. 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

29 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.
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 essay, 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.

2.8.1 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.

2.8.2 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.

2.8.3 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.

### 2.8.4 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.
2.9 Tables and Figures

Table 2.1 The Summary Statistics of All Customers

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

Table 2.2 Logit Regression Analysis Results for UBI Adoption

<table>
<thead>
<tr>
<th></th>
<th>Estimate (Std. Error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>0.4652 (0.004)**</td>
</tr>
<tr>
<td>Age</td>
<td>−0.0053 (0.00004)**</td>
</tr>
<tr>
<td>Premium</td>
<td>0.0008 (0.00004)**</td>
</tr>
<tr>
<td>Gender (Male)</td>
<td>−0.0014 (0.0013)</td>
</tr>
<tr>
<td>Dummy_urban</td>
<td>0.0137 (0.0028)**</td>
</tr>
<tr>
<td>New driver</td>
<td>0.0581 (0.0049)**</td>
</tr>
<tr>
<td>State dummies <strong>Included</strong></td>
<td></td>
</tr>
</tbody>
</table>

Sample Size=135540, (‘): p-value < 0.1, (*): p-value < 0.05, (**) : p-value < 0.01
Table 2.3 Cross-Sectional Regression Analysis Results for UBI Score

<table>
<thead>
<tr>
<th></th>
<th>Estimate (Std. Error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>63.47 (0.08)**</td>
</tr>
<tr>
<td>Age</td>
<td>-0.15 (0.01)**</td>
</tr>
<tr>
<td>Age^2</td>
<td>0.02 (0.04)</td>
</tr>
<tr>
<td>Gender (Female)</td>
<td>2.79 (0.03)**</td>
</tr>
<tr>
<td>Age \times gender</td>
<td>0.06 (0.04)</td>
</tr>
<tr>
<td>Single</td>
<td>-0.42 (0.09)**</td>
</tr>
<tr>
<td>New driver</td>
<td>0.26 (0.13)*</td>
</tr>
<tr>
<td>Urban</td>
<td>-0.41 (0.19)*</td>
</tr>
<tr>
<td>Insurance score</td>
<td>0.18 (0.07)**</td>
</tr>
<tr>
<td>Week dummy2</td>
<td>3.60 (0.09)**</td>
</tr>
<tr>
<td>Week dummy3</td>
<td>3.95 (0.09)**</td>
</tr>
<tr>
<td>Week dummy4</td>
<td>4.06 (0.09)**</td>
</tr>
<tr>
<td>Week dummy5</td>
<td>4.18 (0.09)**</td>
</tr>
<tr>
<td>Week dummy6</td>
<td>4.14 (0.09)**</td>
</tr>
<tr>
<td>Week dummy7</td>
<td>4.30 (0.10)**</td>
</tr>
<tr>
<td>Week dummy8</td>
<td>4.43 (0.10)**</td>
</tr>
<tr>
<td>Week dummy9</td>
<td>4.59 (0.10)**</td>
</tr>
<tr>
<td>Week dummy10</td>
<td>4.76 (0.10)**</td>
</tr>
<tr>
<td>Week dummy11</td>
<td>5.13 (0.11)**</td>
</tr>
<tr>
<td>Week dummy12</td>
<td>5.34 (0.11)**</td>
</tr>
<tr>
<td>Week dummy13</td>
<td>5.39 (0.11)**</td>
</tr>
<tr>
<td>Week dummy14</td>
<td>5.32 (0.11)**</td>
</tr>
<tr>
<td>Week dummy15</td>
<td>5.37 (0.11)**</td>
</tr>
<tr>
<td>Week dummy16</td>
<td>5.33 (0.11)**</td>
</tr>
<tr>
<td>Week dummy17</td>
<td>5.32 (0.12)**</td>
</tr>
<tr>
<td>Week dummy18</td>
<td>5.34 (0.12)**</td>
</tr>
<tr>
<td>Week dummy19</td>
<td>5.41 (0.12)**</td>
</tr>
<tr>
<td>Week dummy20</td>
<td>5.53 (0.12)**</td>
</tr>
<tr>
<td>Week dummy21</td>
<td>5.48 (0.12)**</td>
</tr>
<tr>
<td>Week dummy22</td>
<td>5.48 (0.12)**</td>
</tr>
<tr>
<td>Week dummy23</td>
<td>5.60 (0.13)**</td>
</tr>
<tr>
<td>Week dummy24</td>
<td>5.52 (0.13)**</td>
</tr>
<tr>
<td>Week dummy25</td>
<td>5.64 (0.13)**</td>
</tr>
<tr>
<td>Week dummy26</td>
<td>5.68 (0.14)**</td>
</tr>
<tr>
<td>State Fixed effects</td>
<td>Included</td>
</tr>
</tbody>
</table>

Multiple R-squared: 0.208  Adjusted R-squared: 0.198

Sample Size=705752, (·): p-value < 0.1, (*) : p-value < 0.05, (**) : p-value < 0.01
Table 2.4 Fixed-Effects Regression Analysis Results for Three Measures of Driving Behavior

<table>
<thead>
<tr>
<th>Variables</th>
<th>(a) Dependent variable: UBI score Estimate (standard error)</th>
<th>(b) Dependent variable: Hard brakes Estimate (standard error)</th>
<th>(c) Dependent variable: Mileage Estimate (standard error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Week dummy2</td>
<td>2.57 (0.01)**</td>
<td>-0.26 (0.02)**</td>
<td>-0.06 (0.05)</td>
</tr>
<tr>
<td>Week dummy3</td>
<td>2.93 (0.01)**</td>
<td>-0.28 (0.02)**</td>
<td>0.13 (0.07)’</td>
</tr>
<tr>
<td>Week dummy4</td>
<td>3.06 (0.01)**</td>
<td>-0.41 (0.02)**</td>
<td>0.10 (0.09)</td>
</tr>
<tr>
<td>Week dummy5</td>
<td>3.14 (0.01)**</td>
<td>-0.45 (0.02)**</td>
<td>0.26 (0.12)*</td>
</tr>
<tr>
<td>Week dummy6</td>
<td>3.28 (0.01)**</td>
<td>-0.48 (0.02)**</td>
<td>0.19 (0.13)</td>
</tr>
<tr>
<td>Week dummy7</td>
<td>3.40 (0.01)**</td>
<td>-0.47 (0.02)**</td>
<td>0.16 (0.13)</td>
</tr>
<tr>
<td>Week dummy8</td>
<td>3.41 (0.01)**</td>
<td>-0.43 (0.02)**</td>
<td>0.07 (0.14)</td>
</tr>
<tr>
<td>Week dummy9</td>
<td>3.49 (0.01)**</td>
<td>-0.48 (0.02)**</td>
<td>0.10 (0.15)</td>
</tr>
<tr>
<td>Week dummy10</td>
<td>3.77 (0.01)**</td>
<td>-0.51 (0.02)**</td>
<td>0.06 (0.15)</td>
</tr>
<tr>
<td>Week dummy11</td>
<td>4.34 (0.01)**</td>
<td>-0.48 (0.02)**</td>
<td>0.04 (0.20)</td>
</tr>
<tr>
<td>Week dummy12</td>
<td>4.42 (0.01)**</td>
<td>-0.48 (0.02)**</td>
<td>0.17 (0.21)</td>
</tr>
<tr>
<td>Week dummy13</td>
<td>4.27 (0.01)**</td>
<td>-0.47 (0.02)**</td>
<td>0.15 (0.23)</td>
</tr>
<tr>
<td>Week dummy14</td>
<td>4.33 (0.01)**</td>
<td>-0.49 (0.02)**</td>
<td>0.35 (0.24)</td>
</tr>
<tr>
<td>Week dummy15</td>
<td>4.29 (0.01)**</td>
<td>-0.48 (0.02)**</td>
<td>0.46 (0.24)’</td>
</tr>
<tr>
<td>Week dummy16</td>
<td>4.24 (0.02)**</td>
<td>-0.50 (0.02)**</td>
<td>0.45 (0.26)’</td>
</tr>
<tr>
<td>Week dummy17</td>
<td>4.29 (0.02)**</td>
<td>-0.51 (0.02)**</td>
<td>0.48 (0.26)’</td>
</tr>
<tr>
<td>Week dummy18</td>
<td>4.37 (0.02)**</td>
<td>-0.53 (0.02)**</td>
<td>0.54 (0.28)’</td>
</tr>
<tr>
<td>Week dummy19</td>
<td>4.36 (0.02)**</td>
<td>-0.57 (0.02)**</td>
<td>0.53 (0.29)’</td>
</tr>
<tr>
<td>Week dummy20</td>
<td>4.40 (0.02)**</td>
<td>-0.61 (0.02)**</td>
<td>0.53 (0.30)’</td>
</tr>
<tr>
<td>Week dummy21</td>
<td>4.44 (0.02)**</td>
<td>-0.59 (0.03)**</td>
<td>0.55 (0.31)’</td>
</tr>
<tr>
<td>Week dummy22</td>
<td>4.47 (0.02)**</td>
<td>-0.59 (0.03)**</td>
<td>0.57 (0.31)’</td>
</tr>
<tr>
<td>Week dummy23</td>
<td>4.50 (0.02)**</td>
<td>-0.60 (0.03)**</td>
<td>0.60 (0.32)’</td>
</tr>
<tr>
<td>Week dummy24</td>
<td>4.54 (0.02)**</td>
<td>-0.62 (0.03)**</td>
<td>0.61 (0.35)’</td>
</tr>
<tr>
<td>Week dummy25</td>
<td>4.57 (0.02)**</td>
<td>-0.60 (0.03)**</td>
<td>0.60 (0.34)’</td>
</tr>
<tr>
<td>Week dummy26</td>
<td>4.59 (0.02)**</td>
<td>-0.61 (0.03)**</td>
<td>0.59 (0.36)</td>
</tr>
</tbody>
</table>

Multiple R-squared

<table>
<thead>
<tr>
<th></th>
<th>Estimate (standard error)</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Multiple R-squared</td>
<td>0.419</td>
<td>0.386</td>
<td>0.286</td>
</tr>
</tbody>
</table>

Sample Size=705752, (’): p-value < 0.1, (*): p-value < 0.05, (**) : p-value < 0.01
Table 2.5 Fixed-Effects Regression Results for Number of Daily Hard Brakes to Capture the Effect of Negative Signal on Performance

<table>
<thead>
<tr>
<th></th>
<th>Estimate (Std. Error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Negative feedback</td>
<td>-0.174 (0.05)**</td>
</tr>
<tr>
<td>Monday</td>
<td>0.226 (0.08)**</td>
</tr>
<tr>
<td>Tuesday</td>
<td>0.168 (0.08)*</td>
</tr>
<tr>
<td>Wednesday</td>
<td>-0.091 (0.07)</td>
</tr>
<tr>
<td>Thursday</td>
<td>0.132 (0.07)'</td>
</tr>
<tr>
<td>Friday</td>
<td>0.203 (0.08)**</td>
</tr>
<tr>
<td>Saturday</td>
<td>0.105 (0.06)</td>
</tr>
<tr>
<td>Insurance score</td>
<td>-0.32 (0.03)**</td>
</tr>
<tr>
<td>Week dummy2</td>
<td>-0.39 (0.03)**</td>
</tr>
<tr>
<td>Week dummy3</td>
<td>-0.36 (0.03)**</td>
</tr>
<tr>
<td>Week dummy4</td>
<td>-0.45 (0.04)**</td>
</tr>
<tr>
<td>Week dummy5</td>
<td>-0.47 (0.04)**</td>
</tr>
<tr>
<td>Week dummy6</td>
<td>-0.46 (0.04)**</td>
</tr>
<tr>
<td>Week dummy7</td>
<td>-0.42 (0.04)**</td>
</tr>
<tr>
<td>Week dummy8</td>
<td>-0.49 (0.04)**</td>
</tr>
<tr>
<td>Week dummy9</td>
<td>-0.47 (0.04)**</td>
</tr>
<tr>
<td>Week dummy10</td>
<td>-0.53 (0.05)**</td>
</tr>
<tr>
<td>Week dummy11</td>
<td>-0.58 (0.05)**</td>
</tr>
<tr>
<td>Week dummy12</td>
<td>-0.55 (0.05)**</td>
</tr>
<tr>
<td>Week dummy13</td>
<td>-0.53 (0.05)**</td>
</tr>
<tr>
<td>Week dummy14</td>
<td>-0.57 (0.06)**</td>
</tr>
<tr>
<td>Week dummy15</td>
<td>-0.54 (0.06)**</td>
</tr>
<tr>
<td>Week dummy16</td>
<td>-0.58 (0.06)**</td>
</tr>
<tr>
<td>Week dummy17</td>
<td>-0.55 (0.06)**</td>
</tr>
<tr>
<td>Week dummy18</td>
<td>-0.60 (0.06)**</td>
</tr>
<tr>
<td>Week dummy19</td>
<td>-0.62 (0.06)**</td>
</tr>
<tr>
<td>Week dummy20</td>
<td>-0.64 (0.07)**</td>
</tr>
<tr>
<td>Week dummy21</td>
<td>-0.61 (0.07)**</td>
</tr>
<tr>
<td>Week dummy22</td>
<td>-0.64 (0.07)**</td>
</tr>
<tr>
<td>Week dummy23</td>
<td>-0.60 (0.07)**</td>
</tr>
<tr>
<td>Week dummy24</td>
<td>-0.64 (0.07)**</td>
</tr>
<tr>
<td>Week dummy25</td>
<td>-0.62 (0.07)**</td>
</tr>
<tr>
<td>Week dummy26</td>
<td>-0.174 (0.05)**</td>
</tr>
</tbody>
</table>

Multiple R-squared: 0.222  Adjusted R-squared: 0.219

Sample Size=4936264, (‘): p-value < 0.1, (*) : p-value < 0.05, (**) : p-value < 0.01
### Table 2.6 Weekly Changes in UBI Score Estimation for Customers in Fault vs. No-Fault States (8 States)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Fault states (Std. Error)</th>
<th>No-Fault × week_dummies (Std. Error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Week dummy2</td>
<td>1.84 (0.06)**</td>
<td>0.43 (0.14)**</td>
</tr>
<tr>
<td>Week dummy3</td>
<td>2.37 (0.06)**</td>
<td>0.21 (0.14)</td>
</tr>
<tr>
<td>Week dummy4</td>
<td>2.94 (0.06)**</td>
<td>0.18 (0.14)</td>
</tr>
<tr>
<td>Week dummy5</td>
<td>3.39 (0.06)**</td>
<td>0.12 (0.14)</td>
</tr>
<tr>
<td>Week dummy6</td>
<td>3.47 (0.06)**</td>
<td>0.24 (0.15)</td>
</tr>
<tr>
<td>Week dummy7</td>
<td>3.62 (0.06)**</td>
<td>0.28 (0.15)*</td>
</tr>
<tr>
<td>Week dummy8</td>
<td>3.69 (0.06)**</td>
<td>0.31 (0.15)*</td>
</tr>
<tr>
<td>Week dummy9</td>
<td>3.75 (0.06)**</td>
<td>0.46 (0.15)**</td>
</tr>
<tr>
<td>Week dummy10</td>
<td>3.91 (0.07)**</td>
<td>0.42 (0.16)**</td>
</tr>
<tr>
<td>Week dummy11</td>
<td>4.24 (0.07)**</td>
<td>0.65 (0.16)**</td>
</tr>
<tr>
<td>Week dummy12</td>
<td>4.46 (0.07)**</td>
<td>0.46 (0.16)**</td>
</tr>
<tr>
<td>Week dummy13</td>
<td>4.52 (0.07)**</td>
<td>0.40 (0.16)**</td>
</tr>
<tr>
<td>Week dummy14</td>
<td>4.54 (0.07)**</td>
<td>0.39 (0.16)**</td>
</tr>
<tr>
<td>Week dummy15</td>
<td>4.58 (0.07)**</td>
<td>0.45 (0.16)**</td>
</tr>
<tr>
<td>Week dummy16</td>
<td>4.51 (0.08)**</td>
<td>0.53 (0.16)**</td>
</tr>
<tr>
<td>Week dummy17</td>
<td>4.57 (0.08)**</td>
<td>0.56 (0.17)**</td>
</tr>
<tr>
<td>Week dummy18</td>
<td>4.61 (0.08)**</td>
<td>0.60 (0.17)**</td>
</tr>
<tr>
<td>Week dummy19</td>
<td>4.59 (0.08)**</td>
<td>0.64 (0.17)**</td>
</tr>
<tr>
<td>Week dummy20</td>
<td>4.65 (0.08)**</td>
<td>0.68 (0.17)**</td>
</tr>
<tr>
<td>Week dummy21</td>
<td>4.68 (0.09)**</td>
<td>0.64 (0.17)**</td>
</tr>
<tr>
<td>Week dummy22</td>
<td>4.74 (0.09)**</td>
<td>0.73 (0.18)**</td>
</tr>
<tr>
<td>Week dummy23</td>
<td>4.76 (0.09)**</td>
<td>0.78 (0.18)**</td>
</tr>
<tr>
<td>Week dummy24</td>
<td>4.73 (0.09)**</td>
<td>0.84 (0.18)**</td>
</tr>
<tr>
<td>Week dummy25</td>
<td>4.81 (0.09)**</td>
<td>0.87 (0.18)**</td>
</tr>
<tr>
<td>Week dummy26</td>
<td>4.88 (0.09)**</td>
<td>0.89 (0.18)**</td>
</tr>
<tr>
<td>Multiple R-squared</td>
<td></td>
<td>0.522</td>
</tr>
</tbody>
</table>

Sample Size=383829, (‘): p-value < 0.1, (*): p-value < 0.05, (**): p-value < 0.01

### Table 2.7 Long-term Effect of Changes in UBI Score on Changing the Insurance Score

<table>
<thead>
<tr>
<th>Variables</th>
<th>First renewal</th>
<th>Second renewal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>4.73 (0.15)**</td>
<td>9.04 (0.14)**</td>
</tr>
<tr>
<td>Age</td>
<td>−0.06 (0.005)**</td>
<td>−0.09 (0.02)**</td>
</tr>
<tr>
<td>Gender (male)</td>
<td>−0.14 (0.06)*</td>
<td>−0.32 (0.17)’</td>
</tr>
<tr>
<td>Δ UBI</td>
<td>0.07 (0.03)*</td>
<td>0.09 (0.04)*</td>
</tr>
<tr>
<td>Multiple R-squared</td>
<td>0.48</td>
<td>0.45</td>
</tr>
</tbody>
</table>

Sample size of first renewal observations = 20,754; sample size of second renewal observations = 7,178.,

(‘): p-value < 0.1, (*): p-value < 0.05, (**): p-value < 0.01
Figure 2.1 Flowchart of Customer and Firm Decisions in UBI Policy

1. Customer chooses insurance coverage and submits the quote request.
2. The company provides a quote for the standard policy based on the coverage and insurance score of the customer and an initial temporary discount if the customer accepts UBI.
3. UBI policy or not? (Yes or No)
   - No (traditional): The customer will pay constant monthly initial premium till end of the contract.
   - Yes (UBI adoption):
     - The firm will monitor the daily driving behavior of the customer by telematics device.
     - The customer will pay the discounted monthly initial premium (up to 10%).
4. Before 75 days of monitoring:
   - Cancel UBI policy? (Yes or No)
     - Yes (Cancel): The insurer switches the customer to non-UBI program and there is no UBI discount.
     - After 75 days of monitoring:
       - Firm offers updated initial discount based on monitored driving behavior.
       - During 6 months of usage:
         - The customer can cancel the UBI policy and switch.
         - Yes (Cancel): The firm offers the adjusted permanent discount based on all days of monitored driving behavior.
5. Customer will receive permanent discount based on his 6 months of driving performance.
Figure 2.2 Weekly Dropout Within UBI Program

Figure 2.3 Weekly Average UBI Score

(a) Weekly average UBI score observed for all drivers

(b) Average UBI score_drivers used the device for 6 months
Figure 2.4 Average Daily Number of Hard Brakes

Figure 2.5 Average Daily Mileage
Figure 2.6 Fixed-Effects Estimation of Daily Changes in Driving Behavior of UBI Customers
Figure 2.7 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.
Figure 2.8 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.

Figure 2.9 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.
Chapter 3: Threats to Privacy versus Saving Money: A Study of Consumers’ Adoption and Usage of Usage-Based Insurance

3.1 Introduction

Detailed data on individual consumers are becoming one of the most valuable assets for companies in almost all industries. The wireless connectivity, the increasing usage of real-time sensor data and machine-to-machine (M2M) communication are presenting companies with unprecedented transformational opportunities and challenges. Firms are investing in their ability to collect, store, manage and analyze vast amounts of variable, individual-level data to solve complex problems in order to better serve customers, gain competitive advantage and improve profitability. Such vast amounts of collected data have obvious and substantial economic value. Individuals’ traits, attributes, attitudes, and behavior are increasingly regarded as business assets that can be used to target services or offers, to set prices, to provide relevant advertising or to be traded with other parties. Among consumers, the reactions to these developments are more ambivalent. While some appreciate the ability of companies to provide customized services and prices, others are concerned that this personal information will be used to earn higher profits at the expense of the consumer, and that what was previously considered private will now become public. More generally, at both an individual and a societal level, individuals, government officials and policymakers are worried about the implicit loss of privacy as ever more personal information is collected. It is important to understand how individuals perceive the value and risk of their privacy when they decide whether to adopt new technology largely driven by big data.\(^{30}\)

\(^{30}\) https://digitalguardian.com/blog/us-consumers-ignorance-data-breaches-bliss
Despite considerable discussion, little is empirically known about whether consumption
decisions are actually influenced by the perceived loss of privacy.

In this essay, we examine the tradeoff that consumers make between their cost of being
monitored (including privacy) and the savings in auto insurance premium costs. Such programs,
known as Usage-Based Insurance (UBI), are widely offered, as we discuss more fully below, by
most but not all major US auto insurance companies. We build a dynamic structural model by
using individual-level data recording consumers’ decisions about whether or not to allow their
private driving behavior to be monitored over time in return for a long-term reduction in their
auto insurance premiums. The discount is based on how well they drive while being monitored
and how long they allow themselves to be monitored. To control for the so-called “privacy
paradox” observed in experimental studies, in which people underestimate their willingness to
release private information in exchange for personalized services (Norberg et al., 2007), our
empirical study is based on actual choice behavior in a field setting. Furthermore, during the time
period of our study (2012 to 2014), a widely covered data breach at Target department stores was
announced on December 15, 2013. This allowed us to employ a quasi-experimental design to
examine whether this data breach had a significant effect on the willingness of auto insurance
customers in our sample to adopt, be monitored by and to remain in the UBI program.

The auto insurance market is the largest insurance market segment in the US, and it is
extremely competitive, as insurers try to attract the more profitable low-risk drivers and retain
these customers over time. Hundreds of auto insurance writers are essentially competing for the
same premium base, which is relatively stable over time, at least in the US. Auto insurance is fast
becoming a big data industry, with telematics-based auto insurance poised to potentially change the business of insurance. Usage-based insurance (UBI), a recent innovation that more closely aligns driving behaviors with premium rates for auto insurance, is a significant example of such a change. With the telematics, a driver’s behavior is monitored directly while he or she drives. Traditional rating factors, including drivers’ demographics and past driving history, tend to be proxies for actual driving behaviors and the risk of accidents and injury. The idea of UBI is to measure factors that determine risk directly on an individual level and set each policyholder’s premium based on his or her monitored driving performance. By using UBI rating factors instead of traditional rating proxies, according to at least one industry observer, insurers could offer an 80% discount to the very best drivers and still be profitable. In the case of the company in our study, it offered a maximum permanent discount of 25%, amounting to several hundred dollars to those who qualified.

UBI can potentially provide a great opportunity for insurance companies to increase their profits and market share. For consumers, the UBI programs boost affordability for lower-risk drivers. More importantly, the UBI programs give consumers the ability to control their premium costs by incentivizing them to reduce miles driven and adopt safer driving habits, such as limiting the number of hard brakes. Fewer miles and safer driving also aid in reducing accidents, congestion, and vehicle emissions, which benefits the society. Soleymanian et al. (2019) find that this monitoring program and its economic incentives can encourage UBI adopters to improve their driving behavior and get a higher UBI discount, possibly compensating for the cost of

losing privacy. The issue of allowing access to otherwise private information goes beyond that of the customer and the client, as privacy is a public policy concern that governments are increasingly regulating. The complexity and relevance increase if the loss of privacy allows for improved public health—in this case, in the form of reduced road accidents, resulting in less cost and fewer injuries and deaths. While these macro issues of privacy are critically important, our empirical study focuses directly on how people’s perception of privacy risk affects their use of new technologies that offer direct economic and health benefits.

Inevitably, telematics devices involve loss of privacy for consumers who allow the insurance company to monitor where, when and how they drive. The loss of privacy and the inconvenience of installing the device may limit the widespread adoption of telematics devices. The UBI program uses location-based services (LBS) to measure different elements of actual driving behavior. Prior to the introduction of LBS, firms were not able to observe consumer actions and personal information at this 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.

UBI is an excellent setting for studying the economic significance of privacy for several reasons. First, UBI is an option (as we discuss in more detail in section 3.3) that the customer can choose to enroll in or not. In other words, the customer can obtain the same auto insurance policy with or without agreeing to be monitored; the only difference is that the monitored customer is able to earn a discount on the premium paid. Moreover, while the maximum monitoring period in our study is 26 weeks, the customer can drop out of the program and still be covered by the
same insurance policy. This is unlike many innovations, such as Google Maps, where disclosing private information is not optional if the full benefit of the service is to be realized. Second, the consumer knows what information is being monitored, as compared to many apps in which it is unclear what behaviors are actually being tracked. Third, the consumer receives a direct economic benefit, so that the cost of adopting and being monitored can be compared to the monetary value to each individual. Fourth, given that adoption rates are sufficiently high, 30% among the customers in our study, it’s apparent that not only technophiles are adopting the program.

In summary, we develop a dynamic structural model that allows us to estimate the (possibly heterogeneous) costs of using UBI, including the privacy cost, with a unique dataset of individual daily driving records for a company’s new UBI customers. The clear tradeoff between the expected premium saving as the benefit of using UBI and the cost (including privacy) of UBI allows us to quantify the cost parameters of different groups of customers. More specifically, in this study we aim to answer the following three research questions:

1- How do consumers trade off the cost saving in insurance premium both while they are being monitored and in the long run with the one-time cost of installing, using and being monitored by the telematics device required for participation in the UBI program?
2- How to quantify the individual cost of adopting and using a new technology that relies on sharing private data, including the cost of privacy concern?
3- What is the effect of changes in customer perception about privacy on their willingness to be monitored in the UBI program?
We use an internal database from a major US automobile insurance company to identify the effects of premium savings and costs of using UBI on participation and usage of this program based on the customers’ actual behavior. We observe information from more than 130,000 new customers who submitted a quote request to purchase an insurance policy from March 2012 to November 2014. We observe the customers’ UBI adoption decisions in addition to demographic and premium rates of each customer. For all customers who adopted the UBI policy, we have daily information on their driving performance, which determines the discount they get on this policy. We also observe any dropouts from the UBI policy if the customers decide to cancel before 6 months of usage. (This company monitors customers for a maximum of 6 months; customers can drop out at any time.) By developing a dynamic structural model, we consider the forward-looking behavior of customers and estimate the cost parameters. We find that the customers incur significant initial and per-period costs of using UBI, and these costs are heterogeneous across age and gender. Furthermore, we utilize a natural experiment by considering a major data breach that happened in the US during the time of our study to examine the effect of any changes in privacy perception on the cost of using UBI. The results show that shifts in customer perceptions significantly change the cost parameters in our model, which suggests that privacy concern is one of the major elements in the cost of using UBI.

Our research is the first study in marketing that quantifies the individual cost of adopting and using a data-based new technology, including the cost of privacy concern. With the data-breach incident, we can test if the consumers change their UBI usage decision in the short term due to the changes in privacy concern. Although we cannot separate the cost of privacy from
other usage costs, we at least estimate an upper bound of privacy cost and the changes of privacy cost due to the data breach.

The rest of this chapter is organized as follows. After reviewing the literature related to our research questions, we discuss the sensor data used in our analysis and some key patterns observed in the data. We then set up our dynamic structural model to capture the benefits and costs of using UBI by considering the forward-looking behavior of customers. The estimation and empirical results based on the proposed model are presented in section 3.5. Finally, we provide some concluding comments on managerial and public policy issues related to the customers’ responses to pricing strategies and their sensitivity to privacy concerns.

3.2 Literature Review

To our knowledge, our study is the first empirical research analyzing customers’ sensor-based data to investigate how customers trade off the benefits and costs of being monitored, including the privacy issues, to adopt and keep a new usage-based pricing system. Our paper is related to different streams of research including measuring privacy, the effect of privacy on innovations and customer responses and dynamic structural modeling.

*The challenges of defining and measuring privacy.* As discussed above, the innovative UBI policy helps the insurance company to set more accurate premiums by observing individual-level sensor-based data. The program also provides information to consumers that may help them to improve their driving. At the same time, the UBI policy raises privacy issues for consumers who may not want the firm to know where, when and how they drive or to provide that
information to other companies or government agencies. Many consumer surveys indicate that only a limited portion of the population is willing to share private information in return for a specific benefit. For example, a survey of users of mobile phones found that 40% say they would provide location data in exchange for better-targeted goods or services. While reports of attitudes and behavioral intentions are important, Norberg et al. (2007) highlight the difference between the intentions and behaviors of individuals in terms of sharing personal information; they call the relationship between individuals’ intentions to disclose personal information and their actual personal disclosure behaviors the “privacy paradox.” We attempt to quantify the costs of being monitored, including the privacy cost, using adoption and retention behavior of customers in the UBI context.

Privacy is difficult to define, and there are different definitions in the literature. For example, Westin (1967) described it as the control over and safeguard of personal information. However, Schoeman (1992) defined privacy as an aspect of dignity, autonomy, and ultimately human freedom. While seemingly different, these definitions are related, because they pertain to the boundaries between self and others, between private and shared, or public (Altman, 1975). Consumers constantly navigate those boundaries, and the decisions made in this regard determine tangible and intangible benefits and costs for individuals and for society. In addition, it is often said that information is power, so control over personal information can affect the balance of economic power among parties.

Acquisti et al. (2015) differentiate three themes to organize and draw connections between different streams of privacy research. The first theme is people’s uncertainty about the nature of privacy tradeoffs and their own preferences about them. People are often unaware of the information they are sharing—unaware of how it can be used and uncertain about their own preferences for privacy and sharing. At times, even people who say they would not share information actually do so, which may lead to the “privacy paradox” mentioned above. The second theme is the powerful context-dependence of privacy preferences: The same person can in some situations be oblivious to, but in other situations be actually concerned about, privacy issues. When people are uncertain about their preferences, they often search for cues in their environment to provide guidance. Context-dependence privacy issues mean that, depending on situations, individuals can exhibit a wide range of responses to privacy issues, from great concern to indifference. In our study, the widely covered data breach at Target department stores provides a cue to make consumers more alert about their privacy protection. We aim to test whether such an alert in an unrelated industry could affect the consumers’ UBI usage and adoption behavior for car insurance. The third theme that Acquisti et al. (2015) identify is the malleability of privacy preferences. The manipulation of factors that activate or suppress privacy concern can be seen in different cases—such as the choice of sharing defaults (e.g., whether the default is to opt in or opt out of a specific option) on social networks, or the provision of greater control on social media, which may create an illusion of safety and encourage greater sharing. These themes highlight the challenges of measuring the value of privacy. They also suggest that with changes in the firms’ and government’s public policy, the consumers’ concern about privacy can be adjusted. In a group of experiments, Adjerid, Acquisto, and Lowenstein (2018)
examine how choice architecture and framing can affect a series of consumer choices concerning the sharing of private information.

Only a few studies examine actual behavior of customers in a field setting instead of customers’ attitude and intention related to privacy. By running a field experiment, Tsai et al. (2011) found that consumers are sometimes willing to pay a price premium to purchase goods from merchants who offer more privacy-protective ones. They designed an experiment in which a shopping search engine interface clearly and compactly displays privacy policy information. When such information is made available, consumers tend to purchase from online retailers who better protect their privacy. Beresford et al. (2012) measured willingness to pay for privacy in a field experiment by studying the actual behavior of subjects buying a DVD from one of two competing online stores. One store consistently required more sensitive personal data than the other, but otherwise the stores were identical. In one treatment, DVDs were one Euro cheaper at the store requesting more personal information, and almost all buyers chose the cheaper store. Surprisingly, in the second treatment when prices were identical, participants bought from both shops equally often. Reynolds et al. (2011) analyzed a sample of Facebook users via the scraping of data and the collection of questionnaire data. The collected actual behavioral data allow for a contrast between implicit and explicit attitudes regarding Facebook and online sharing. The analysis reveals that while overall privacy concerns are not reflected in posting behavior, awareness of and familiarity with privacy controls are.

In terms of the effect of privacy perception on changing customer behavior, Janakiraman et al. (2018) investigated the effect of a data-breach announcement on a multichannel retailer’s
customers’ behavior. They found that although the data breach resulted in a significant decrease in customer spending, customers of the firm migrated from the breached (physical stores) to the unbreached (internet and catalog) channels of the retailer. In contrast to Janakiraman et al. (2018), we study the effect of a data breach from an outside source on a company in another industry, thus looking at a more general effect of a data breach, and specifically recognize the multiple decisions that a consumer makes that relate to his or her privacy concerns. Miller and Tucker (2017) explored how state genetic privacy laws affect the diffusion of personalized medicine, using data on genetic testing for cancer risks; empirical results show that approaches to genetic and health privacy that give users control over redisclosure encourage the spread of genetic testing, but that notification deters individuals from obtaining genetic tests. The authors found no effects of state genetic antidiscrimination laws on genetic testing rates.

**Privacy and innovation.** While privacy has traditionally been an issue of interest to individuals and society (Bloom, Milne, and Adler 1994), the recent availability of low-cost technologies for data manipulation generates new concerns about personal information processing (Varian 1997). Laudon (1997) proposed the creation of information markets where individuals own their personal data and can transfer the rights to that data to others in exchange for some type of compensation. Following the widespread adoption of the internet and proliferation of databases containing consumer information, a number of studies documented the value to companies of detailed, individual-level behavioral data. In online advertising, by examining past surfing and click behavior, firms can learn about current needs as well as general preferences. Beales (2010) documented that in 2009 the price of behaviorally targeted advertising was 2.68 times the price of untargeted advertising. Lambrecht and Tucker (2011)
further showed that the performance of behavioral targeting can be improved when combined with clickstream data that help to identify the consumers’ degree of product search. In the health-care sector, Miller and Tucker (2011) noted that the use of patient data by hospitals helps to improve monitoring and the accuracy of patient medical histories.

The potential for a consumer’s need to trade off innovation and privacy spans many industries. Surveys of individuals repeatedly find that people are concerned about the sharing of their private information; see, for example, Westin (2005) in the health-care sector regarding digital medical records, Turow et al. (2009) in customizing online advertising, and Rainie and Duggan (2015) in setting insurance premiums. Mao and Zhang (2014) more generally examine the effect of privacy on location-based services available on mobile phones and find in a survey-based study that higher privacy concern is negatively related to customers’ adoption of LBS services. In brief, survey-based studies show that consumers are concerned about the protection of their personal information, and this concern about privacy has a negative effect on adoption of new technologies and the consumer’s relationship with companies that have access to private information. An interesting question is whether concern about privacy is increasing over time. Goldfarb and Tucker (2012b) use respondents’ willingness to disclose information about income in periodic surveys as a proxy for their changing concerns about privacy and find that refusals to reveal income information have risen over time. Additionally, people who are older and females as compared to males are consistently less likely to answer questions about their income.

In summary, we study costs and concerns related to privacy in order to examine the effect of customers’ perception about privacy cost on the success of a UBI program, and whether
changing perceptions of potential privacy costs lead to greater or lesser willingness to allow private behavior to be monitored.

Dynamic structural model. To understand the consumers’ UBI adoption and termination decisions, we develop a single-agent dynamic structural model in which agents are forward-looking and maximize expected intertemporal payoffs. Chintagunta and Nair (2011) discuss several reasons to consider the dynamic aspects of consumer demand. The main demand-side factors are storability, durability, experience goods and complementarities; and they specify the models to capture the forward-looking behavior. An attractive feature of the structural model’s literature is that structural parameters have a transparent interpretation within the theoretical model that frames the empirical investigation. Moreover, econometric models in this class are useful tools for the evaluation of alternative (counterfactual) policies.

More specifically related to adoption of new technologies and services, Yang and Ching (2013) develop a dynamic structural model to investigate consumers’ adoption of and usage decisions for ATM cards when consumers are forward-looking and heterogeneous. They use the nested fixed-point algorithm (Rust 1987) to estimate the structural parameters of the model. Considering the monetary benefits of adopting the innovation allows them to recover the monetary value of total adoption costs. Several other studies in the marketing literature use the discrete choice dynamic programming framework and individual-level data to assess consumers’ technology-adoption decisions. Sriram et al. (2010) present a framework of durable goods purchasing behavior in related technology categories. Ryan and Tucker (2012) estimate the demand for a video-calling technology in the presence of both network effects and heterogeneity
by considering a dynamic structural model. Unlike our framework, the last two papers’ framework cannot recover the monetary value of total adoption costs. As we discuss later in detail, our model can separately quantify the two cost parameters—initial cost of adoption and per-period cost of using UBI—because we observe the consumers’ adoption and termination decisions.

Considering the unobserved heterogeneity is another common specification that leads to more precise modeling and estimation. Accounting for unobserved state variables can control for dynamic selection, allowing the individual’s choices and the transitions of the state variables to be correlated with each other and across time (Aguirregabiria and Mira 2002, 2007).

The Expectation-Maximization (EM) algorithm can be used to estimate models with unobserved heterogeneity in two stages, as discussed in Arcidiacono and Miller (2010). The expectation step is the first stage in this algorithm, where we need to update the conditional probabilities of being in each unobserved state, and update the population probability of being in each unobserved state given values for the first-period state variables. The second stage is the maximization stage, and these steps are repeated until convergence, with each step increasing the log likelihood of the original problem. Because the EM algorithm treats the unobserved state as known in maximization, Arcidiacono and Miller (2010) show that it is easily adapted to the conditional choice probability estimation developed before.

In this paper we develop a finite-horizon dynamic structural model of consumers’ decisions to adopt UBI and to allow themselves to be monitored for a period of up to 6 months at
most. We estimate the baseline model using the full solution method. We also use the Expectation-Maximization method to estimate the dynamic model by considering the unobserved heterogeneity.

3.3 Data

We study customers’ decision to adopt and keep the UBI policy based on data from a major US insurance company that offers the UBI program as an option alongside its 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 and the offer of a discount if they enroll in the UBI program. Customers are free to leave the UBI program at any time and continue with the firm’s traditional insurance, even though participation in the UBI program can lead to a lower premium. The UBI discount depends upon a score based on a number of factors related to actual driving behavior and how long (up to 6 months at most) they remain in the UBI monitoring program. In other words, the customers choose to adopt and keep the UBI policy based on their belief about current driving behavior and expected future performance.

Based on information in corporate annual reports, the insurance company started to offer usage-based insurance as a new policy in order to better target safer drivers and thus to increase the company’s profit by attracting and keeping more profitable customers. Like almost all 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 program by offering an initial (temporary) discount (typically 5%) as soon as they enroll in the UBI. The new UBI policyholder receives a telematics device to be plugged into the car, which enables the insurance company to monitor many aspects of the customer’s driving behavior. The customer can monitor her own performance from real-time feedback: Whenever she hard-brakes, the telematics device beeps to let her know, or she can monitor her performance on a daily basis via an app. If a customer withdraws from the UBI program before 75 days, she will not receive a discount. After 75 days of using the monitoring device, the customer receives an updated discount based on actual driving performance. From 75 days until 180 days, 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 180 days, at which time the telematics device is removed, and the customer is offered a permanent UBI discount—up to 25% based on her daily driving scores after 6 months, but the average discount rate is 12% with a standard deviation of 5%. While some drivers (less than 1% in our sample) may be offered no discount, a surcharge is never imposed. Customers know the initial discount, the range of the discount and the average discount because this information is provided on the company’s website.

Our empirical research builds on a number of datasets containing information about individual drivers’ auto insurance choices, their demographic characteristics, premiums and risk scores defined by the insurance company. For the drivers choosing UBI, we observe sensor-based information on their actual daily driving behavior (UBI scores) and whether or not they drop out early (and when) from the monitoring program during the 6 months.
Table 3.1 reports some summary statistics about the customers in our sample. The first column shows a data summary for all customers, with the second and third columns related to the data summary of non-UBI and UBI customers, respectively. The average UBI acceptance rate is about 30%. In addition, the average age of the UBI policyholders (39.3) is much lower than for the non-UBI customers (48.7), suggesting that the UBI program is more attractive for younger drivers. One possible explanation is that the insurance company assigns a relatively high-risk level to the young drivers due to the lack of sufficient driving history. Hence, this group pays a substantially higher initial premium. The UBI program can provide a great opportunity for younger drivers to demonstrate their actual driving behaviors, and as a result they can receive a discount rate according to their performance. Therefore, the incentive for younger drivers seems to be higher to adopt the UBI program compared to older, or experienced drivers. The higher average monthly premium of UBI drivers compared to non-UBI customers also shows that the program seems to be more attractive for the customers who are paying more, because their expected savings after using UBI can be greater.

In addition, we observe the daily driving score that all UBI customers enrolled in this policy receive at the end of each day as long as they are using the telematics device and don’t drop out. This score represents daily driving performance by aggregating the measures of all factors that are considered to be important by the insurance company (mileage, hard braking, time of driving, etc.).

Figure 3.1 shows the timeline for the UBI policy. As we discussed above, the maximum monitoring time is 6 months (180 days), but the UBI customers can drop out before that. We
label the UBI customers who drop out before 75 days of monitoring as “early dropouts.” These customers receive the initial UBI discount for the period of using the telematics device, and after dropping out they will not receive the UBI permanent discount. The “informed dropout” UBI customers are those who drop out between days 75 and 90, just after being informed of their updated UBI discount based on their actual driving behavior in the first 75 days of monitoring.

The third group of UBI customers are “late dropouts” who terminate the monitoring program later than the “informed dropouts” group after getting more feedback in UBI but don’t keep the UBI policy for the whole 6 months. The last two groups, despite dropping out early (before 6 months), receive a (adjusted) permanent discount that applies to their automobile insurance premiums. Finally, the “loyal” UBI customers are those who keep the telematics device for the whole 6 months. They are monitored for 180 days and receive the permanent UBI discount based on their actual driving behavior during the 6 months.

Table 3.2 compares the 4 groups of UBI customers that we defined on a number of variables of interest.

The fraction of enrollees in Table 3.2 shows the proportion of UBI customers in each group. For example, about 4% of UBI customers drop out before obtaining the updated discount on day 75. It’s interesting to note that 15% of UBI customers drop out between days 75 and 90, just after getting the updated discount in this period and the opportunity to have a permanent discount; by contrast, around 64% of UBI customers stay in the program for the whole 6 months. The average age of loyal UBI drivers is significantly lower than of dropouts, showing that the younger drivers tend to stay longer in the program. Average UBI score for loyal UBI customers is significantly higher than for dropouts, which shows that the actual driving performance may
be associated with the customers’ dropout decision: Safer UBI drivers with higher UBI scores remain in the UBI monitoring program longer. The customers who stay longer in the UBI program obtain a higher average permanent discount based on their actual driving behavior and duration of being in the program.

In general, the summary statistics in Tables 3.1 and 3.2 suggest that the customers may systematically make adoption and dropout decisions.\(^{33}\)

### 3.3.1 Data Breach and Consumer Adoption and Termination

As discussed above, the UBI program is based on the continuous monitoring of drivers for up to 6 months, so privacy concern may be a prominent factor for customers in choosing to adopt or to keep this optional policy. As a result, any significant changes in customer perception about privacy concerns may affect the customers’ decision to adopt or keep the UBI policy.

In the US, a major data breach was announced on December 15, 2013, namely a breach of credit and debit card data at discount retailer Target that affected as many as 40 million shoppers who went to the stores in the three weeks after Thanksgiving in 2013. More specifically, Target Corp announced this event on December 15, and immediately after that the news about Target’s data breach was widely reported. It’s clear from Figure 3.2 that there is a spike in the “data breach” searched keyword in Google in the period of December 15 to

\(^{33}\) For reduced-form analysis of the adoption and dropout decisions by using a logit model, please see the Appendix B.
December 19. No other data breach of this magnitude was announced during the time period of our study. Although the data breach happened in an unrelated industry and there is no direct monetary loss by the auto insurance consumers, the event could generate a panic that extends beyond those directly affected by the breach.

It’s worthwhile to consider this data-breach event as a natural experiment to examine the effect of privacy perception on UBI adoption and termination. The timing of the Target data breach is in the middle of the time period of our dataset. It allows us to use data before and after the breach and do a Diff in Diff (DID) to control for seasonality by comparing the data patterns in the previous year (2012). In this section, we provide model-free and reduced-form model results for a preliminary look at this issue.

In this section, we compare the UBI adoption rate and the “informed dropout” rate of UBI customers in 4 periods, as shown in Figure 3.3. We consider the periods 1 (November 15, 2012, up to December 15, 2012) and 2 (December 15, 2012, to January 15, 2013) as benchmarks to account for possible seasonality effects. Our key focus is the change from Period 3 (November 15, 2013, up to December 15, 2013) before the data breach to Period 4 (December 15, 2013, to January 15, 2014) after the data breach. To compare the UBI adoption rate of insurance policyholders, we compute the percentage of new customers who adopted the UBI policy in each period \( AD_t, \ t = 1,2,3,4 \). Figure 3.4.1 shows the UBI adoption rate of customers who submitted an insurance quote request in each period. The UBI adoption rate in the period (15 Dec- 15 Jan) is higher than the previous month (15 Nov- 15 Dec) in each of the two years, which may be because of time trend, seasonality differences and any other unobserved factors; but the
increase in adoption rate of period 4 compared to period 3 (when the data breach happened) is smaller than the difference between the adoption rate of first two periods. We will test the significance of the differences later in this section by considering a reduced-form logit model.

Next, we look at the “informed dropout” (ID) rate of UBI customers who adopted the UBI policy before the data breach and who can make their “informed dropout” decision after 75 days of using the UBI in each of four periods shown in Figure 3.4.2. For example, the customer who adopted the UBI policy at October 5, 2013, and kept the policy for 75 days should make her “informed dropout” decision at December 20, 2013, so her decision will be considered in period 4. Figure 3.4.2 shows the “informed dropout” rate in each period. The “informed dropout” rate in period 4 (after data breach) is higher than period 3 (before data breach), while the dropout rate in period 2 is lower than in period 1, which we use to control for seasonal effects. So, it seems that the data-breach event is correlated with the “informed dropout” rate, and the UBI dropout rate is higher after the data breach.

3.3.2 Model-free and Reduced-form Analysis Results

We use the DID (difference in differences) approach in a reduced-form logit model to test for the effect of data breach on UBI adoption and “informed dropout” rate. We run the extended logit model (4) for a subset of customers who submitted the insurance quote request during the 4 months (periods) shown in Figure 3.3.
\[ UBI\ acceptance_i = \logit(\text{age}_i, \text{Premium}_i, \text{state}_i, \text{gender}_i, \text{year}_i, \text{month}_i, \text{year}_i \ast \text{month}_i) \] (3.1)

Where,

\[ \text{year}_i = \begin{cases} 1 & \text{if the customer submitted the quote in period 3 or 4 (2013)} \\ 0 & \text{if the customer submitted the quote in period 1 or 2 (2012)} \end{cases} \]

\[ \text{month}_i = \begin{cases} 1 & \text{if the customer submitted the quote in period 2 or 4 (December 15 to January 15)} \\ 0 & \text{if the customer submitted the quote in period 1 or 3 (November 15 to December 15)} \end{cases} \]

By definition, the year and month dummies’ coefficients capture the main effects of year and month, respectively, while the coefficient of year and month interaction (\(\text{year}_i \ast \text{month}_i\)) captures the difference between adoption rate of period 3 and 4 beyond the year and month (seasonal) effects. Table 3.3 shows the estimation results for the logit model (4), illustrating that the adoption rate is significantly higher in year 2 (2013) compared to year 1 (2012) and in the second month compared to the first month. Interestingly, the estimated coefficient of the year and month interaction is marginally \((p = 0.08)\) negative significant, suggesting a negative but marginal relationship between the data breach and the adoption rate.

We run a similar analysis for a subset of UBI customers who should make their “informed dropout” decision in the defined 4 periods (months).
\[ p(\text{UBI informed dropout}_i|\text{stayed in the program for at least 75 days}) \]

\[ = \text{logit}(\text{age}_i, \text{gender}_i, \text{premium}_i, \text{average UBI score}_i, \text{changes in UBI score}_i, \text{year}_i, \text{month}_i, \text{year}_i \times \text{month}_i, \text{state}_i,) \quad (3.2) \]

As we discussed above, the interaction term of year and month can capture the effect of data breach on “informed dropout” rate. Table 3.4 shows the estimation results for the logit model (5). The coefficient of the interaction term is positive and significant at the 0.01 level, which shows that the “informed dropout” rate is significantly higher after controlling for the demographic, drivers’ performance and seasonal effects.

The descriptive analysis of this section suggests that there are important factors that affect the customers’ decision to adopt and keep the UBI policies. Insurance premium, demographic information and driving performance may affect the customers’ UBI adoption and dropout decision. In general, there is a tradeoff between the benefit of choosing and keeping the UBI policy and the cost of it, which leads to the variation in the adoption and dropout decisions across different groups of customers. The model-free and reduced-form logit model results for the data-breach effect suggest that customers may consider their privacy concerns in their adoption and dropout decisions, and the cost of losing privacy can be one of the major factors for the insurance policyholders in deciding whether to choose or keep the UBI policy.

In the next section, we model the customers’ decisions in the UBI program to better understand the tradeoff between the benefits of using UBI and the cost of it. Developing a dynamic structural model can help us identify the cost of using UBI for different groups of
customers and the changes in the perceived privacy cost of using UBI after the data-breach event.

3.4 Model Setup

In order to answer the research questions presented in section 3.1, we first develop a baseline dynamic structural model to capture the consumers’ tradeoffs between the cost of being monitored when using UBI and their long-term saving on their insurance premium. We then extend the baseline model by allowing for observed and unobserved heterogeneity to study the differences in cost of being monitored across different groups of customers. In addition, to study the effect of privacy perception on customers’ decisions, we consider a major data-breach incident during the time period of our study (see section 3.3); by using a subsample of our data, for the consumers who might be affected by the data-breach news during their UBI adoption and usage period, we extend our baseline dynamic structural model to capture possible changes in the customers’ perceived cost of monitoring. The data breach might change the perception of privacy from the customer’s perspective right after this event, and we can test it by modeling the customers’ decision before and after the data breach to determine whether it has a significant effect on their behavior.

3.4.1 Dynamic Structural Model

In this part, we propose a dynamic approach to model the customer’s decision process for UBI program adoption and termination. To receive a permanent price discount on her insurance
premium, a consumer has to bear a short-term cost in using the UBI device; hence a consumer has to make a tradeoff between a long-term benefit and a short-term cost. We believe that a dynamic setting can better capture the customers’ forward-looking decision process in UBI program adoption and usage.

Although we have data on a daily basis, we aggregate our data into 15-day periods (semi-monthly) to limit the impact of random variation on a daily basis and for computational efficiency. We chose 15 days as one decision period, as 15 days is sufficiently long to achieve these goals and because 15 is an integer divisor of the 75 days when customers first receive a revised discount and can elect to withdraw from the program and still gain a permanent discount.

Since we only observe the consumers’ decision within the insurance company, we focus on their choices between the UBI and the regular insurance without discount. In addition, we model the consumers’ adoption and termination decisions only if they adopt the UBI program, but we treat the (annual) renewal decision as exogenous. In this model, a consumer’s decision process is defined as follows. At time $t = 0$, a consumer decides whether to adopt UBI or not. If a consumer does not choose UBI, then she will pay the full premium and has no further decision to make afterwards. If a consumer adopts UBI, we assume that he or she makes decisions every 15 days after adopting the UBI policy. Specifically, at the end of each period, UBI customers observe their latest period driving performance and decide to keep or drop out of the UBI policy. Figure 3.5 describes the timeline of the decision process, where we consider a finite time horizon model to our problem since a customer will be monitored for 12 periods at most. We also note that there are a few critical time points during the 180 days. In particular, at day 0, a consumer...
makes an adoption decision at the beginning of the decision process. After 75 days of monitoring (after adoption), right after a consumer makes the 5th keep or dropout decision (d5), she is obtaining a permanent discount based on her 75 days’ driving performance. As we discussed in the data section, about 15% of UBI consumers drop out at decision d6. The final decision a consumer has to make is d12 before the maximum monitoring period is reached.

After 180 days of UBI usage, monitoring ends and the customers are required to return the device to the company, with no more monitoring after that. The consumers will get permanent discounts for their insurance premium from the company. So, we have 13 decision points in this setting, including the UBI adoption decision in the initial period (labeled as d0), and the keeping or dropping out of the UBI policy in the following periods (1 adoption and 12 dropout decision points). We formalize a consumer’s decision as follows. For the initial decision point,

\[ d_{i0} = \begin{cases} 1 & \text{adopt UBI} \\ 0 & \text{choose the traditional insurance} \end{cases} \]

If a consumer adopts UBI at \( t = 0 \), then her decision for subsequent periods is

\[ d_{it} = \begin{cases} 1 & \text{Keep UBI} \\ 0 & \text{drop out at the end of period } t \end{cases} \quad t = 1, 2, 3, ..., T = 12 \]

So \( d_{i0} \) represents the adoption decision of customer i, and \( d_{i1}, ..., d_{i12} \) represent the customer decision to keep or terminate the UBI service. Once a customer drops out, she cannot return to being monitored.
To clarify the decision process in this context, we illustrate the process of decision making for the customers at day 0 ($d_{i0}$) and day 15 ($d_{i1}$) in Figure 3.6. At time $t = 0$, the customers should decide whether they want to choose the UBI policy or the traditional auto insurance policy. As for the information available at this decision point, the customers know their demographic information, the initial premium to pay, and their past driving history, which helps them better predict their ability to get the benefit of a UBI policy, as well as the one-time cost of switching to the UBI policy and the cost of using UBI as a new and innovative technology to adopt.

After adoption of the UBI policy at $t = 0$, the customers plug in the telematics device and their driving behavior is monitored. So, in the first 15 days (day 1 to 15) the customers observe their actual driving performance (UBI score), and at the end of this time period they decide whether they want to keep the UBI policy or drop out and switch to the traditional policy. Before making the decision at the end of the first period ($d_1$), the customers know their UBI score at period 1, the cost of using UBI, and the premium to pay.

The per-period utility functions at subsequent time periods will be different, and it depends on each specific period $t$.

$$U_{i0} = -\alpha . P_{i1} . (1 - \text{discount}_{i0} (d_{i0})) - (C_0 + C_1) . I(d_{i0} = 1) + \varepsilon_{i1} \quad (3.3)$$

$$U_{it} = -\alpha . P_{i1} . (1 - \text{discount}_{it} (d_{it}, S_{it})) - C_1 . I(d_{it} = 1) + \varepsilon_{it} \quad t = 1, 2, 3, \ldots, 11 \quad (3.4)$$

where $P_{i1}$ is initial (first year) semimonthly premium set for the customer $i$.

$\text{discount}_{it}$: The UBI discount rate for customer $i$ at period $t$.

$C_0$: The initial fixed cost for customers to adopt the UBI policy.
\( C_1 \): The semimonthly cost of UBI usage.

\( \alpha \): Price sensitivity coefficient.

The immediate utility at the first period (\( U_{i0} \)) depends on customer i’s decision at the starting point (\( t = 0 \)). If the customer adopts the UBI policy, there is a one-time adoption cost (\( C_0 \)) to this new technology that does not depend on the length of UBI usage time and the semi-monthly cost (\( C_1 \)) of being monitored by the telematics device. We should note that both cost parameters in our model may include the privacy cost. A market research company (Pinnacle) studied the important factors that act as barriers to adopting and using UBI. For auto insurance customers who did not adopt UBI, the research company reported Privacy, Rate can go up, and Concerned about results\(^{34} \) as major negative feelings among non-UBI customers that lead to not adopting UBI. Among UBI customers who used the device, Hard-brakes beeping, Not fair evaluation (UBI score), and Installation were reported as the major complaints. When a consumer decides whether to adopt UBI or not, she needs to consider whether she is willing to share personal, private information with the insurance company. After she has adopted UBI, she needs to consider whether she is willing to share additional private information about her behavior during the upcoming period. In general, the customer’s immediate utility at each time period t (\( U_{it} \)) depends on the dropout decision at the beginning of that period (\( d_{it} \)) and also the effective expected UBI discount that the UBI customer can receive in the current time period based on the driving behavior and the customer’s decision.

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\(^{34}\) That is, the respondent is concerned about how the company uses the results of monitoring later on.
Since the consumers obtain a permanent discount after 75 days of UBI, we also need to consider the consumers’ long-term savings after they exit the UBI program. Ideally, we should model a consumer’s renewal decision to estimate the potential saving in the long term. However, since we don’t observe the consumers’ choices outside the company, it is impossible to build a full-fledged structural model by considering both annual renewal and UBI adoption and usage decisions. For our empirical application, we consider a 3-year time horizon for our model. In other words, a consumer expects that the average time of buying her auto insurance from the same company is 3 years. We calculate the expected present value of auto insurance cost for the next two and a half years after the first 6 months of UBI enrollment. We know that the insurance premium may vary over time for the policyholders beyond the benefit of the UBI program in the traditional form by having, for example, accident-free driving performance. So, we consider the P_{i2} and P_{i3} as the (semi-monthly) premium for customer i to pay at year 2 and 3, respectively. The permanent discount is the UBI discount that each UBI customer can receive after using the UBI policy, and this discount will be effective as long as the customer continues with this company.

We can calculate the residual utility of each customer for the remaining two and a half years (the blue region in Figure 3.7) without considering any benefit and discount of the UBI policy. In other words, we want to know the total cost for the blue region (Figure 3.7) in the traditional form of auto insurance. If we have P_{i1}, P_{i2} and P_{i3} as the basic semi-monthly

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35 As a robustness check, we also estimate the model based on a 5-year horizon. The parameter values for our key variables of interest retain their level of significance when we use a 5-year horizon as well.
premiums that customer $i$ should pay for the first 3 years without considering the UBI discount, then we have:

$$residual\ value_i = -\alpha \ast \left( \sum_{\tau=0}^{11} \beta^\tau \ast P_{i1} + \sum_{\tau=12}^{35} \beta^\tau \ast P_{i2} + \sum_{\tau=36}^{59} \beta^\tau \ast P_{i3} \right) \tag{3.5}$$

where $\beta$ is the semi-monthly present-value discount factor. In other words, $residual\ value_i$ shows the cumulative expected utility for customer $i$ without considering the UBI discount in the remaining two and a half years. We use this residual utility in calculating the valuation functions.

In the dynamic setting, the customer makes a decision based on the valuation function at each decision point. We can write the valuation function as a function of “state” and the customer’s decision at each period. We start by writing the valuation function for the last decision point ($T = 12$).

$$\bar{V}_{i12}(d_{i12} = 1, S_{i12}) = E[residual\ value_i$$

$$\ast (1 - E[permanent\ discount_i(d_{i12} = 1, S_{i12})])] \tag{3.6}$$

$$\bar{V}_{i12}(d_{i12} = 0, S_{i12}) = E[residual\ value_i \ast (1 - E[permanent\ discount_i(d_{i12} = 0, S_{i12})])]$$

where $S_{i12}$ is the state level related to decision point 12 (last decision), and $permanent\ discount_i$ is the UBI permanent discount that the customer $i$ receives.

So, we can easily find the expected valuation functions at the last decision point for all the customers if we know the permanent discount function (we describe the permanent discount...
function below) and the state level for each customer. For all other decision points, the valuation function will be as below.

\[ V_{it}(d_{it}, S_{it}) = \begin{cases} 
\sum_{j=t}^{11} \beta^{j-t} \cdot E[U_{ij}|d_{it} = 0, S_{it}] + \beta^{12-t} \cdot \text{residual value}_i \cdot (1 - E[\text{permanent discount}_i(d_{it} = 0, S_{it})]) \
U_i + \beta \cdot \tilde{V}_{i(t+1)}(d_{i(t+1)}) 
\end{cases} \]

\[ = 0, 1, ..., 11 \quad (3.7) \]

And

\[ \tilde{V}_{i(t+1)}(d_{i(t+1)}) = E_{S_{i(t+1)}} \left[ \max_{d_{i(t+1)}} V_{i(t+1)}(d_{i(t+1)}, S_{i(t+1)}) \right] \quad (3.8) \]

In other words, we have a dynamic stopping problem in which there is no opportunity for the UBI customer to come back to UBI usage later if she decides to drop out at any time period.

### 3.4.2 Discount Function

Before setting the state variables in state space, we first discuss the UBI discount functions here. We know from the company’s UBI policy that UBI customers receive a 5% initial discount just for signing up, and this remains effective for the first 75 days of monitoring if they keep this policy. If they drop out before 75 days, there is no further UBI discount and the customers no longer get the initial benefit of the UBI policy. So, we have:

\[ \text{discount}_{it} = \begin{cases} 
\text{permanent discount}_i = 0 & d_{it} = 0 \\
0.05 & d_{it} = 1 
\end{cases} \quad \text{for } t = 0, 1, 2, ..., 5 \]
After 75 days and in time period 6, the UBI customers will receive the updated discount based on their driving performance. At the end of this period \(d_{i6}\), the customers can decide whether they want to keep the UBI policy or drop out. In both cases, they will receive the updated discount for the next period.

\[
discount_{i6} = \begin{cases} 
\text{permanent discount}_i = f_{0,6}(UBI\text{Score}_{i6}) + \varepsilon_{i6} & d_{i6} = 0 \\
\text{discount}_{i6} = f_{1,6}(UBI\text{Score}_{i6}) + \varepsilon_{i6} & d_{i6} = 1 
\end{cases} \tag{3.9}
\]

After period 6, the customers can keep the updated UBI discount they received on day 75 if they want to continue using the UBI policy; however, if they decide to drop out, they will get an adjusted permanent UBI discount.

\[
discount_{it} = \begin{cases} 
\text{permanent discount}_i = f_{0,t}(UBI\text{Score}_{it}) + \varepsilon_{it} & d_{it} = 0 \\
\text{discount}_{i6} & d_{it} = 1 \text{ for } t \\
= 7,8, ..., 11 \tag{3.10}
\end{cases}
\]

\[
\text{permanent discount}_i = \begin{cases} 
f_{0,12}(UBI\text{Score}_{i12}) + \varepsilon_{i12} & d_{i12} = 0 \\
f_{1,12}(UBI\text{Score}_{i12}) + \varepsilon_{i12} & d_{i12} = 1 
\end{cases} \tag{3.11}
\]

We don’t know the exact formula used by the company for \(f_{0,t}\) and \(f_{1,t}\), but we can estimate these functions empirically based on the observed discount and customers’ UBI score in our dataset. We assume there is a one-by-one mapping for UBI score and UBI discount, so considering the UBI score as the state variable in the state space we use the expected value of discount in our model as the true value, which is not observed for some state levels.
3.4.3 State Space and Transition Probabilities

After setting the valuation and discount functions, we now specify the state space. Figure 3.6 helps us to define the state variables. At the adoption time \(d_{i0}\), the UBI customers observe the demographic information, insurance score and the premium. So, we define:

\[
S_{i0} = (Premium_i, Demographic_i, insurance\ score_i) \quad (3.12)
\]

A consumer uses the observed information \(S_{i0}\) to predict her UBI score and the discount she can obtain based on her driving behavior. After the initial period, the UBI customers observe additional information about their actual driving performance (UBI score) and then make the decision to drop out or not. So,

\[
S_{it} = (Premium_i, Demographic_i, UBI\ score_{it}, t) \quad t = 1,2,...,6 \quad (3.13)
\]

Note that after UBI adoption, a consumer’s insurance score is irrelevant after controlling for the traditional premium.

After being informed of the updated discount at period 6 and before the end of the 6 months, there is no new updated discount based on current UBI score if the customers decide to continue using UBI, and the UBI discount will be the last updated discount they receive after just 75 days \(f_{1,6}(UBI\ score_{i6})\). So, we should include the \(UBI\ score_{i6}\) in addition to the most current UBI score in state space for \(t = 7,8,...,T = 12\).
\begin{align*}
S_{it} &= (\text{Premium}_i, \text{Demographic}_i, \text{insurance score}_i, \text{UBI score}_{it}, \text{UBIScore}_{it_6}, t) \quad t \\
&= 7,8, ..., T = 12 \quad (3.14)
\end{align*}

We assume a Markov process for the transition of UBI score.\textsuperscript{36} We consider the UBI score of customer \( i \) at period \( t \) (\( \text{UBIScore}_{it} \)) as a random variable that follows the Markov process. We assume this process has a fixed transition matrix \( M_S \)\textsuperscript{37} and can be estimated empirically by using the UBI panel data.

\begin{align*}
M_S &= \text{pr}(\text{UBIScore}_{t} = S^j|\text{UBIScore}_{t-1} = S^i) \quad t = 2,3, ..., 12 \quad (3.15)
\end{align*}

We also need one more transition probability—the distribution of \( S_{i1}|S_{i0} \), which is the mapping for a consumer’s observed states including the insurance score, premium and demographics to her UBI score:

\begin{align*}
M_0 &= \text{pr}(\text{UBIScore}_{1} = S^j|S_{i0}) \quad (3.16)
\end{align*}

It also will be estimated in next section.

This model setup enables us to capture the cost of adopting and using a UBI policy. We detail in the next section how to estimate the functions and parameters of the dynamic structural model.

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\textsuperscript{36} The UBI score is the only stochastic component in state space that can change over time.

\textsuperscript{37} We discretize the UBI score variable to form the discrete transition probabilities for the UBI score. We explain in detail the dimension of this matrix in the next section.
3.4.4 Structural Modeling to Capture the Effect of Data Breach

To capture the effect of an exogenous data-breach event on the cost of using UBI (including privacy), we add one more dimension to our state space in the dynamic model we have proposed. In the new setting, we assume in addition to the state variables of UBI score, demographic information, premium and time, the customers also observe a major data breach that can threaten their privacy and thus affect their cost of being monitored. So, based on the observed states, the customers make their decisions in the UBI program.

\[
U_{i0} = -\alpha P_i (1 - \text{discount}_{i0}) - (C_0 + C'_0 (\text{breach})).I(d_{i0} = 1) + \epsilon_{i0}
\]

\[
U_{it} = -\alpha P_i (1 - \text{discount}_{it}) - C'_t (\text{breach}).I(d_{it} = 1) + \epsilon_{it} \quad t = 1,2, ..., T = 11 \quad (3.17)
\]

\[
C'_t (\text{breach})
\]

\[
= \begin{cases} 
C_1 + \gamma & \text{if customer } i \text{ observes the breach at the beginning of time period } t \\
C_1 & \text{No observed data breach at the beginning of time period } t
\end{cases} 
\]

\[
= 0,1, ..., 11 \quad (3.18)
\]

In this setup, \(C'_t (\text{breach})\) determines the level of the variable cost of being monitored based on whether the data breach is observed or not.

We assume non-stochastic process for the data-breach state. In other words, if a customer doesn’t observe the data breach at the beginning of period \(t\), she expects not to observe a data breach at the beginning of period \(t+1\) with probability 1 and vice versa. If a consumer observes a data breach, she expects that the data breach exists in all the periods afterwards.
Following the setup discussed in this section, we next estimate the coefficients of the dynamic structural model based on our dataset.

3.5 Estimation and Empirical Results

In this section we first estimate the transition probabilities of state variables, UBI discount functions and second-year and third-year semi-monthly expected premiums ($P_2$ and $P_3$) based on our dataset. In the second part, we use the estimated parameters of the first step to estimate the parameters of the dynamic structural model.

3.5.1 Transition Probabilities’ Estimation

As explained in section 3.4, the UBI score ($UBIScore_{it}$) is the only stochastic time-variant state variable that the customers have uncertainty about in their forward-looking behavior. We assume that the consumers have a rational expectation on the transition of their UBI scores over time. Following the Markov property, we need to estimate the distribution of 

$(UBIScore_{it})|(UBIScore_{it-1})$ for $t = 2, 3, ..., 12$ and of the initial UBI score conditional on a consumer’s insurance score and other observed characteristics $(UBIScore_{t1})|S_{i0}$. The estimation of these distributions helps us define the expected driving performance (UBI score) at the next period given the current state level in order to solve the valuation functions in our dynamic setting.
First, we discretize the UBI score levels in our state space, which helps us to use the full solution methods for estimating the parameters of the dynamic structural model. The UBI score potentially can be between 0 and 100, but in our dataset the minimum average semi-monthly UBI score is 32.4 and the maximum is 99.1. So, we consider 68 integer levels for the UBI scores in the range of $[32,99]$. Each observed UBI score is approximate to the nearest integer between 32 and 99. Next, we estimate the distribution of $(UBIScore_{it})|(UBIScore_{it-1})$ $t = 2, 3, \ldots, 12$ based on the observed UBI score for all UBI customers.\(^{38}\) Considering the average semi-monthly UBI score improvement pattern (increasing exponential decay form), we try both exponential decay function and power function to capture this general pattern of our data. We found the power function outperforms the exponential decay function. Specifically, we consider the model (20) to estimate the conditional distribution of $(UBIScore_{it})|(UBIScore_{it-1})$.

$$\log(UBIScore_{it}) - \log(UBIScore_{it-1}) = \mu_0 + \delta \times (\log(t) - \log(t - 1)) + \varepsilon_{it}, \varepsilon_{it} \sim N(0, \tau_1^2) \tag{3.19}$$

This model can capture the increasing exponential decay pattern of UBI score in our dataset. The estimated coefficients of model (3.19) are reported in Table 3.5. From model (3.19), we are able to predict the transition probability of UBI from $t-1$ to $t$ based on the estimated parameters of this model.

\(^{38}\) Since we only observe the loyal UBI customers’ UBI scores for the entire 12 periods, here we assume that all consumers’ UBI scores follow the same transition process for identification purposes.
In addition, we need to estimate the distribution of \((UBIScore_{i1})|S_{i0}\) which means the distribution of first-period UBI score given the observed state variables before adopting the UBI policy. Model (21) assumes that all customers can predict their first-week UBI score based on a few observed state variables (insurance score, age, gender, state of residence), but estimating model (21) based on just our observed first-period UBI scores may lead to selection issue because we only observe the UBI scores (outcomes) for the customers who adopt the UBI policy. It is possible that UBI adopters are systematically different from non-adopters in their driving performance. This selection issue can result in biased estimation in the coefficients of our regression model.

\[
UBI\ Score_{i1} = \alpha_0 + \alpha_1 \times insurance\ score_i + \alpha_2 \times age_i + \alpha_{1,2} \times insurance\ score_i \times age_i + \alpha_3 \times Male_i + state_i + \epsilon_i \sim N(0, \sigma^2) \quad (3.20)
\]

We use the Heckman approach to correct the selection bias in the estimated coefficients of our model. We follow Ahn and Powell (1993), who suggest a semi-parametric estimation of censored selection models with a nonparametric selection mechanism. Consequently, we propose the two-step procedure below to estimate the coefficients of model (21) considering selection bias correction.

**Step 1:**

We need to have an estimate of UBI acceptance probabilities for all customers given the state variables before adopting the UBI \((S_{i0})\). We add the average income in the zip code and the number of the insurance company’s agents in the state where the consumer lives as the
instrumental variables (IV) to our first-step selection model. We assume that the income level of the customer and the number of agents may affect her UBI adoption decision, but it doesn’t have a direct effect on her UBI performance in the first period ($UBI_{Score_{i1}}$). Specifically, we assume

$$P_i(S_{i0}) = f(S_{i0}) = (age_i, gender_i, premium_i, new\ driver_i, married_i, State_i, income_i, agents_i)$$  \hspace{1cm} (3.21)

Based on our data and parameter estimates for (3.21), we can calculate the predicted probabilities of adopting the UBI policy for all customers ($\hat{P}_i$).

Step 2:

Using the estimates of adoption probabilities ($\hat{P}_i$), we then estimate the selectivity-corrected outcome equation (UBI score).

$$UBI\ Score_{i1} = \alpha_0 + \alpha_1 * insurance\ score_i + \alpha_2 * age_i + \alpha_{1,2} * insurance\ score_i * age_i + \alpha_3 * Male_i + state_i + \Lambda(\hat{P}_i) + \varepsilon_i$$  \hspace{1cm} (3.22)

The control function $\Lambda(\hat{P}_i)$ can be approximated using polynomials or smoothing splines parameter.

Following the above procedure, we use the nonparametric packages in R to estimate the UBI adoption probabilities ($\hat{P}_i$) given the state space variables before adoption decision ($S_{i0}$).
Table 3.6 shows the estimation of bandwidths for all variables. The bandwidths show the degree of curve smoothness in Kernel density estimation.

In step 2, we use GAM (generalized additive model) to estimate the model (3.22) by considering the smoothing splines\(^\text{39}\) parameter for the control function. The estimated coefficients of this model are reported in Table 3.7. The result shows that the customers with a higher insurance score and older drivers have a higher expected UBI score in the first period, whereas males have a significantly lower first-period UBI score compared to females.

### 3.5.2 Discount Function Estimation

As discussed earlier, the insurance company did not disclose its exact UBI discount functions to us. In this part, we estimate all the UBI discount functions defined in the Model Setup section. Considering the driving performance of customers in each period (UBI score), we observe the actual UBI discount rate that the customers receive based on their decisions at different time periods. So, we can specify a simple regression model to estimate the UBI discount functions. The updated discount on period 6 \((\hat{f}_{1,6}(UBIScore_{i6}))\) and the discount for the loyal customers \((\hat{f}_{1,12}(UBIScore_{i12}))\) are estimated by a simple linear regression specification shown in equation (3.23):

\[
discount_{i6} = \hat{f}_{1,6}(UBIScore_{i6}) = \alpha_6 + \beta_6 \times UBIScore_{i6} + \varepsilon_{i6} \tag{3.23}
\]

---

\(^{39}\) We use smoothing splines instead of polynomial function because it’s a more general and flexible model (Zhang and Wang 2016).
\( permanent \text{ discount}_{i12} = \hat{f}_{1,12}(UBI\text{score}_{i12}) = \alpha_{12} + \beta_{12} \ast UBI\text{score}_{i12} + \epsilon_{i12} \)

For the cases in which the UBI customers drop out before 6 months of UBI usage, the discount functions \( f_{0,t} \) for \( t = 6, 7, ..., 12 \) can be estimated based on the discount received at the dropout time. We consider a functional form for the adjusted discount function as below.

\[
f_{0,t} = (\beta_0 + \alpha_0 \ast (t - 6) + \rho_0 \ast (t - 6)^2) + (\beta_1 + \alpha_1 \ast (t - 6) + \rho_1 \ast (t - 6)^2) \ast UBI\text{score}_{it} + \epsilon_{it}
\]

for \( t = 6, 7, ..., 12 \)  \( (3.24) \)

Figure 3.8 shows the estimated plots for adjusted permanent discount at different stopping points based on model (3.24) specification.

The estimated plots show that the customers who drop out later receive a higher adjusted permanent discount than those who drop out earlier; and more interestingly, the effect of UBI score on the adjusted discount is greater when the UBI customers drop out at later periods. In other words, the customers can obtain a greater benefit (higher permanent discount) at any level of UBI score if they drop out later.

3.5.3 Second – and Third – Year Premiums

In our dynamic setting, all customers need to predict their future (semi-monthly) premiums in the second and third years. These expectations help the customers to find their expected future valuations for all decision alternatives. Based on our dataset, we run a simple linear regression over all the company’s customers to model \( P_{i2} \) and \( P_{i3} \) considering the initial premium, the customers’ age, gender and state of residence.
\[ P_{12} = \alpha_0 + \alpha_1 * P_{11} + \alpha_3 * age_i + \alpha_4 * Male_i + state_i + \epsilon_i \]

\[ P_{13} = \beta_0 + \beta_1 * P_{11} + \beta_3 * age_i + \alpha_4 * Male_i + state_i + \epsilon_i \]  

(3.25)

Table 3.8 shows the estimated coefficients for regression models (3.25) for all customers in our sample (who remain with the company long enough to be quoted a second- or third-year premium). The results show that the younger drivers have a greater reduction in their renewal insurance premium compared to initial premium than do older drivers, and a male’s premium reduction on average is more than a female’s at renewal times. We use the estimated model (3.25) to find the expectation of second- and third-year premiums for each customer.

### 3.5.4 Dynamic Structural Model Parameters’ Estimation

In this part we discuss our estimation method for the single-agent dynamic structural model developed in section 3.4 and show the results based on the selected approaches.

In general, four main methods/algorithms have been applied to the estimation of single-agent models: (1) Rust's nested fixed-point algorithm; (2) Hotz-Miller's Conditional Choice Probability (CCP) method; (3) the Nested Pseudo Likelihood (NPL) algorithm, a recursive CCP method that Aguirregabiria and Mira (2002) proposed; and (4) a simulation-based CCP method developed by Hotz et al. (1994) that does not possess terminal states. The first of these is a full solution method, i.e., the DP problem is solved for every trial value of the parameters. Methods (2)-(4) avoid repeated full solutions of the DP problem, taking advantage of the existence of an
invertible mapping between conditional choice probabilities and differences in choice-specific value functions, a result due to Hotz and Miller (1993). These methods can generally be applied to both infinite and finite horizon problems.

Because our baseline model can be solved and estimated in a computationally efficient way by the full solution method, we chose that approach. With this method, we can solve the valuation functions for all possible state variables at each decision point by backward induction and maximize the likelihood function based on the expected valuation functions to estimate the parameters of the structural model. The low dimensionality of our state space, the UBI score discretization explained before, and the number of decision points that is reasonable (13) will allow us to use the full solution method. More specifically, in the backward induction, we start from the end and solve the valuation functions for all possible values of the state variables and decisions. For example, we start from T = 12 (the last decision point) and find the expected value function. We have $V_{t12}(d_{t12}, S_{t12})$ for both $d_{t12} = 0, 1$ based on equation (3.6) in section 3.4. So, if we know the observed state variables at period 12 ($S_{t12}$), we can find the expected valuation function for each customer at the last decision point. Given the solved valuation functions at T = 12 and the equations (3.7) and (3.8) in section 3.4, we can find the $V_{t11}(d_{t11}, S_{t11})$ for both keeping UBI and dropout decisions at this decision point. We repeat the same procedure to solve the valuation functions for all $t = 0, 1, \ldots, 12$.

If the error terms in equations (3.3) and (3.4) follow the extreme value distribution, the probability of customer i’s decision in UBI policy will be as below.
\[
P(d_{it} = 1|S_{it}, \theta = (\alpha, C_0, C_1, \beta, \sigma^2)) = \frac{\exp(V_{it}(d_{it} = 1, S_{it}))}{\exp(V_{it}(d_{it} = 0, S_{it})) + \exp(V_{it}(d_{it} = 1, S_{it}))}
\] (3.26)

In this way, we assume that the customers have forward-looking behavior in making their decision to keep the UBI policy or drop out.

Based on the observed state variables and the customers’ decisions about staying in or dropping out of the UBI monitoring program, we can form the likelihood function and maximize it to estimate the parameters of the structural model \( \theta = (\delta, C_0, C_1, \beta) \). For identification purposes we need to fix \( \beta \) (semi-monthly present-value discount factor). Table 3.9 shows the estimated coefficients of the structural model in equations (3.3) and (3.4). We set \( \beta = 0.995 \), which will be equal to a 12% annual discount rate.\(^{40}\) To estimate the baseline model, we also assume the same state space transition distributions specified in equation (3.15) for all customers.

The results show that all three estimated coefficients are significant at the 0.01 level. The difference between \( C_0 \) and \( C_1 \) indicates that the customers have much higher initial cost for using UBI compared to the per-period cost of being monitored. There are many concerns from a customer’s perspective that may be included in \( C_0 \), such as the switching cost from traditional insurance to UBI, trust in the company’s argument that there is no penalty, general concern about being monitored and privacy issues. On the other hand, \( C_1 \) is the per-period cost of using UBI

\(^{40}\) It’s common to fix the annual discount factor in the range of 10-15%.
after adopting the policy. So, it’s more related to the customer’s privacy concerns, ongoing inconvenience of using the telematics device and the possibly annoying feedback system in which the UBI driver, for example, hears a beep every time she hard-brakes. We should note that our setting imposes $C_0$ as a one-time cost while $C_1$ is the cost of using UBI in each period. In terms of dollar value, we can interpret that the customers trade off the benefits of using UBI with the costs of $\frac{72.48}{0.46} = 157.56$ initially and $\frac{8.24}{0.46} = 17.91$ semi-monthly to choose the UBI policy and keep it. The high estimated initial cost ($C_0$) of adopting UBI can help explain the relatively low adoption rate (30%), and $C_1$ can explain the customers’ dropout decision after adopting UBI.

### 3.5.5 Observed Heterogeneity across Age and Gender Groups

Our data reveal significant differences in the UBI adoption and dropout rates of Millennial (ages 18-35) and Senior (65 or older) drivers. Table 3.10 summarizes the adoption and dropout rate among age and gender groups of customers.

The data patterns show a significant difference between Millennials and senior drivers’ adoption and dropout behavior, while there is only a limited difference between males and females. We find a lower adoption rate and a higher dropout rate for seniors. We use our structural model to explore the differences between age and gender groups. Based on our model, there are different factors that can explain the heterogeneous behavior across age groups. Higher adoption or lower dropout rate of younger drivers can be explained by higher (expected) benefits that younger drivers can gain compared to senior drivers, or lower cost of using UBI. The proposed dynamic structural model helps us capture this tradeoff and identify the differences.
Based on the utility function specified in equation (3.3), the customers can get more benefit from UBI if they have a higher premium, higher UBI discount, greater expected improvement in driving behavior (which leads to higher expected discount for the future), and higher price sensitivity. So, the difference in the adoption rate of millennials and senior drivers may be due to differences in these elements. On the other hand, it’s possible that the different cost of being monitored in UBI ($C_0$ and $C_1$) leads to significantly different adoption and dropout rates for younger drivers compared to seniors.

We consider two subsets of our data including the young and senior drivers. For each subset, we separately implement the baseline estimation procedure we discussed before to estimate the parameters of a dynamic structural model in each age group. In other words, we first estimate the state variables’ transition distributions separately in each age group. The estimated coefficients of power functions for the two age groups show that the younger drivers expect to improve their driving behavior significantly more than senior drivers do. This is consistent with Soleymanian et al. (2019), whose work captures the different patterns of improvement in UBI score across age groups. The expected premiums for both age groups are estimated separately by considering model (25). Based on the results of the first-stage estimation, we estimate the structural parameters of each group. Table 3.11 shows the estimation of structural parameters for the two age groups we’ve been discussing, millennials and seniors.

Although the UBI adoption rate of millennials is higher than that for senior drivers, the estimated initial cost of using UBI $C_0$ for younger drivers is significantly higher than for seniors, which is counterintuitive. This interesting result can be explained by higher premium and higher
expected improvement in UBI score for millennials compared to senior drivers. It means that the higher adoption rate of younger drivers is likely the result of the higher benefits of UBI for these customers and not the lower initial cost of adopting UBI for this age group.

On the other hand, the higher estimated semi-monthly cost of using UBI for senior drivers suggests that UBI is more annoying and costly for senior drivers during the 6 months of telematics device usage. Another possibility is that younger drivers, who are typically more computer literate and tech savvy than older drivers, are more cautious about this new technology before adoption; but after adoption, they have less concern about their UBI usage. We repeat the same analysis for males and females separately and summarize the results of parameter estimation in Table 3.12. These results show that females on average have a significantly higher level of initial cost $C_0$ than males, but the semi-monthly costs of being monitored for the two gender groups do not differ significantly.

### 3.5.6 Unobserved Heterogeneity within Age Groups

In this part we extend our baseline model and consider unobserved heterogeneity for the two cost parameters ($C_0$ and $C_1$) in the dynamic structural model. We consider $K$ unobserved classes and assume the customers can be in each class with probability $\pi_k, k = 1, 2, ..., K$. We also specify the $k$ levels of costs as $C_{0k}$ and $C_{1k}, k = 1, ..., K$. So, we add one more dimension to our state space, which is the class level of each customer. To estimate the extended finite time horizon model by considering the customer’s unobserved heterogeneity, we consider two-stage approaches. Arcidiacono and Miller (2013) developed an approach for CCP estimation of
dynamic discrete choice models with unobserved heterogeneity. We follow their approach to estimate the parameters of our structural model by considering the unobserved heterogeneity for two age-group subsets. Table 3.13 reports the estimated coefficients when $K = 3$. Interestingly, we find a large variation in the cost of usage for Millennials. One major latent class of Millennials (55%) has both the lowest initial and semi-monthly costs compared to other latent classes in the Millennial group. We find no such pattern among the 3 classes of senior drivers.

### 3.5.7 Effect of Data Breach

We follow the model (19) in section 3.4 and try to capture the effect of a widely reported though unrelated data breach on changing the semi-monthly cost of using UBI $C_1$.\(^{41}\) The Target stores’ data breach was announced on December 15, 2013, so customers who enrolled in the UBI program between September 1 and September 30, 2013, would have completed their 75 days in the program before the data-breach announcement, but those customers who enrolled after September 30 and before Oct 30 learned about the data-breach incident before they received the updated UBI discount on day 75 after their enrollment. To control for the seasonality, as we discussed in section 3.3 (reduced-form analysis), we consider two subsets of our data, designating all customers who submitted the quote request in the period of “1 Sep-30 Oct 2012” as the control group and those submitting during “1 Sep-30 Oct 2013” as the treatment group.\(^ {42}\)

\(^{41}\) From our reduced-form results, we find a stronger impact of the data breach on consumers’ dropout decisions. Given the smaller sample size we use for this exercise, we focus on the change of $C_1$ that has a direct impact on dropout decisions but keep $C_0$ constant in the model.

\(^ {42}\) We limit our data sample in a short time span to study the short-term impact of data breach. It also allows us to focus on the change of $C_1$ only. Allowing for both changes of $C_0$ and $C_1$ will impose more challenges in model identification.
We run the extended model (19) separately with these two subsets to see the effect of the data-breach event on $C_1$.

For year 2013, we assume that before the data breach, the semi-monthly cost of UBI usage is $C_1$, and after the data breach, the semi-monthly cost of UBI usage changes to $C_1 + \gamma$.\footnote{43} Similarly, in year 2012, we assume that the cost is $C_1$ if the dropout decision is before Dec 15 and $C_1 + \gamma$ after Dec 15. The results in Table 3.14 show that in the second subset in 2013—during which the data breach happened—the estimation of $\gamma$ is positive and significant, which shows that after the data breach the semi-monthly cost of being monitored $(C_1 + \gamma)$ is significantly higher than before, which is $C_1$.\footnote{44} We did the same analysis for the customers who submitted the quote request in September and October of 2012 to control for possible seasonality and trend. The non-significant result for the coefficient $\gamma$ for the 2012 subset suggests that the higher cost of being monitored after the data breach exists only in 2013, with no effect in 2012. So, we can argue that the data-breach event could significantly increase the customers’ perceived valuation of the cost of being monitored in UBI, given that privacy concern is one of the important elements in $C_1$.

3.5.7.1 Heterogeneous Effect of Data Breach

\footnote{43} Note that since the consumers did not expect the data breach when they made their adoption decisions, they expected their cost of using UBI would be $C_1$ for all periods when they made their adoption decision.

\footnote{44} Monetary value of change in privacy cost is equivalent to around $2 per semi-month. $\frac{0.919}{0.49} = 1.87$
In the previous subsection, we showed that the data-breach event significantly increases the per-period cost of being monitored ($C_1$), which means the UBI customers assign a higher cost of using UBI after the data breach compared to before this event. In this subsection, we want to see how different groups of customers respond differently to a data-breach event. In other words, we estimate the $\gamma$ parameter (changes in semi-monthly cost of using UBI) separately for different age and gender groups of customers. Table 3.15 shows the estimation results of the extended model to capture the effect of the data breach for males versus females. To estimate the model, we use two subsets of males and females who made their adoption decision in September and October 2013. The results show that the females are more sensitive to the data-breach event— their semi-monthly cost of using UBI is significantly higher than before this event. However, we did not find a significant (at $p < 0.05$) change in semi-monthly cost of using UBI for males after the data breach compared with before. This result suggests that females protect their privacy more than males if there is any threat.

We carry out a similar analysis to find any possible heterogeneous effect of data breach across two age groups. We consider millennials, who are customers under 35, and older drivers, who are above 50 years old. As illustrated in Table 3.16, both groups of drivers show a significant increase in the semi-monthly cost of using UBI after the data breach compared to before this event. The simple t-test to find the difference between the $\gamma$ estimations for the two groups doesn’t yield any significant results. So, there is no significant difference between the responses of younger and older drivers to the data-breach event in terms of protecting their privacy.
3.6 Counterfactual Analysis

In this section, we run a counterfactual analysis to evaluate the effect of possible changes in cost parameters of our model on UBI usage patterns. In this setting we report the counterfactual analysis results of a ± 20% change in $C_0$ and $C_1$. We allow for either of these two parameters to be reduced (increased) in value and for both to be reduced (increased), the latter to check for possible interaction effects. Reduction in the cost parameters can be achieved by the company’s efforts to make using the UBI policy and device easier or more convenient, to provide better customer service and to convince more customers to adopt and/or continue using the UBI monitoring device. The company may also initiate actions that reduce the possibility that private information will be inappropriately shared. In addition to that, the general trend of using IoT services that rely on private data may lessen the consumer’s concern about privacy and thus reduce the cost of sharing private information.

On the other hand, any threat to customers’ privacy that is either specific to the company or more general (as in the data breach studied above), along with regulations that make UBI devices more difficult to use, may lead to a significant increase in the cost parameters of our model (similar to the data-breach event we discussed before). Therefore, our counterfactual analysis considers increases as well as decreases in the $C_0$ and $C_1$ parameters. To focus on the key issue of privacy cost, we assume that any change in privacy cost extends throughout the entire period of our analysis.
More specifically, we first reduce the estimated cost parameters in the baseline model (per-period utility functions are defined in equation (3.3) and (3.4)) by 20% and simulate the customers’ decision and UBI score based on the estimated model. The reduced cost parameters are $C_0^- = 57.98$ and $C_1^- = 6.59$, respectively. To run the counterfactual analysis, we assume the customers are forward-looking and maximize their expected valuation function in each decision period based on the new reduced cost parameters, and other estimated functions and coeffects in the baseline model. Figure 3.9 shows the counterfactual estimation of adoption rate of the UBI policy by considering different scenarios (reductions in cost parameters).

We first consider the results for adoption rates, and then examine the results for dropout rates and other measures of driving performance. The reduction in the cost parameters leads to higher adoption rate compared to actual and simulated data based on estimated parameters in the baseline model. Interestingly, the effect of a reduction in the two cost parameters is not additive; that is, the UBI adoption rate when both cost parameters are reduced (0.56) improves more than the sum of the changes in adoption rate in the case that each cost parameter is reduced separately. The reduction in initial cost ($C_0$) also seems to have a slightly greater impact on adoption rate than per-period cost of being monitored ($C_1$).

To examine the effect of increasing the cost parameters on adoption, we repeat the above counterfactual analysis. In these scenarios, we increase the estimated cost parameters by 20% and simulate the UBI usage patterns. The increased cost parameters are $C_0^+ = 86.9$ and $C_1^+ = 9.88$, respectively. Figure 3.10 shows the counterfactual estimation of adoption rate of the UBI policy by considering possible increases in the cost parameters. Once again there is an interactive
effect of increasing both $C_0$ and $C_1$, and the increase in initial cost ($C_0$) also seems to have a slightly greater impact on decreasing the adoption rate than the per-period cost of being monitored ($C_1$).

We now examine the effect of changes in cost parameters on UBI dropout rate. Figure 3.11 shows the dropout rate (early, informed, and late) of UBI customers when we reduce the cost parameters in different scenarios. We should note that the number of UBI customers is different across scenarios, because the UBI adoption rates are different (Figure 3.9). As a consequence of this changing mix of consumers, the dropout rate is lowest when we reduce only the per-period cost of being monitored ($C_1$).

We repeat the similar analysis after increasing the cost parameters. Figure 3.12 shows the estimation of dropout rates. It’s interesting to note that while reduction in $C_1$ significantly decreases the UBI dropout rates, reduction in initial cost ($C_0$) increases the UBI dropout rate. Similar to the results for decreasing costs, one explanation could be the higher adoption rate of the latter scenario where more customers (including less careful drivers) adopt the UBI policy because of lower initial cost of adoption. So, the dropout rate could be higher for this group of UBI customers.

3.7 Discussion

Usage-based auto insurance (UBI) was introduced to help insurers improve their profits by better targeting pricing (premiums) to the actual driving behavior of their customers, to attract
customers from other insurers that did not (yet) offer UBI, and to increase customer retention. In this paper we develop empirical models to better understand the adoption and retention of customers in the UBI program and the tradeoff between savings in premium and costs of using UBI, including privacy considerations. The latter element was dissected to determine the importance of privacy concerns for different groups of customers. A particular concern of ours was to see whether a data breach outside the company could affect the behavior of UBI customers. We used a unique dataset from a major US insurance company to address our research questions.

Our setting is a particularly appropriate one in which to examine these effects, as the customer always has the option of obtaining the same product benefits—auto insurance—whether or not she is enrolled in the UBI program. This is unlike many other situations, such as Google Maps, where without yielding private information about your location and destination, you are unable to receive guidance. Thus, we have a sensitive environment in which to test the effects of privacy.

The model-free and reduced-form models’ results in section 3.3 and in Appendix B show that the insurance customers may systematically choose to adopt and keep the UBI policy. For example, age (but not gender) and current insurance premiums differ between adopters and non-adopters of UBI. In addition, the estimated parameters of the baseline dynamic structural model developed in this paper indicate the crucial role of both initial and semi-monthly costs on the customers’ adoption and dropout decisions. Because customer decisions depend upon their driving behavior over time and the consequently changing expected benefits, it is important to
have a dynamic structural model to capture these effects. We also study the heterogeneity across age and gender and find the younger drivers (millennials) on average have a higher initial cost of adoption compared to senior drivers, while the semi-monthly cost of being monitored among younger drivers is significantly lower than among senior drivers. Probing further into the millennial group, we add the possibility of unobserved heterogeneity into our specification to model the customers’ decisions in different latent classes. There is one major class in the millennial group in which the estimated initial and semi-monthly costs of UBI are significantly lower than in other groups. Comparing males to females, we find significant differences in initial adoption and semi-monthly costs, which shows that the estimated cost parameters for females are higher than for males.

Interestingly, the natural experiment resulting from a widely covered data breach helps us identify the effect of changing privacy perception on UBI usage. The results of the data-breach analysis suggest that after the data breach the UBI customers have a higher cost of being monitored. Assuming the other costs of being monitored (inconvenience of using the telematics device and annoying feedback system) are constant before and after the data breach, the privacy concern embodied in the semi-monthly cost of being monitored is higher after the data-breach event than before. This result suggests that news of the event changed the customers’ privacy perception and ultimately their dropout decisions with regard to being monitored as part of the UBI policy. In brief, UBI customers seem to care about privacy issues and are sensitive to

\[\text{The results of the reduced-form model also imply a marginally significant negative effect of the data breach on the likelihood of adopting the UBI policy.}\]
threats in this area. Our results indicate that in an actual field setting where consumers have a clear choice as to whether or not to share private information, consumers consider the economic benefits of sharing their private information and the cost of yielding such information. Moreover, consumers differ in how they trade off these costs and benefits. Our study also shows that privacy concerns in the use of one company’s products can be influenced by external events occurring outside that company.

3.7.1 Implications

Big data and GPS tracking have provided the basis for a revolutionary new set of products and services that better target individual-level customer needs. The benefits of innovative products and services that rely on using vast amounts of private and sensor data manifest when customers adopt these services and share their private data with the companies, so the benefits must be offset against the cost of being monitored and sharing data. It’s critical for firms offering these types of services to better understand the obstacles to adoption on the part of customers and their willingness to share their private data. UBI insurance is a prominent example of a new technology providing personalized products and services based on a consumer’s own usage experiences. However, consumers have to share their personal information in order to get the personalization benefits. Therefore, privacy concerns have become a major obstacle to the adoption of these types of new products. The results of our study can give firms and policymakers better insight into the privacy issues associated with adoption of a new technology that relies on using customers’ private data. These issues are not limited to a particular industry, as various types of companies are trying to define business models involving new, improved, or
better targeted services based on using the customers’ private data. For example, Amazon and Google are developing “smart home” devices and services using the collected sensor data of customers to optimize efficiency and product quality. In another recent example, John Hancock (a life insurance company) announced plans to transform the life insurance industry into a “wellness” model by using wearable devices to collect personal metrics involved in fitness and lifestyle of their customers. Therefore, our results—which quantify and help explain the impact of privacy concerns and other costs of adoption and usage of new products—are relevant in a broader scope and not just for the user-based auto insurance industry.

In addition to new product adoption, our results can help firms to better understand the retention behavior of customers when they use the new technologies that rely on their private data. While most studies of new technology focus on adoption costs, our study shows that there are significant costs to the consumer of remaining in the program and continuing to share private data. Encouraging customers to keep using the new products and share their private data for a longer period of time is crucial because it allows the firms to collect more private information and actual behavior from each customer and thus continuously improve efforts to better target their products and marketing programs. Our setting and the results suggest that in addition to the initial adoption cost of the UBI policy, the customers perceive a significant per-period cost of being monitored. Considering these costs can help companies carry out CRM and monitoring strategies more efficiently, decrease the per-period cost of being monitored and ultimately

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increase the firm’s profit by reducing the dropout rate; keeping costs down also encourages customers to stay longer in the program.

The counterfactual estimation results to study the effect of changes in privacy costs on customers’ willingness to adopt and use UBI technology have implications in a broader context related to IoT and the policymakers concerned about this industry. The counterfactual analysis results offer fresh insight to policymakers in IoT or AI (Artificial Intelligence) areas in terms of consumer responses to changes in privacy issues, which is of ongoing concern in these industries. The results show that efforts to decrease privacy costs may significantly increase the adoption and retention of new technologies that rely on using private data. The results of the present work clearly indicate that companies should roll out their data-driven new products with privacy protection in mind. Numerous studies conclude that transparency about the use and protection of consumers’ data reinforces trust and increases new-product adoption.

There are a number of implications for public policymakers. First, the results indicate that beyond attitudinal and behavioral intentions surveys, people’s actual behavior is affected by privacy concerns. Regulations and laws that reduce the threat to privacy—by limiting the amount of information that companies can access, by defining as illegal certain uses of private information, and by providing enforceable privacy protection that restricts the use and sharing of private information—not only help protect individuals but may also increase the adoption rate of new technologies. However, at the extreme, privacy protection may limit the effectiveness of new technology and thereby limit its adoption. Unlike companies, government regulators need to consider the effect not just of an individual sharing his or her own information, but the societal
effects resulting from the widespread availability of information. Policymakers may also need to consider whether the best default option is to opt-in or opt-out of sharing private information, and public agencies must work to make consumers aware of their options with regard to sharing private information and the benefits and costs of doing so. Moreover, public policy officials need to be concerned about any negative impacts on people who choose not to share their private information. Possibly, the price such customers have to pay could be higher or the options available to such privacy-concerned people may be limited or lower in quality, as a company or industry’s focus turns to those who are willing to share their private information.

3.7.2 Limitations and Future Research

In this paper we have some limitations in our model that could be addressed by future research. First, we impose the fixed transition probabilities for UBI score in our model as discussed earlier. In other words, we assume all the customers have the same belief and expectation to change (improve) their driving behavior. However, Soleymanian et al. (2019) discuss the mechanism of learning and improvement in driving behavior and find the economic incentives and negative feedback can change the learning and improvement patterns in driving behavior. So, a future research project could be to extend our current baseline model by considering the effort of customers to change their driving behavior as an additional decision variable and model the learning of customers along with the adoption and retention decisions in the dynamic structural setting. Such an extension would be quite challenging, but it could lead to a more realistic model and estimation of cost parameters.
In addition, in the current setting discussed in the paper, we assume a fixed time horizon for the dynamic model. The renewal decision of customers to choose the insurance policy from their existing company or switch to another company can directly affect the expected benefit of customers from UBI, so incorporating the renewal decision of customers in the model could be another extension of this work to capture the endogeneity in renewal decisions of customers.

On the other hand, the captured observed and unobserved cost parameters’ heterogeneity in our results can be important for the firm to set more efficient pricing and monitoring strategies to maximize the benefits of the UBI for both customers and the company. If we assume there are two types of customers (safe, careless) in the auto insurance market, the self-selection mechanism of good drivers with a UBI policy may decompose the market into two pools: pool (a) which consists of customers who adopted the UBI policy and on average have safer driving behavior (because of self-selection mechanism), and pool (b) which are non-adopters of UBI. The base insurance premium for the customers in pool (b) over the long term will increase and eventually will be higher than UBI premiums because on average there will be more careless drivers in pool (b) over time. If the insurance customers don’t adopt the UBI policy simply because they are not good drivers, the mechanism works and seems to be fair. But as discussed above, the adoption and usage costs including privacy cost constitute a major obstacle to adoption of a UBI policy; and if some of the customers in the current setting decide to choose a traditional insurance policy and become non-adopters because of these concerns, they are not necessarily careless drivers. Then the implications for the long-term insurance price will be different. Therefore, the captured heterogeneities in our results can help to better distinguish
customers in terms of their perceived costs of using the UBI technology and to design a mechanism that leads to more efficient pricing and monitoring strategies.
3.8 Tables and Figures

Table 3.1 Summary Statistics of UBI Adoption

<table>
<thead>
<tr>
<th></th>
<th>Total</th>
<th>Non-UBI</th>
<th>UBI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of customers</td>
<td>135540</td>
<td>95013</td>
<td>40527</td>
</tr>
<tr>
<td>UBI acceptance rate</td>
<td>0.30</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fraction male</td>
<td>0.53</td>
<td>0.53</td>
<td>0.52</td>
</tr>
<tr>
<td>Average age</td>
<td>45.8</td>
<td>48.7</td>
<td>39.3</td>
</tr>
<tr>
<td>Average monthly premium ($)</td>
<td>109.1</td>
<td>107.6</td>
<td>112.4</td>
</tr>
</tbody>
</table>

Table 3.2 Summary Statistics of “Loyal” and “Dropout” UBI Customers

<table>
<thead>
<tr>
<th></th>
<th>Early dropouts (&lt;75 days)</th>
<th>Informed dropouts (75-90 days)</th>
<th>Late dropouts (90-179 days)</th>
<th>Loyal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fraction of enrollees</td>
<td>0.041</td>
<td>0.149</td>
<td>0.172</td>
<td>0.638</td>
</tr>
<tr>
<td>Average age at adoption</td>
<td>42.54</td>
<td>41.17</td>
<td>39.15</td>
<td>38.43</td>
</tr>
<tr>
<td>Fraction male</td>
<td>0.52</td>
<td>0.53</td>
<td>0.51</td>
<td>0.51</td>
</tr>
<tr>
<td>Average UBI score</td>
<td>62.47</td>
<td>65.09</td>
<td>66.33</td>
<td>66.89</td>
</tr>
<tr>
<td>Average UBI discount</td>
<td>0</td>
<td>0.074</td>
<td>0.081</td>
<td>0.092</td>
</tr>
<tr>
<td>(Adjusted) average permanent discount</td>
<td>0</td>
<td>0.075</td>
<td>0.113</td>
<td>0.164</td>
</tr>
</tbody>
</table>
Table 3.3 Estimated Effect of Data Breach on UBI Adoption Rate

<table>
<thead>
<tr>
<th>Estimate (Std. Error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
</tr>
<tr>
<td>0.4959(0.0318)**</td>
</tr>
<tr>
<td>Age</td>
</tr>
<tr>
<td>-0.0058(0.0003)**</td>
</tr>
<tr>
<td>Premium</td>
</tr>
<tr>
<td>0.0040(0.0014)**</td>
</tr>
<tr>
<td>Gender (Male)</td>
</tr>
<tr>
<td>-0.0218(0.0086)*</td>
</tr>
<tr>
<td>Year</td>
</tr>
<tr>
<td>0.0425(0.0119)**</td>
</tr>
<tr>
<td>Month</td>
</tr>
<tr>
<td>0.0248(0.0120)*</td>
</tr>
<tr>
<td>Year*Month</td>
</tr>
<tr>
<td>-0.0203(0.0119)'</td>
</tr>
<tr>
<td>State dummies</td>
</tr>
<tr>
<td><strong>Included</strong></td>
</tr>
</tbody>
</table>

(‘): p-value < 0.1, (*): p-value < 0.05, (**): p-value < 0.01

Table 3.4 Estimated Effect of Data Breach on UBI “informed dropout” Rate

<table>
<thead>
<tr>
<th>Estimate (Std. Error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
</tr>
<tr>
<td>0.3381(0.0421)**</td>
</tr>
<tr>
<td>Age</td>
</tr>
<tr>
<td>0.0324 (0.0113)**</td>
</tr>
<tr>
<td>Premium</td>
</tr>
<tr>
<td>-0.0106(0.0035)**</td>
</tr>
<tr>
<td>Gender (Male)</td>
</tr>
<tr>
<td>-0.0095(0.0076)</td>
</tr>
<tr>
<td>Average UBI Score</td>
</tr>
<tr>
<td>-0.0322 (0.0218)*</td>
</tr>
<tr>
<td>Change in UBI Score</td>
</tr>
<tr>
<td>-0.0254 (0.0072)**</td>
</tr>
<tr>
<td>Year</td>
</tr>
<tr>
<td>-0.0464(0.0159)**</td>
</tr>
<tr>
<td>Month</td>
</tr>
<tr>
<td>-0.02304(0.0220)</td>
</tr>
<tr>
<td>Year*Month</td>
</tr>
<tr>
<td>0.0897(0.0329)**</td>
</tr>
<tr>
<td>State dummies</td>
</tr>
<tr>
<td><strong>Included</strong></td>
</tr>
</tbody>
</table>

(‘): p-value < 0.1, (*): p-value < 0.05, (**): p-value < 0.01
Table 3.5 Estimated Coefficients of Power Function for Conditional Distribution of UBI Score

<table>
<thead>
<tr>
<th>Variables</th>
<th>Estimate (Std. Error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-0.002(0.0003)**</td>
</tr>
<tr>
<td>( \log(t) - \log(t - 1) )</td>
<td>0.039(0.0055)**</td>
</tr>
</tbody>
</table>

R-squared: 0.0910

(‘): p-value < 0.1, (*): p-value < 0.05, (**) p-value < 0.01

Table 3.6 Nonparametric Estimation of UBI Adoption Rate

<table>
<thead>
<tr>
<th>Dep. Var. Bandwidth(s)</th>
<th>Exp. Var. Bandwidth(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>UBI Acceptance</td>
<td>Age</td>
</tr>
<tr>
<td>0.04241</td>
<td>4.31</td>
</tr>
<tr>
<td>Correct Classification Ratio by Outcome</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>0.856</td>
</tr>
</tbody>
</table>

Table 3.7 Generalized Additive Regression Model Estimation for First-period UBI Score

<table>
<thead>
<tr>
<th>Estimate (Std. Error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>((\text{Intercept}))</td>
</tr>
<tr>
<td>(\text{Insurance score})</td>
</tr>
<tr>
<td>(\text{Age})</td>
</tr>
<tr>
<td>(\text{Gender (Male)})</td>
</tr>
<tr>
<td>(\text{Age}^\ast\text{insurance score})</td>
</tr>
<tr>
<td>(\text{Control function})</td>
</tr>
</tbody>
</table>

(‘): p-value < 0.1, (*): p-value < 0.05, (**) p-value < 0.01
Table 3.8 Estimation of Insurance Premiums at Second and Third Years

<table>
<thead>
<tr>
<th>Coefficients</th>
<th>Second-year premium</th>
<th>Third-year premium</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-8.183(0.39)**</td>
<td>-9.351(0.91)**</td>
</tr>
<tr>
<td>Initial premium</td>
<td>0.947(0.05)**</td>
<td>0.917(0.08)**</td>
</tr>
<tr>
<td>Age</td>
<td>0.196 (0.04)**</td>
<td>0.246(0.07)**</td>
</tr>
<tr>
<td>Gender_Male</td>
<td>-0.387 (0.22)*</td>
<td>-0.425 (0.26)*</td>
</tr>
</tbody>
</table>

State dummies: Included

Adjusted R-squared: 0.81, 0.72

(*): p-value < 0.1, (*): p-value < 0.05, (**): p-value < 0.01

Table 3.9 Estimated Coefficients of Structural Model (3-year time horizon)

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Fixed</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta )</td>
<td>0.995</td>
<td></td>
</tr>
<tr>
<td>( \alpha )</td>
<td>0.46 (0.07)**</td>
<td></td>
</tr>
<tr>
<td>( C_0 )</td>
<td>72.48 (0.79)**</td>
<td></td>
</tr>
<tr>
<td>( C_1 )</td>
<td>8.24 (0.46)**</td>
<td></td>
</tr>
</tbody>
</table>

(*): p-value < 0.1, (*): p-value < 0.05, (**): p-value < 0.01

Table 3.10 UBI Adoption and Dropout Rate among Different Age and Gender Groups of Customers

<table>
<thead>
<tr>
<th>Age groups</th>
<th>Adoption rate</th>
<th>Early dropout rate</th>
<th>Informed dropout rate</th>
<th>Late dropout rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Millennials (18-35)</td>
<td>47.3%</td>
<td>3.7%</td>
<td>9.3%</td>
<td>7.6%</td>
</tr>
<tr>
<td>Senior (65 or older)</td>
<td>19.8%</td>
<td>12.5%</td>
<td>18.1%</td>
<td>17.7%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Gender groups</th>
<th>Adoption rate</th>
<th>Early dropout rate</th>
<th>Informed dropout rate</th>
<th>Late dropout rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>30.3%</td>
<td>4.5%</td>
<td>15.2%</td>
<td>15.9%</td>
</tr>
<tr>
<td>Female</td>
<td>31.1%</td>
<td>5.3%</td>
<td>14.3%</td>
<td>16.7%</td>
</tr>
</tbody>
</table>
Table 3.11 Structural Model Parameter Estimation for Two Age Groups

\[ \beta = 0.995 \]

<table>
<thead>
<tr>
<th></th>
<th>Millennials</th>
<th>Seniors</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha )</td>
<td>0.516(0.08)**</td>
<td>0.437(0.11)**</td>
</tr>
<tr>
<td>( C_0 )</td>
<td>86.82(0.95)**</td>
<td>64.79(0.86)**</td>
</tr>
<tr>
<td>( C_1 )</td>
<td>7.623(0.34)**</td>
<td>9.892(0.48)**</td>
</tr>
</tbody>
</table>

(‘): \( p \)-value < 0.1, (*): \( p \)-value < 0.05, (**) : \( p \)-value < 0.01

Table 3.12 Structural Model Parameter Estimation for Two Gender Groups

\[ \beta = 0.995 \]

<table>
<thead>
<tr>
<th></th>
<th>Males</th>
<th>Females</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha )</td>
<td>0.416(0.06)**</td>
<td>0.492(0.07)**</td>
</tr>
<tr>
<td>( C_0 )</td>
<td>75.28(0.59)**</td>
<td>86.63(0.65)**</td>
</tr>
<tr>
<td>( C_1 )</td>
<td>8.435(0.32)**</td>
<td>9.070(0.45)**</td>
</tr>
</tbody>
</table>

(‘): \( p \)-value < 0.1, (*): \( p \)-value < 0.05, (**) : \( p \)-value < 0.01

Table 3.13 Structural Model Parameter Estimation for Two Age Groups with Unobserved Heterogeneity

\[ \beta = 0.995 \]

<table>
<thead>
<tr>
<th></th>
<th>Millennials</th>
<th>Seniors</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha )</td>
<td>0.492</td>
<td>0.441</td>
</tr>
<tr>
<td>( \pi )</td>
<td>0.32</td>
<td>0.55</td>
</tr>
<tr>
<td>( C_0 )</td>
<td>89.39</td>
<td>59.87</td>
</tr>
<tr>
<td>( C_1 )</td>
<td>7.94</td>
<td>6.65</td>
</tr>
</tbody>
</table>
Table 3.14 Extended Structural Model Parameter Estimation Considering Data-Breach Event

<table>
<thead>
<tr>
<th></th>
<th>1 Sep-30 Oct 2012</th>
<th>1 Sep-30 Oct 2013</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha )</td>
<td>0.452 (0.09)**</td>
<td>0.491 (0.08)**</td>
</tr>
<tr>
<td>( C_0 )</td>
<td>83.61 (0.62)**</td>
<td>73.04 (0.76)**</td>
</tr>
<tr>
<td>( C_1 )</td>
<td>9.851 (0.51)**</td>
<td>8.147 (0.45)**</td>
</tr>
<tr>
<td>( \gamma )</td>
<td>-0.171 (0.14)</td>
<td>0.919 (0.17) **</td>
</tr>
</tbody>
</table>

\( (*) \): \( p \)-value < 0.1, \( (*) \): \( p \)-value < 0.05, \( (**) \): \( p \)-value < 0.01

Table 3.15 Extended Structural Model Parameter Estimation Considering Data-Breach Event (Heterogeneity across Genders)

\( \beta = 0.995 \)

<table>
<thead>
<tr>
<th></th>
<th>Males</th>
<th>Females</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha )</td>
<td>0.426(0.10)**</td>
<td>0.481(0.11)**</td>
</tr>
<tr>
<td>( C_0 )</td>
<td>72.82(0.71)**</td>
<td>85.76(0.65)**</td>
</tr>
<tr>
<td>( C_1 )</td>
<td>8.277(0.58)**</td>
<td>8.732(0.46)**</td>
</tr>
<tr>
<td>( \gamma )</td>
<td>0.267(0.14)’</td>
<td>0.742(0.16)**</td>
</tr>
</tbody>
</table>

\( (*) \): \( p \)-value < 0.1, \( (*) \): \( p \)-value < 0.05, \( (**) \): \( p \)-value < 0.01
Table 3.16 Extended Structural Model Parameter Estimation Considering Data-Breach Event (Heterogeneity across Age Groups)

| \( \beta = 0.995 \) |
|------------------|------------------|
| \( \alpha \)     | Millennials      | Older drivers (above 50) |
|                  | 0.496(0.11)**    | 0.449(0.09)**            |
| \( C_0 \)        | 82.95(1.06)**    | 73.37(0.89)**            |
| \( C_1 \)        | 7.062(0.47)**    | 8.559(0.39)**            |
| \( \gamma \)     | 0.587(0.20)**    | 0.878(0.18)**            |

(‘): p-value < 0.1, (*): p-value < 0.05, (**) : p-value < 0.01
Figure 3.1 UBI Policy Timeline for Adoption and Dropouts

Figure 3.2 “Data Breach” Searched Keyword in US

Figure 3.3 Data-Breach Event
Figure 3.4 UBI Adoption and Informed Dropout Rate across 4 Periods

Figure 4.1: UBI Adoption rate in 4 periods

Figure 4.2: "Informed dropout" rate of UBI customers in 4 periods

Figure 3.5 Timeline of Decision Process in the Model

Updated discount

0 15 30 45 60 75 90 105 120 135 150 165 180

d0 d1 d2 d3 d4 d5 d6 d7 d8 d9 d10 d11 d12

Adoption time

Informed dropout decision

Figure 3.6 Decision-Making Process at t = 0.1

Premium to pay

Switching cost from traditional to UBI

And cost of being monitored

Demographic information

Insurance score (past driving history)

Adoption decision?

0

Adoption time

UBI customers observe the latest driving performance (UBI score) during time period 1

Customers decide whether they want to continue UBI for one more period or not?

15

Cost of being monitored (privacy...)

Premium to pay
Figure 3.7 UBI Monitoring and Remaining Periods in 3-year Time Horizon

Figure 3.8 Estimated Adjusted Permanent Discount Functions

Figure 3.9 Simulated Adoption Rate in Counterfactual Analysis by Reducing the Costs
Figure 3.10 Simulated Adoption Rate in Counterfactual Analysis by Increasing the Costs

![Graph showing adoption rates](image)

Figure 3.11 Counterfactual Estimation of Dropout Rates after Reduction in Costs

![Graph showing dropout rates](image)
Figure 3.12 Counterfactual Estimation of Dropout Rates after Increase in Costs

<table>
<thead>
<tr>
<th></th>
<th>Actual data</th>
<th>Simulated Data</th>
<th>Increase in C0</th>
<th>Increase in C1</th>
<th>Increase in both</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Early Dropouts</strong></td>
<td>0.04</td>
<td>0.019</td>
<td>0.012</td>
<td>0.028</td>
<td>0.022</td>
</tr>
<tr>
<td><strong>Informed Dropouts</strong></td>
<td>0.149</td>
<td>0.143</td>
<td>0.114</td>
<td>0.196</td>
<td>0.178</td>
</tr>
<tr>
<td><strong>Late Dropouts</strong></td>
<td>0.173</td>
<td>0.185</td>
<td>0.153</td>
<td>0.202</td>
<td>0.192</td>
</tr>
</tbody>
</table>
Chapter 4: The Effect of Lower Prices and Better Information on Insurance Coverage Choices: Insights from Usage-based Auto Insurance

4.1 Introduction

Customer relationship management (CRM)\textsuperscript{47} focuses on approaches to retain existing customers and to increase margin and profits from such customers. Upselling and cross-selling are two common practices in many industries for this purpose. Upselling attempts to persuade customers to purchase a more expensive, upgraded, add-ons or premium version of the chosen item both to improve customers utility and increase the company’s profits. Cross-selling seeks to generate more sales by suggesting additional, related or complementary products and services to a buyer who’s already committed to making a purchase. Businesses often combine upselling and cross-selling techniques in an attempt to increase order value and maximize profit. For instance, electronic equipment retailers frequently offer a wide range of accessories, such as carrying cases and memory cards, to consumers who purchase digital cameras or laptop computers. Insurance companies often try to sell a higher premium plan to customers or encourage the customers to buy additional insurance products. In the car rental market, the rental companies try to sell add-on products (like GPS) or convince their customers to opt for full insurance coverage or upgraded car. All these examples illustrate how upselling and cross selling are commonly being used by firms in different industries to increase their profits. If upselling and cross-selling are

\textsuperscript{47} Winer, Russell S. "A framework for customer relationship management." California management review
part of a strategy involving long term customer relationships, as in the auto insurance industry we study here, successful programs require that the customers value the enhanced products as having value beyond the additional price they pay. This is often possible as the offered products and services can be targeted to the customer’s needs and it is often less expensive to provide services to existing customers than to acquire new customers\textsuperscript{48}. From the firm’s perspective, upselling and cross selling can help the firms to build deeper relationships with customers and lead to increased customer lifetime value (CLV). Also, it’s usually easier for the firms to upsell to existing customers than to acquire new ones\textsuperscript{49}. These advantages are particular crucial in industries such as auto insurance where overall growth, at least in the US, is relatively stable and competition is intense, as we discuss further below. Therefore, it’s crucial for the firms to better understand the customers’ responses in upselling and cross-selling efforts in order to set better the pricing strategies to increase their profits.

Previous chapters of this thesis have focused on customer behavior primarily during the enrollment process, considering in Chapter 2 (published as Soleymanian et al. (2019)) the issue of whether UBI customers become safer drivers while enrolled in the program and, in Chapter 3, sensitivity to privacy concerns. In this chapter, we turn to customer behavior at the time of renewal to address important issues with regard to CRM. First, we estimate whether UBI customers as compared to non-UBI customers are more likely to change their insurance coverage

\textsuperscript{48} IDC reports that insurers are spending up to seven times more to attract new customers than retain existing ones (Chew, Li-May. “Global Insurance 2015 Top 10 Predictions: Perils and Prospects for the New Year.” IDC Financial Insights. January 2015.)

at the time of first (annual) renewal. Such a difference is possible, because UBI customers have a permanent price discount (averaging 12%) that better targets their actual driving behavior. This lower price would likely tend to increase the amount of insurance coverage purchased. However, UBI customers, while no longer being monitored, have more accurate information than non-UBI customers about their actual driving behavior. Customers may vary in how they respond to such information. Some may choose to decrease their coverage, perhaps because they judge themselves to be safer drivers than they thought they were at the time of enrollment, while others may use this information to decide that they need a higher level of coverage with this more accurate perception of their risk factors. Our data are not sufficient to test the casual factors underlying renewal patterns, but our descriptive analysis finds that UBI customers are more likely to change their coverage than non-UBI customers and that of the 24% who change their coverage at the one year point, 17% choose greater coverage and 7% choose lesser coverage, suggesting that more than the price discount is being considered by customers. At the time of the second renewal, UBI and non-UBI customers have the same likelihood of changing their insurance coverage, consistent with the view that the information revealed during the monitoring period and the permanent discount effect occurs at the first opportunity to renew, but not beyond that point. In terms of CRM, these results suggest that the auto insurance companies, the appropriate time to focus on upselling and cross-selling is at the first renewal after enrollment in the UBI program. However, they need to recognize that despite the permanent price discount, some customers will actually want to reduce their coverage and that this decision should be facilitated as well.
The insurance market is undergoing a major paradigm shift mainly because of stiff competition and stable market. For example, in automobile insurance 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 it critical for the firms to find more innovative ways to increase the profit. As the cost of acquiring new customers increases, insurers are putting greater emphasis on retaining their current customers. Carefully analyzing data on their current customers, insurers attempt to sell more extensive versions of the existing policies (upselling) and/or sell other types of services (cross-selling) to current customers. The success of insurers critically depends on the long-term relationship with their customers (Kim and Kim, 1999).

Related to CRM, customer retention and cross-selling (or upselling) are two of the most critical profit drivers for an insurer and using new technologies could play a crucial role in achieving these goals.

Insurers are fundamentally changing their relationship with consumers through the use of real-time monitoring and visualization. By analyzing such data, insurers can offer usage-based policies and determine claims liability easily and accurately. Since insurance companies generally have fewer interactions with their customers compared to other industries, every moment of contact is critical and UBI could provide a great opportunity for the insurers to significantly increase the interactions with customers and ultimately improve the customer experience and life-time value. In our study, we try to evaluate the effectiveness of UBI policy on upselling efforts as one of the major sources of profit for insurers.
For this purpose, we use a unique database from a major US automobile insurance company. We observe information from approximately 93,000 new customers who submitted a quote request to purchase an insurance policy from March 2012 to November 2014. As we only consider customers for whom we can observe at least the first renewal decision, our sample is reduced from that in the previous chapters. We observe the customers’ UBI adoption decisions in addition to demographic, insurance coverages, and premium rates of each customer. For all customers who adopted the UBI policy, we have daily information on their driving performance which determines the discount they get in this policy. We also observe the retention decision (whether to renew, and coverage choice at renewals) of customers one and two years after initial purchase and the premium to pay at renewals for all customers. Our setup and comparing the UBI and non-UBI customers’ coverage choice changes over time allow us to capture the effect of offering UBI on the effectiveness of upselling in insurance industry. We also consider heterogeneity in UBI customers choice of renewal options based on gender, driving experience, etc.

Our research is the first study in marketing that study the changing in insurance coverage choice by considering usage-based insurance policy. It’s also important to note that the findings in our paper could add one more benefit to the existing values of UBI in the literature by supporting the effectiveness of upselling efforts and cross-selling to insurance market.

The rest of this paper is organized as follows. After reviewing the literature related to our research, we discuss the sensor data used in our analysis and some key patterns observed in the insurance coverage choice of different groups. We then set up our model to examine the effect of
UBI policy on effectiveness of selling a more comprehensive coverage (upselling) at renewal time. The estimation and empirical results are presented and discussed in section 4.4. Finally, we provide some concluding comments and discussion on limitations of the current research in section 4.5.

4.2 Literature Review

To our knowledge, our research is the first empirical study analyzing insurance customers’ coverage choice and changes in the customers’ decisions at renewal time in the context of usage-based insurance. As we discussed above, there are two major differences between UBI and non-UBI customers in terms of information or feedback that UBI customers receive and the price (premium) changes where the UBI customers could obtain a significant UBI discount (up to 25%) over the initial premium if they show safe driving behavior. Our paper is related to different streams of research in the literature including usage-based pricing and insurance; information, feedback and change in customer belief and decision; and mental accounting (budgeting) effect.

4.2.1 Usage-Based Insurance

UBI could be categorized as one type of usage-based pricing (UBP) that the customer pays for the service or product based on her usage. In the telecommunication and software subscription industries, 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. More specifically and related to UBI, Soleymanian, Weinberg, and Zhu (2019) find that a UBI monitoring program and the economic incentives it provides can encourage UBI adopters to improve their driving behavior, which is heterogeneous across different groups of customers, and to thereby obtain a higher UBI discount. They find the improvement in driving behavior is not just limited to the period of monitoring; the UBI customers show long-term improvement even after finishing the UBI monitoring period. UBI enables an insurance company to customize the product offering to each consumer based on his or her driving behavior by providing individualized price discount. It can also affect a consumer’s coverage choice if a consumer is responsive to the insurance’s price change. Our paper tries to capture the differences in changing the insurance choice coverage between UBI and non-UBI customer.

4.2.2 Mental Accounting (Budgeting) and Consumer Decisions

Mental budgeting is consistent with well-known research on mental accounting (Henderson and Peterson 1992; Kahneman and Tversky 1984; Thaler 1985) that demonstrates that people use resources differently depending how they are labeled. Heath and Soll (1999) show that how
budget setting and expense tracking can alter consumer choice. According to research on budgeting and mental accounting, people assign spending limits to different categories of goods and services—for example they might have a budget for holidays, a budget for home improvement, and a budget for insurance. Then, if there is a price change in one category, for example, insurance, then they are more likely to adjust their spending for other insurance products and services than to adjust their spending over the full range of products and services they purchase. They highlight that budget setting leads people to overconsume some goods and underconsume others. In our research as we discussed above, price (premium) changes could be one of the key factors in changing the insurance coverage at the one year renewal time among UBI customers. Related to mental budgeting, if the company’s customers set a budget for their auto insurance expenditures, when they use UBI and achieve significant UBI discount at the renewal time, they are more likely to upgrade and purchase a more comprehensive coverage considering the initial budget setup. Heath et al. (1995) suggest that mental accounting principles, price perception and reference dependence are sensitive to the ways in which deviations from reference states are framed. Heath and Soll (1999) interpret some demonstrations of mental-accounting effects as evidence of overconsumption. For example, O’Curry (1996) find that when asked to imagine a cross-category price discount on beer, beer drinkers stated that they would use the extra funds to buy higher quality beer, but they would not do so when they receive an equivalent amount of wealth as a gift. The pattern could be interpreted as evidence that consumers overconsume beer when the price falls and the beer budget contain a surplus. These results show that the mental accounting (budgeting) effect could be one potential explanation for the effectiveness of upselling more comprehensive insurance.
coverage at the renewal time for UBI customers who receive UBI discount compared to non-UBI customers.

4.2.3 Information, Feedback, and Customer Belief

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 could also check their daily driving performance through the app. The information received by the UBI customers may affect their decisions to choose the insurance coverage in different ways. First, receiving feedback and information could change the belief of customers about their driving abilities and the perceived risks which ultimately could change the customers’ insurance coverage choice at the renewal time. Second, Soleymanian et al. (2019) show that the immediate feedback in UBI could significantly improve the driving behavior of customers which may lead to changing the insurance coverage, because the informed drivers with different driving abilities would choose different level of insurance coverages to maximize their utilities. Our paper could also be related to the literature of information and overconfidence. When consumers sign contracts, expectations about future usage of the product or service matter. For example, the value provided by car insurance depends on how likely a consumer believes she is to file a claim; the standard modeling paradigm makes the expedient assumption that consumers have rational expectations. Imposing rational expectations drastically simplifies models and eliminates the need to directly measure beliefs as they coincide with the distribution of observed outcomes. Yet a large literature shows that consumer beliefs often deviate substantially from rational expectations in systematic ways.
The term overconfidence is used broadly in the psychology literature, referring to both overoptimism and overprecision (Grubb 2015). Overoptimistic individuals overestimate their own abilities or prospects, either in absolute terms or in comparison to others. In contrast, overprecise individuals place overly narrow confidence intervals around forecasts, thereby underestimating uncertainty. These biases can lead consumers to misforecast their future product usage, or to overestimate their abilities to navigate contract terms. Poor choices based on biased estimates of a product’s expected costs or benefits are the result. For instance, overoptimism about self-control is a leading explanation for why individuals overpay for gym memberships that they underutilize (DellaVigna and Malmendier 2006). Overoptimism leads consumers to overestimate gym attendance and hence to overweight the membership benefit of avoiding per-visit gym fees. Similarly, overprecision is a leading explanation for why individuals systematically choose the wrong calling plans, racking up large overage charges for exceeding usage allowances in the process (Grubb 2009; Grubb and Osborne 2015). Overprecision leads consumers to underestimate the variance of future calling, and hence to underweight the cost of calling plans under both low and high usage. The evidence for overconfidence—both in the form of overoptimism and overprecision—is rooted in more than 59 years of research in psychology (Lichtenstein, Fischhoff, and Phillips 1982). Evidence for consumer overconfidence comes from different sources. First, there are experiments in market-relevant settings. For instance, Silk’s (2004) experiments suggest that individuals are overoptimistic about the likelihood of redeeming mail-in rebates. Second, field data on consumer choices provides evidence of consumer overconfidence. Consumer beliefs can be inferred from contract choices (or elicited by survey) and compared to later usage to identify bias. For example, in a study of a New England health
club, DellaVigna and Malmendier (2006) show that users who chose a monthly membership could have saved an average of more than 40 percent by foregoing a membership and paying per-visit. This finding is consistent with overoptimism about gym attendance due to overoptimism about self-control. For economists, a common question is “Doesn’t overconfidence go away with learning?” On the one hand, learning can mitigate overconfidence with appropriate feedback (Bolger and Önkal-Atay 2004). On the other hand, Gabaix and Laibson (2006) show that competition need not give firms an incentive to educate or de-bias consumers, and lab experiments show that outcome feedback of the sort consumers likely receive in practice is often ineffective (Subbotin 1996). Moreover, field studies of consumer choice confirm that learning is no panacea for avoiding past mistakes. Choices may improve slowly (Grubb and Osborne 2015), or lessons may be forgotten (Agarwal et al. 2013).

These findings about overconfidence and belief biasness are highly relevant in the insurance context. The insurance customers at purchase time might be overconfident about their driving performance and the risk of having accident. So, there are bias in evaluating the risks and finding the right insurance coverage. The group of customers who adopt the UBI policy, because receive daily feedback, are more likely to fix this biasness and overconfidence. Therefore, the UBI customers are more likely to change their insurance coverage at renewal time compared to non-UBI customers.

In summary we study the difference in coverage choice pattern between UBI and non-UBI customers by considering the price change and information (feedback) as two major sources
of the differences affecting the distinction between the coverage choice of UBI and non-UBI customers.

### 4.3 Data

We study insurance customers’ decision to change their insurance coverage based on data from a major US insurance company that offers the UBI program as an optional policy alongside its 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 after choosing the desired insurance coverage receive both a traditional premium quote based on a formula filed with each state’s regulators and the offer of a discount if they enroll in the UBI program. Customers who choose the UBI program, receive feedback from their actual driving behavior because of using a telematics device. These customers can also receive up to a 25% discount if they show safe driving behavior while using the device. The UBI discount depends upon a score based on a number of factors related to actual driving behavior and how long, up to 6 months at most, they remain in the UBI monitoring program. On the other hand, the non-UBI customers pay the initial premium set at the beginning. After finishing the first year, all customers make renewal (whether or not they stay with the company) and coverage choice (primarily how high a deductible to self-pay in case of an accident for which they are liable) decisions. So, we observe in the dataset not only the initial coverage choice, but also the renewal coverage choice for both UBI and non-UBI customers. Figure 4.1 shows the flow of events and decisions in our setting.
In this paper we try to evaluate the differences between UBI and non-UBI customers’ tendency to change their insurance coverages compared with initial coverage choices. Based on information in corporate annual reports, the insurance company started to offer usage-based insurance as a new policy in order to better target safer drivers and thus to increase the company’s profit by attracting and keeping more profitable customers. Like almost all 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 the new customers to sign up for a UBI policy by offering an initial (temporary) discount (typically 5%). The initial discount is given to the customers as soon as they enroll in the UBI program. If the policyholder accepts the UBI policy, she will receive a telematics device that should be plugged into the car. This device enables the insurance company to monitor many aspects of the driving behavior of the customer. The customer can monitor her performance from real-time feedback: whenever the customer hard-brakes, the telematics device beeps to let the driver know or the driver can monitor her performance on a daily basis via an app. The monitoring period lasts for a maximum of 180 days, at which time, the telematics device is removed, and the customer is offered a permanent UBI discount. The driver will receive up to 25% permanent discount based on her daily driving scores after six months of usage, but the average discount rate is 12 % with a standard deviation of 5 %. While some drivers (less than 1% in our sample) may be offered no discount, a surcharge is never imposed. Customers know the initial discount, the range of the discount (including the no surcharge policy), and the average discount as this information is provided in the company’s website. In general, there are two major differences between the UBI and non-UBI customers’ journeys. First, the UBI customers receive immediate and daily
feedback about their actual driving behavior which doesn’t happen for non-UBI customers. Second, the UBI customers have this opportunity to lower their premium by showing the safe driving behavior.

Our empirical research builds on a number of datasets that contain information about individual drivers’ auto insurance choices (UBI and non-UBI policies), insurance coverage choices, their demographic characteristics, premium, and risk scores defined by the insurance company. For the drivers who choose UBI, we observe sensor-based information on their actual daily driving behavior (UBI scores). We also observe whether or not UBI drivers drop out early (and when) from the monitoring program during the 6 months of using this policy. At the end of year, we also observe the renewal decisions for all customers and the insurance coverage choices for the customers who renew their insurance for one more year.

Table 4.1 reports some summary statistics about the customers in our sample. The first column of Table 4.1 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 UBI acceptance rate is about 30%. In addition, the average age of the UBI policyholders (39.3) is much lower than for the non-UBI customers (48.7), suggesting that the UBI program is more attractive for younger drivers. One possible explanation is that the insurance company, as is common in the industry, assigns a relatively high-risk level to the young drivers due to the lack

50 The UBI customer receives a permanent UBI discount as long as she remains in the program for 75 days.
51 The last column in Table 1 shows the p-value of t-tests for comparison of UBI and non-UBI customers.
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 demonstrate their actual driving behaviors, and as a result they can receive a discount rate according to their performance. Therefore, the incentive for younger drivers seems to be higher to adopt the UBI program comparing to older, or experienced, drivers. The higher average monthly premium of UBI drivers compared to no-UBI customers also shows the program seems to be more attractive for the customer who are paying more, because their expected savings after using UBI can be higher than others.

Table 4.1 also shows the distribution of insurance coverage choice for each group of customers. The insurance company offers many types of auto coverage in terms of third party liability and collision options. In our dataset, we found 5 levels of insurance coverage for drivers as shown in the table. Comparing the percentage of UBI customers who chose each coverage with non-UBI customers, we find that the UBI customers are more likely to choose less coverage (just liability and liability+1000) compared to non-UBI customers. The renewal rate of UBI customers in both first and second years are higher than for non-UBI customers.

We also run a simple logit model to capture the effect of different factors in choosing the initial insurance coverage. For simplicity we aggregate the coverage choices into two levels; minimal or less inclusive (just third-part liability without collision coverage) and more inclusive (combining all the collision coverages into this group).

52 We introduce later the comprehensive policy which is an add-on to all these 5 coverages. Comprehensive coverage refers to non-driving related risks, such as fire. We excluded the comprehensive policy from our analysis for now in order to focus on driving-related outcomes.
\[
\text{prob (choosing more inclusive coverage})_i = \logit(\text{age}_i, \text{gender}_i, \text{new driver}_i, \text{Initial insurance score}_i, \text{State}_i, \text{UBI adoption}_i)
\] (4.1)

The results in Table 4.2 show that age and new driver covariates are significantly related to the initial coverage choice and the senior drivers are more likely to choose more inclusive coverages, while the new drivers are more likely to choose less inclusive (basic) coverages compared to experienced drivers. In addition, males are less likely to choose the more inclusive coverages than females and interestingly the UBI adoption coefficient is just marginally significant which means the UBI adoption is not significantly associated with initial coverage choice at 0.05 level\(^{53}\) after controlling for other customer characteristics.

As we explained above, for all customers who renew their insurance policies, we also observe the insurance coverage choices at the renewal times\(^{54}\). Figure 4.2 shows the distribution of coverage choices for both UBI and non-UBI customers at purchase and renewal times. The blue, orange, and gray bars show the distribution of coverage choices at purchase, first renewal, and second renewal times respectively. For non-UBI customers, at the aggregate level, the share of each policy remains relatively constant over the first and second renewal. These plots suggest the UBI customers are more likely to upgrade to higher coverages at first year renewal compared to non-UBI customers. However, the distribution of coverage choices remains relatively constant

\[^{53}\text{It’s important to note the sequence of making decisions in UBI policy. The customers first choose their insurance coverage choice and receive a quote based on their choice and then receive the offer to join the UBI program. So, the adoption decision happens after the coverage choice in our setting.}\]

\[^{54}\text{Since our dataset contains the customers’ data for more than two years, we have this opportunity to observe the coverage choice of customers for up to two renewals. (customers renew their policies annually)}\]
from the first to second renewal for both UBI and non-UBI customers. It’s important to note that the first renewal is the first time when consumers can make a choice among alternatives knowing their driving scores and their permanent discount.

With these results at the aggregate level, we now turn to individual level analysis. We begin by defining two dummy variables to better evaluate the changes (upgrade or downgrade) in coverage choices. These two variables indicate whether each customer upgrades or downgrades her insurance coverage at renewal time.

\[
Upgrade_i = \begin{cases} 
1 & \text{if customer } i \text{ upgrades to a more inclusive coverage at renewal} \\
0 & \text{else}
\end{cases}
\]

\[
Downgrade_i = \begin{cases} 
1 & \text{if customer } i \text{ downgrades to a less inclusive coverage at renewal} \\
0 & \text{else}
\end{cases}
\]

Table 4.3 shows the percentage of UBI and non-UBI customers who upgrade or downgrade their insurance coverages at the first-year renewal. It’s interesting to find that the percentage of UBI customers who upgrade their coverages (17%) is higher\(^{55}\) than for non-UBI customers (8%). The same pattern exists for the downgrade percentage where the UBI customers have significantly\(^{56}\) higher downgrade rate than for Non-UBI customers. In other words, the UBI customers are more likely to change their coverages (both upgrade and downgrade) than non-UBI ones.

\(^{55}\) P-value <0.01
\(^{56}\) P-value<0.05
There are two competing motives for the UBI consumers to change their insurance coverages. Prices are lower, so customers may buy more (consistent with mental budgeting effect), but they also may have evidence that they are safer driver after using UBI (consistent with Soleymanian et al. 2019), so insurance coverage is worth less to those improved drivers. On the other hand, if they are overconfident about their driving ability when they enrolled in the UBI program, the UBI provided information may reduce that overconfidence bias. That is, the UBI usage may decrease the degree of overconfidence because of continuous feedback and adjust the decision bias as well. In next section, we model the changes in coverage choices of customers and discuss the differences in more details. We also try to capture and resolve this tension between these two effects.

In general, the model free results suggest that there could be a significant difference between coverage choice patterns (changes in insurance coverages) between UBI and non-UBI customers. In the next section, we propose reduced-form models to capture these differences in consumer behavior after controlling for other factors. We take this approach, because to the best of our knowledge from reading company documents and discussions with corporate executives, the discounts offered as part of the UBI program and the terms of the monitoring period were designed to attract new customers and to retain them as company customers, not to affect their coverage choices. Thus, our focus is on consumer coverage choice decisions.

4.4 Empirical Analysis and Results
In this section, we analyze how customers decide to change their insurance coverages and capture the differences in changing the coverages between UBI and non-UBI customers. We use simple logit regressions to model the changing coverage decisions (upgrade or downgrade) at the renewal time. The probability of upgrading (downgrading) to a more(less) inclusive coverage at the renewal time is modeled by a multinomial regression in equation (4.2). We consider the age, gender, initial insurance score, state, and initial coverage choice of each customer as the covariate in this model. Our dependent variable has three levels (keep the same coverage, upgrade, and downgrade) and we consider keeping the same coverage as the base level. So, we estimate two sets of coefficients for downgrade and upgrade choices. We are mainly interested in the two coefficients of $UBI\ dummy_i$ which captures the difference between the probability of upgrading (downgrading) between the UBI and non-UBI customers, because $UBI\ dummy_i$ variable is equal 1 if the customer $i$ chooses the UB policy and 0 if not. It’s important to note that in the model we consider the fixed effects of states where the customers live and the initial insurance coverage that each customer chose.

\[
Prob(choice_i) = \text{logit}(Age_i, Gender_i, UBI\ dummy_i, Insurance\ score_i, State_i, Initial\ coverage_i) \quad (4.2)
\]

Table 4.4 summarizes the multinomial regression analysis results for changing the coverage choice to capture the effect of UBI usage on upgrading or downgrading the insurance coverage at the renewal time. The results in Table 4.4 suggest the younger drivers are significantly more likely to upgrade their insurance from lower coverage to a higher level than senior drivers at the renewal time and males are marginally less likely to upgrade their insurance than females. More
importantly, the positive and significant\textsuperscript{57} coefficient of UBI dummy for upgrading choice in Table 4.4 shows the UBI customers are more likely to upgrade their insurance coverage compared to non-UBI customers. In addition, Table 4.4 shows the estimation results for downgrading decision as well. As in the upgrading decision, senior drivers are less likely to downgrade their insurance coverage, while the males are more likely to downgrade their insurance coverage to a lower level than females. The coefficient estimation of the UBI dummy in Table 4.4 for the downgrading option shows that the UBI customers are more likely to downgrade their insurance coverage than non-UBI customers as well. In general, the results in Table 4.4 suggest the UBI customers change (upgrade or downgrade) their insurance coverage significantly more than non-UBI customers after controlling other factors in the multinomial model.

We extend the above analysis to the second renewal decision where the customers have another chance to choose their insurance coverage after the second-year contract. We want to test whether the UBI and non-UBI customers are significantly different in changing their coverage choices at the second renewal compared to what they chose at first renewal. Considering the \textit{choice}_i for the second renewal decision, we run a multinomial regression model similar to equation (4.2). In this case, upgrading means the customers choose a more comprehensive coverage at the second renewal time compared to the first year renewal. The results of this analysis are shown in Table 4.5. It’s important to note that there is no significant difference between UBI and non-UBI customers in the second year, possibly because by definition, the UBI

\textsuperscript{57} P-value \textless 0.01
customers just use the telematics device for the first six months (within first year) and receive no further feedback after the first year. As at the first year, older drivers are less likely to change their coverage than younger drivers, although the result is only marginally significant for downgrading. Males are less likely to upgrade their coverage than females. Combining these results with Table 4.4 estimation results helps us to infer that the UBI usage because of price changes and information in the first year could lead to a higher rate of changing the insurance coverage among UBI customers than non-UBI customers at the first renewal, but not at the second renewal.

We should note that there could be sample selection bias in the above analysis, so it’s difficult to make causal inferences for the effect of UBI usage on changing the insurance coverage compared to non-UBI customers. We have a non-experimental setting where the treatment group (UBI customers) and control group (non-UBI customers) are not assigned randomly. Since our dependent variables are the coverage choice changes within a consumer, we can control for the individual fixed effects implicitly. However, we still have concerns about the correlation of a consumer’s UBI choice and her time varying preferences for auto insurance coverage. A number of approaches have been discussed in the literature to deal with this issue. We use propensity score matching (PSM) technique to estimate the effect of treatment (UBI usage) on probability of upgrading (or downgrading). PSM attempts to reduce the bias due to confounding variables that could be found in an estimate of the treatment effect obtained from simply comparing outcomes among customers that used the UBI policy versus those that did not. In this method, we match each UBI customer in the treatment group with non-UBI customers based on propensity scores and form the new data sample to run the model (4.2). In this case we
might be able to infer the likelihood of causal inference for the effect of UBI usage on probability of upgrading or downgrading the insurance coverages. We implement propensity score and nearest neighbors matching approach like Abadie and Imbeds (2016) to estimate the average treatment (UBI usage) effect on changing the insurance coverage choice. The general procedure to implement the propensity score matching method in our setting is as follow.

1- Run a logistic regression to model the UBI adoption decision

\[
\text{prob (UBI adoption}_i) = \text{logit} (\text{Age}_i, \text{Gender}_i, \text{Insurance score}_i, \text{Urban}_i, \text{New driver}_i, \text{State}_i, \text{Initial coverage}_i) \quad (4.3)
\]

2- Obtain propensity score: predicted probability \((p_i)\) or \(\log [p_i/(1 – p_i)]\).

3- Match each UBI customer to one or more non-UBI customers based on propensity score.
   - We use the nearest neighbor matching in this stage.

4- Run the model (1) and (2) based on new samples (matched customers)

We use the “MatchIt” package in R to implement and run the propensity score matching technique in our empirical setting. The results based on this approach as shown in Table 4.6 is consistent with our findings in Tables 4.4 and 4.5. The UBI users have higher upgrading and downgrading rates of insurance coverage than the non-UBI users in the first renewal, but there is no significant difference in the second renewal.

4.4.1 Information and Price Effects
Considering the results discussed above, it’s important to consider the various sources that could lead to these differences between the UBI and non-UBI customers in changing their insurance coverages to upgrade or downgrade. First, we consider information effects. To this aim, we need to consider the main differences between the two groups that could also affect this significant difference in coverage choice changes. As we discussed before, there are two major differences between the UBI and non-UBI customers in the first year. First, the UBI customers receive immediate and daily feedback about their actual driving behavior which doesn’t happen for non-UBI customers. This is an information effect. Second, the UBI customers not only receive a price discount for participating in the program but they also have the opportunity to lower their premium by improving their actual driving behavior. Both these factors could affect the customers’ decision to change the insurance coverage in different ways. Turning to the first effect, the group of customers who receive immediate and daily feedback about their actual driving behavior could perceive the elements of risk factors differently compared to non-UBI customers who don’t get daily feedback. These changes in risk perception could directly lead to changing the insurance coverage choice.

The overconfidence and belief biasness discussed in literature review could also be a possible explanation for our findings related to effects of information and feedback on changing the insurance coverage choice. Initially the customers could be overconfident with regard to predicting their future performance accurately and the UBI usage would help the customers to get more feedback and information regarding their actual driving performance and adjust their expectations at the renewal decision point. So, fixing the biasness and overconfidence because of valuable information gained by UBI usage may lead the UBI customers to change their insurance
coverage more than non-UBI customers at the renewal time. In addition, consistent with our findings in Chapter 2, the customers who adopt the UBI policy significantly improve their driving behavior and they could update their beliefs about their driving abilities after the first year. So, at the renewal time, the UBI customers are more likely to change their insurance coverage because of changes in the driving behavior. All these possible factors which are directly related to UBI usage could potentially increase the likelihood that the UBI customers would upgrade or downgrade their insurance coverage than non-UBI customers.

On the other hand, we know that UBI usage could help the customers to significantly lower their premiums by getting the UBI discount compared to non-UBI policyholders. So, the premium changes at renewal time compared to the initial premium could be significantly different between UBI and non-UBI customers. So, UBI customers, who receive a substantial UBI discount at the renewal, would be more likely to upgrade their insurance coverage to higher coverages. In this situation, the customers’ mental account of the base coverage and premium (initial premium) which is higher than renewal premium for UBI customers play a crucial role in their add-on (upgrading) purchase decision. Therefore, the mental accounting (budgeting) effect could also explain the higher rate of upgrading among the UBI customers than non-UBI ones. That is, the mental accounting effect could help explain why the savings from the discounted pricing are spent in the auto insurance category and not over a broader range of goods and services.

4.4.2 Change in Insurance Coverage within UBI Customers
After examining differences between UBI and non-UBI customers in changing their insurance coverage, it’s worthwhile to do an analysis within UBI customers to capture possible systematic differences between different types (in terms of performance) of UBI customers in changing their insurance coverage to upgrade at the first renewal time. First, we explore whether the UBI score as a proxy for a customer’s driving behavior and the change of UBI score affect a consumer’s coverage choices. We model the upgrade\(^{58}\) in coverage choice within the UBI customers as below.

\[
\text{Prob}(\text{Upgrade}_i) = \logit \left( \text{Age}_i, \text{Gender}_i, \text{UBI score}_i, \text{Change in UBI score}_i, \text{Insurance score}_i, \text{State}_i, \text{Initial coverage}_i, \text{UBI dropout}_i \right)
\] (4.4)

\(\text{UBI score}_i\) and \(\text{Change in UBI score}_i\) are defined as the average UBI score and changes in UBI score\(^{60}\) of customer \(i\) respectively. \(\text{UBI dropout}_i\) is also a dummy variable which indicates whether the customer \(i\) dropped out from UBI policy and switched to traditional insurance policy while adopted to UBI earlier\(^{61}\). The estimation results are summarized in Table 4.7.

The results in Table 4.7 suggest that the UBI customers who have UBI discount are more likely to upgrade their initial insurance coverage to a higher coverage. However, the negative and

\(^{58}\) We did the same analysis for downgrading decision, but couldn’t find any significant effect.

\(^{59}\) Since the insurance score and premium are highly correlated, we can’t consider both covariates simultaneously in the equation.

\(^{60}\) During their usage period (not necessarily in 6 months)

\(^{61}\) The UBI customers who dropout after 75 days of UBI usage and switch to traditional insurance policy before using the telematics device for the whole 6 months are defined as dropout customers.
significant coefficient of change in UBI score variable shows the UBI customers who improve their driving behavior more are less likely to upgrade their insurance coverage after controlling other factors. The UBI customers who drop out from UBI policy and switched to traditional insurance are also less likely to upgrade their insurance coverage. In summary, the results show the UBI customers may systematically make their upgrading decisions based on their performance in UBI program (UBI score) and ultimately the discount they receive in UBI program.

As we discussed earlier, the difference between risk perception of UBI and non-UBI customers and the possible heterogeneous change in risk perception of UBI customers because of receiving immediate and daily feedback could potentially explain the difference between UBI and non-UBI customers’ insurance coverage choice patterns. On the other hand, mental accounting with regard to the budgeting of money allocated for auto insurance could affect the changes and differences in upgrading patterns between UBI and non-UBI customers because of UBI discount over the base premium for the UBI customers. Therefore, the two effects are confounded and it’s hard to separately capture these two effects. Theoretically, if we could control changing risk perception effect and still find a significant difference between the upgrading decision of UBI and non-UBI customers, we could argue that the price effect exists and it’s playing a role in UBI customers’ decision to choose the add-on product (upgrade). To do so, we study another choice of coverage, comprehensive insurance, which is not directly related to driving behavior of customers.
4.4.3 Comprehensive Coverage and the Role of Price

Comprehensive coverage is a kind of add-on product that the insurance policyholders could add to the 5 levels of coverages we explained before. The benefits of comprehensive coverage are not directly related to driving behavior or the car accidents. This coverage is solely about other events that could happen (e.g., theft, fire, or natural disaster) to protect the drivers for the incurred costs. Adding this coverage increase the premium to pay, but it doesn’t cover any kind of risks associated with driving behavior. So, by definition, if we define the upgrading as the decision to just add comprehensive to the current coverage or not, we may be able to capture the price effect, because changing the risk perception of driving and getting actual driving feedback are less likely to change the customers’ decision to add the comprehensive coverage.

For the empirical analysis of this issue, we consider a subset of our data in which the customers keep the same insurance coverage with regard to liability or just add the comprehensive choice at the renewal. That is, our sample is people who did not initially adopt the comprehensive coverage and did not change their liability coverage at the time of first renewal. Table 4.8 shows the percentage of UBI and non-UBI customers that belong to each category. The data summary shows that the UBI customers are significantly more likely to add the comprehensive coverage to their current coverage at renewal time than non-UBI customers.

To examine the effect of the size of the UBI discount on the customers’ decision to add the comprehensive coverage, we consider a logit model to capture the effect of different factors.
including the level of the UBI discount on probability of adding the comprehensive coverage to the current coverage at the renewal time among participants in the UBI program.

\[
\text{Prob(Just adding comprehensive)}_i = \logit(Age_i, Gender_i, UBI\ discount_i, \text{Insurance score}_i, \text{State}_i, \text{Coverage}_i, \text{new driver}_i)
\] (4.5)

The results in Table 4.9 suggest that the UBI customers who have higher UBI discount are significantly more likely to add just the comprehensive coverage to their current coverage. This result suggests a price effect which is likely more pronounced than would otherwise be expected due to the mental accounting budgeting effect. In particular, the pricing effect is stronger for the UBI customers with higher UBI discount and the probability of adding just the comprehensive coverage (buying add-on product) is higher for this group of customers, while the effect of receiving feedback and changing the risk perception may not play a role in this setting as we explained before.

4.4.4 Heterogeneous Effect of UBI Usage on Changing the Insurance Coverage

As we discussed before, the results in Table 4.4 show the main effect of UBI usage on changing the insurance coverage and we found the UBI customers are more likely to change (upgrade or downgrade) their coverages than non-UBI customers. In this subsection we extend model (1) by adding the interactions of different groups of customers and UBI dummy to study the heterogeneous effect of UBI usage on changing the insurance coverage. We consider the interactions of UBI dummy with age, new driver, and gender to capture whether the effect of
UBI usage on changing coverage choice is different between new versus experienced drivers or males versus females. The heterogenous effect of UBI usage on changing the insurance coverage across different groups could exist because of various reasons. The price and information effects we discussed before could be different across genders or experienced versus new drivers. For example, the difference between the UBI and non-UBI customers within new drivers’ group in terms of information and price changes could be significantly more than for experienced drivers. On the other hand, the price changes in UBI program at renewal within new drivers on average is much higher than experienced drivers. Therefore, there are some potential factors that may lead to existence of heterogeneous effects.

\[
Prob(\text{upgrade}_i) = \logit(Age_i, Gender_i, new\text{\,driver}_i, UBI\text{\,dummy}_i, Age_i \\
* UBI\text{\,dummy}_i, Gender_i \ast UBI\text{\,dummy}_i, new\text{\,driver}_i \\
* UBI\text{\,dummy}_i, Insurance\text{\,score}_i, State_i, Initial\text{\,coverage}_i) \quad (4.6)
\]

The estimation results in Table 4.10 show that there is a significant difference between the new drivers versus experienced drivers in the effect of UBI usage on upgrading the coverage choice. The difference between UBI and non-UBI customers to change their insurance coverage choice is greater among new drivers versus experienced drivers. It shows that the new customers are more sensitive in changing their coverage when they adopt the UBI policy compared to

\[62\] The value of information the new drivers receive could be significantly more than for experienced drivers to make their decisions because the new drivers haven’t had any driving experience before.
experienced drivers. The negative and significant coefficient of age and UBI dummy interaction term also shows that the effect of age on upgrading is stronger (more negative) in UBI customers than non-UBI customers. In other words, within UBI customers the senior drivers are less likely to upgrade their insurance coverage to more inclusive coverages than younger drivers and this effect is less among non-UBI customers.

4.5 Discussion

Firms in a variety of different industries sell add-on products or features that enhance the value of a base product. So, it’s important for the companies and marketers to better understand how customers buy add-on or upgrade the base products. In general, upselling and cross selling are important parts of customer relationship management in many industries including the auto insurance industry that we study here. In this study, we examine and evaluate the effect of adopting and using the UBI policy on consumers’ decision to upgrade and buy add-on products (higher insurance coverage over the basic coverage) or to decrease coverage at the renewal time. While our focus is not on the management of the renewal process, this study and its findings could be important for management because it explores another benefit of offering UBI program for the firm. As noted earlier, to the best of our knowledge, the current UBI program offered by the company we study was designed to acquire new customers and retain customers, so that the design of the program did not specifically consider the possibility of upselling and cross-selling.

The results of the study suggest that the UBI and non-UBI customers have different patterns in changing the distribution of insurance coverage choices at the (first) renewal time compared to the initial purchase time. The UBI customers are more likely to change their
coverage choice than non-UBI customers. In particular, UBI customers are more likely to upgrade their insurance coverage at the renewal time after controlling for other factors. We employ the propensity score matching (PSM) technique to help control for the selection bias issue. The results after considering the PSM method are consistent with the main results which provides support for possible causal inferences about the effect of the UBI program participation on the upgrading decision. Moreover, the differences between UBI and non-UBI customers do not hold at the time of second renewal, suggesting the information gained and price discounts obtained during the monitoring period have an immediate effect on changing choices and the updated choice persist over a longer term without further changes. These results are also consistent with the argument that any effects obtained with regard to changes in coverage choice are not due to sample selection.

Within UBI customers we also find that the customers who show better driving behavior (higher UBI score) and get greater discounts are more likely to upgrade their insurance coverage to the higher levels. We also examine separately the mental accounting effect by introducing the comprehensive coverage which is not directly related to driving behavior. Focusing on customers who just add comprehensive coverage to their insurance policy to rule out other explanations for the addition of comprehensive coverage (such as increasing the deductible to save money on other coverage), the results suggest that UBI customers are significantly more likely than non-UBI customers to add just the comprehensive coverage to their current insurance policy. In addition, within the UBI group, the UBI customers who show better driving behavior and ultimately receive a higher UBI discount are more likely to add the comprehensive coverage. This is an evidence which shows the mental accounting effect exists and the customers who get
lower premium at renewal time because of UBI discount are more likely to pay for comprehensive coverage and add it.

With regard to the impact of information and feedback on the UBI consumers’ coverage choices, we find that the consumers with greater UBI score improvement are less likely to upgrade their insurance coverage. It is consistent with the notion that the consumers learn about their risk of driving and choose the coverage meeting their needs accordingly. In addition, we find that new drivers and younger drivers are more likely to upgrade their coverage after controlling for the UBI discount they receive. On possible explanation is that the less experienced drivers are more likely to be overconfident in their driving skills. UBI provides them valuable information to update their belief of their true risk levels. Finally, we also find that comparing with the consumers who drop out of the UBI program earlier, the consumers who stay in the UBI program for the entire 6 months are more likely to upgrade their coverages, implying that more information and feedback enhances the consumers’ learning.

4.5.1 Future Research and Limitations

In this study we considered simple models to describe the effect of UBI usage on upselling and changing the insurance coverage choice. As we discussed earlier, there could be several possible explanations to support our findings that the UBI customers are significantly more likely to change their insurance coverage than non-UBI customers, but we haven’t employed a structural model to explain the mechanism of customers’ decision-making process to make the upgrading or downgrading decision. So, our current study has limitations on explaining these mechanisms
and quantifying different factors that could affect the customers’ decisions. In future research, it would be interesting to study separately the different mechanisms we discussed in this paper as the factors to change the customers’ decisions on coverage choices. Considering the income level and the automobile type and models in our current setting could be helpful to capture the heterogeneous patterns found in changing the insurance coverage choice as well. In addition, our discussion on separating and quantifying the information and price effects in this research might be useful for future research on these topics to identify separately the factors which could explain our results.
4.6 Tables and Figures

Table 4.1 The Summary Statistics of Customers

<table>
<thead>
<tr>
<th></th>
<th>Total</th>
<th>Non-UBI</th>
<th>UBI</th>
<th>T-test (p-value)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Number of customers</strong>(^{63})</td>
<td>93602</td>
<td>66458</td>
<td>27144</td>
<td></td>
</tr>
<tr>
<td>UBI acceptance rate</td>
<td>0.29</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Fraction male</strong></td>
<td>0.53</td>
<td>0.53</td>
<td>0.52</td>
<td>0.12</td>
</tr>
<tr>
<td>Average age</td>
<td>46.8</td>
<td>49.8</td>
<td>40.2</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td><strong>Average initial insurance score</strong></td>
<td>52.06</td>
<td>53.31</td>
<td>49.14</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Initial coverage choice (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Liability</td>
<td>28%</td>
<td>26%</td>
<td>30%</td>
<td>0.02</td>
</tr>
<tr>
<td>Liability+ collision (1000 deductible)</td>
<td>19%</td>
<td>17%</td>
<td>23%</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Liability+ collision (500 deductible)</td>
<td>24%</td>
<td>27%</td>
<td>20%</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Liability+ collision (200 deductible)</td>
<td>18%</td>
<td>20%</td>
<td>16%</td>
<td>0.03</td>
</tr>
<tr>
<td>Liability+ collision (100 deductible)</td>
<td>11%</td>
<td>10%</td>
<td>11%</td>
<td>0.24</td>
</tr>
<tr>
<td><strong>Average monthly premium ($)</strong></td>
<td>109.1</td>
<td>107.6</td>
<td>112.4</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>First-year renewal rate</td>
<td>0.8</td>
<td>0.77</td>
<td>0.86</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Second-year renewal rate(^{64})</td>
<td>0.85</td>
<td>0.83</td>
<td>0.89</td>
<td>&lt;0.01</td>
</tr>
</tbody>
</table>

\(^{63}\) In total we have 135,540 customers in our dataset. That is, for customers who enrolled in the first 9 months of our data period, we can observe up to 2 renewals. This subset consists of 27,345 customers. Of customers who enter in the next 12 months, we have the opportunity to observe only 1 renewal (66,257). For the remaining customers, numbering 41,938, they are excluded from the analysis in this paper as we cannot observe a renewal decision for them.

\(^{64}\) As a fraction of first year renewal.
Table 4.2 Logit Regression Analysis Results for Initial Coverage Choice

<table>
<thead>
<tr>
<th></th>
<th>Estimate (Std Dev)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age</strong></td>
<td>0.011 (0.001) **</td>
</tr>
<tr>
<td><strong>New driver</strong></td>
<td>-0.04 (0.02) *</td>
</tr>
<tr>
<td><strong>Initial insurance score</strong></td>
<td>0.009 (0.002)**</td>
</tr>
<tr>
<td><strong>Gender (Male)</strong></td>
<td>-0.02 (0.008)*</td>
</tr>
<tr>
<td><strong>UBI adoption</strong></td>
<td>0.012 (0.007)’</td>
</tr>
</tbody>
</table>

State fixed effects included

Sample size: 135,54065, (‘): p-value < 0.1, (*): p-value < 0.05, (**) : p-value < 0.01

Table 4.3 Upgrading and Downgrading Percentages for UBI and Non-UBI Customers.66

<table>
<thead>
<tr>
<th></th>
<th>Non-UBI Customers</th>
<th>UBI Customers</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of customers who upgrade</td>
<td>0.08</td>
<td>0.17</td>
</tr>
<tr>
<td>% of customers who downgrade</td>
<td>0.05</td>
<td>0.07</td>
</tr>
</tbody>
</table>

Table 4.4 Multinomial Regression Analysis Results for Changing the Coverage Choice

<table>
<thead>
<tr>
<th></th>
<th>Estimate (Std Dev)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age</strong></td>
<td>-0.0066 (0.002) **</td>
</tr>
<tr>
<td><strong>Initial insurance score</strong></td>
<td>-0.0008 (0.0007)</td>
</tr>
<tr>
<td><strong>Gender (Male)</strong></td>
<td>-0.0023 (0.0013)’</td>
</tr>
<tr>
<td><strong>UBI dummy</strong></td>
<td>0.0367 (0.0039) **</td>
</tr>
</tbody>
</table>

State and Coverage fixed effects included

Sample size: 93,602, (‘): p-value < 0.1, (*): p-value < 0.05, (**) : p-value < 0.01

65 Since we analyze the initial coverage choice here, we consider the sample of all customers (not necessarily the customers who renewed their coverages)

66 Sample size: 93,602
Table 4.5 Multinomial Regression Analysis Results for Changing the Coverage Choice at Second Renewal

<table>
<thead>
<tr>
<th></th>
<th>Estimate (Std Dev)</th>
<th>Estimate (Std Dev)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Upgrading Coefficients</td>
<td>Downgrading Coefficients</td>
</tr>
<tr>
<td>Age</td>
<td>-0.006 (0.003)*</td>
<td>-0.0035 (0.002)'</td>
</tr>
<tr>
<td>Initial insurance score</td>
<td>0.0007 (0.0006)</td>
<td>-0.001 (0.001)</td>
</tr>
<tr>
<td>Gender (Male)</td>
<td>-0.0031 (0.0015)*</td>
<td>0.0048 (0.0029)'</td>
</tr>
<tr>
<td>UBI dummy</td>
<td>0.013 (0.0095)</td>
<td>0.0102 (0.0081)</td>
</tr>
</tbody>
</table>

*State and Coverage fixed effects included*

Sample size: 27345, (‘): p-value < 0.1, (*): p-value < 0.05, (**): p-value < 0.01

Table 4.6 Estimation Changes in Insurance Coverage Choice Using Propensity Score Matching

<table>
<thead>
<tr>
<th></th>
<th>Estimate of UBI effect</th>
<th>Estimate of UBI effect</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Upgrading Coefficients</td>
<td>Downgrading Coefficients</td>
</tr>
<tr>
<td><strong>First renewal</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model (1)</td>
<td>0.0367 (0.0039) **</td>
<td>0.0146 (0.0072)*</td>
</tr>
<tr>
<td>Propensity score matching</td>
<td>0.0424 (0.0029)**</td>
<td>0.0149 (0.0066)*</td>
</tr>
<tr>
<td><strong>Second renewal</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model (1)</td>
<td>0.013 (0.0095)</td>
<td>0.0102 (0.0081)</td>
</tr>
<tr>
<td>Propensity score matching</td>
<td>0.017 (0.012)</td>
<td>0.0097 (0.0088)</td>
</tr>
</tbody>
</table>

*State and Coverage fixed effects included*

Sample size1: 93,602, Sample size2: 27345, (‘): p-value < 0.1, (*): p-value < 0.05, (**): p-value < 0.01
Table 4.7 Logit Regression Analysis Results within UBI Customers for Upgrading Decision in First Renewal

<table>
<thead>
<tr>
<th>Estimate (Std Dev)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age</strong></td>
</tr>
<tr>
<td>-0.0061 (0.002) *</td>
</tr>
<tr>
<td><strong>Initial insurance score</strong></td>
</tr>
<tr>
<td>-0.002 (0.001)</td>
</tr>
<tr>
<td><strong>Gender (Male)</strong></td>
</tr>
<tr>
<td>-0.0032 (0.0018) *</td>
</tr>
<tr>
<td><strong>UBI discount</strong></td>
</tr>
<tr>
<td>0.08 (0.02)**</td>
</tr>
<tr>
<td><strong>Change in UBI</strong></td>
</tr>
<tr>
<td>-0.0091 (0.004)*</td>
</tr>
<tr>
<td><strong>UBI dropout dummy</strong></td>
</tr>
<tr>
<td>-0.03 (-0.009)**</td>
</tr>
</tbody>
</table>

State and Coverage fixed effects included

Sample size: 24,326, (’): p-value < 0.1, (*): p-value < 0.05, (**) : p-value < 0.01

Table 4.8 Comparing UBI and Non-UBI Customers in Adding the Comprehensive Coverage at Renewal

<table>
<thead>
<tr>
<th>Keep the same coverage</th>
<th>Just add the comprehensive</th>
</tr>
</thead>
<tbody>
<tr>
<td>UBI customers</td>
<td>0.97</td>
</tr>
<tr>
<td>Non-UBI customers</td>
<td>&gt;0.99</td>
</tr>
</tbody>
</table>

Table 4.9 Logit Regression Results for Comprehensive Decision within UBI Customers

<table>
<thead>
<tr>
<th>Estimate (Std Dev)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age</strong></td>
</tr>
<tr>
<td>0.0094 (0.003)**</td>
</tr>
<tr>
<td><strong>Initial insurance score</strong></td>
</tr>
<tr>
<td>0.0015 (0.0008)**</td>
</tr>
<tr>
<td><strong>Gender (Male)</strong></td>
</tr>
<tr>
<td>-0.011 (0.004)*</td>
</tr>
<tr>
<td><strong>UBI discount</strong></td>
</tr>
<tr>
<td>0.029 (0.008)**</td>
</tr>
</tbody>
</table>

State and Coverage fixed effects included

Sample size: 20548, (’): p-value < 0.1, (*): p-value < 0.05, (**) : p-value < 0.01

67 Sample size: 69,621
Table 4.10 Heterogeneous Effects of UBI Usage on Changing the Coverage Choice

<table>
<thead>
<tr>
<th>Upgrade</th>
<th>Estimate (Std Dev)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Age</td>
</tr>
<tr>
<td></td>
<td>-0.0034 (0.001) **</td>
</tr>
<tr>
<td></td>
<td>New driver</td>
</tr>
<tr>
<td></td>
<td>0.052(0.02)*</td>
</tr>
<tr>
<td></td>
<td>Initial insurance score</td>
</tr>
<tr>
<td></td>
<td>-0.001 (0.0008)</td>
</tr>
<tr>
<td></td>
<td>Gender (Male)</td>
</tr>
<tr>
<td></td>
<td>-0.0016 (0.0009)'</td>
</tr>
<tr>
<td></td>
<td>UBI dummy</td>
</tr>
<tr>
<td></td>
<td>0.0133 (0.006) *</td>
</tr>
<tr>
<td></td>
<td>Age*UBI</td>
</tr>
<tr>
<td></td>
<td>-0.0028(0.0013)*</td>
</tr>
<tr>
<td></td>
<td>New driver*UBI</td>
</tr>
<tr>
<td></td>
<td>0.027(0.009)**</td>
</tr>
<tr>
<td></td>
<td>Gender(Male)*UBI</td>
</tr>
<tr>
<td></td>
<td>-0.006(0.004)'</td>
</tr>
</tbody>
</table>

State and Coverage fixed effects included

Sample size: 93,602, (‘): p-value < 0.1, (*): p-value < 0.05, (**) : p-value < 0.01
Figure 4.1 Events and Decisions’ Flow in our Setting

- Coverage choice
  - Demographic information
  - Insurance score (past driving history)

  Initial Premium to pay

  UBI adoption?

  Yes
  - Receive feedback and UBI discount after 6 months.
  - Keep the same coverage

  No
  - Pay initial premium for 1 year
  - Choose different coverage

Figure 4.2 Coverage Choice Distributions for UBI and Non-UBI Customers
Chapter 5: Conclusion

This thesis provides insight into consumer decision making and behavior in a novel and innovative context related to auto insurance industry. The innovation we study collects sensor-based and private data of customers by using telematics technology to monitor enrolled motorists driving behavior for up to six months. The three essays presented in this thesis study and evaluate the usage-based insurance (UBI) policy from different perspectives, including the potential benefits of UBI for the customers and insurer on one side and the perceived costs of adopting and using this new technology discussed on the other side.

The first essay (Chapter 2) contributes to the marketing literature by using a unique dataset including the sensor-based data of customers’ actual driving behavior at the individual level to explore the effect of the UBI policy on improving driving behavior as one of the potential benefits of UBI policy beyond the self-selection of good drivers. To our knowledge, this research is the first empirical study analyzing customers’ sensor-based data to examine how usage-based insurance affects driving behavior. We find that drivers enrolled in the program have a higher level of their UBI score at the end of the monitoring period as compared to the beginning; moreover, this improved driving period appears to extend until the end of our data monitoring period, which can be up to two years. Our empirical findings reported in the first essay also add to the information and economic incentive effects on changing customers’ behavior literature by capturing the different sources of improvement in driving behavior and discussing the effect of “economic incentives” and “information and immediate feedback” on changing the driving behavior separately in the UBI setting. Our results suggest there are both
economic and information effects on the change in performance as measured by the UBI score. In addition, we find in the first essay that the improvements in driving behavior vary across age groups and by gender.

In terms of limitation, as we discussed more fully in chapter 2 (first essay), the major 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 improvements in driving performance are temporary to earn a discount or are permanent even after the telematics device is removed. While to some extent we try to deal with this issue by considering the driving history of customers after 2 years of adopting and using UBI, we need additional behavioral data for the UBI subscribers to fully answer this question.

In the second essay (Chapter 3), we focus on the customers’ decision to adopt and keep using the UBI policy. We examine the tradeoff that consumers make between their cost of being monitored (including privacy) and the savings in auto insurance premium costs by building a dynamic structural model and using individual-level data recording consumers’ decisions about whether or not to allow their private driving behavior to be monitored over time in return for a long-term reduction in their auto insurance premiums. We place special emphasis on if and when consumers choose to drop out of the UBI program. The second essay is the first study in marketing that quantifies the individual cost of adopting and using a data-based new technology that includes the cost of privacy concern. During the data period of our study, a major and highly publicized data breach occurred at an unrelated company. This data breach incident allows us to test if the consumers change their UBI usage decision in the short term due to the
changes in privacy concern. In general, the empirical findings of our second essay indicate that in an actual field setting where consumers have a clear choice as to whether or not to share private information, consumers consider the economic benefits of sharing their private information and the cost of yielding such information. Moreover, consumers differ in how they trade off these costs and benefits. Our study also shows that privacy concerns in the use of one company’s products can be influenced by external events occurring outside that company. Our findings can help firms to better understand the retention behavior of customers when they use the new technologies that rely on their private data.

The third essay (Chapter 4) extends the first two essays by looking at decisions that occur after the monitoring period is completed and examines customer behavior at the time of first (and second) renewal. It focuses on one more benefit to the existing values of UBI in the literature by supporting the effectiveness of upselling efforts and cross-selling to insurance market. In this essay, we capture the effect of using the UBI policy on changing or upgrading the insurance coverage at the renewal compared to the initial choice. The results of the study suggest that the UBI and non-UBI customers have different patterns in changing the distribution of insurance coverage choices at the (first) renewal time compared to the initial purchase time. The UBI customers are more likely to change their coverage choice than non-UBI customers. In particular, UBI customers are more likely to upgrade their insurance coverage at the renewal time after controlling for other factors. Studying the effects of price discount and information separately is another contribution to the literature of our third essay. With regard to the impact of information and feedback on the UBI consumers’ coverage choices, we find that the consumers with greater UBI score improvement are less likely to upgrade their insurance coverage. In
addition, we find that comparing with the consumers who drop out of the UBI program earlier, the consumers who stay in the UBI program for the entire 6 months are more likely to upgrade their coverages, implying that more information and feedback enhances the consumers’ learning. The effect of price discount on changing the coverage choice was also examined in the third essay by finding that the customers who show better driving behavior and get greater discounts are more likely to upgrade their insurance coverage to the higher levels. In addition, we show that the UBI customers who show better driving behavior and ultimately receive a higher UBI discount are more likely to add the comprehensive coverage. This is an evidence which shows the mental accounting effect exists and the customers who get lower premium at renewal time because of UBI discount are more likely to pay for comprehensive coverage and add it.

This thesis has a number of limitations which we describe in more detail in each of the chapters. We briefly note three concerns. By definition, the monitoring period extends for six months and we cannot directly observe driving behavior beyond that point. We employ several indirect measures to infer driving behavior after the completion of the monitoring period. Future research, perhaps based on data from new cars with enhanced information technology systems or on data from such apps as Google maps may be able to address those concerns, but concerns about privacy need to be carefully considered in using such data. Second, as long as enrolling in UBI programs remains optional, there will always be issues about selection. This thesis has employed a number of approaches to limit such issues but recognizes that such concerns cannot be fully rectified. Third, the results are based on data from one company in one industry. The firm is a major competitor in the industry, so we believe its data are representative of the industry. As our results suggests that monitoring of behavior in this industry can lead to safer
driving behavior but raise concerns about privacy, it would be worthwhile exiling whether safer and healthier behaviors would emerge in other settings, such as physical activity monitoring, and to what extent privacy concerns would be important in other industries. Finally, as safer driving behavior has implications for the public beyond those of the individual consumer and the insurance company, the findings have implications for public policy officials trying to decrease the health, social, and economic costs of unsafe driving behavior.
Bibliography


Altman, I., (1975). The Environment and Social Behavior: Privacy, Personal Space, Territory, and Crowding


Appendices

Appendix A - Chapter 2: Supplemental Analyses

This appendix provides some further analyses that support the validity of our primary analysis and results in chapter 2.

*Daily hard brakes and mileage are significant determinants of daily UBI score.*

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

\[
UBI\ Score_{it} = \beta_0 + \beta_0 * UBI\ Score_{it} + \beta_0 * UBI\ Score_{it} + \epsilon_{it} \quad A-1
\]

For each UBI customer, we have daily observations for up to 180 days.
Table A.1 Regression analysis results for daily UBI score.

<table>
<thead>
<tr>
<th></th>
<th>Estimate (Std. Error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>0.4959(0.0318)**</td>
</tr>
<tr>
<td>Mileage</td>
<td>-0.0058(0.0003)**</td>
</tr>
<tr>
<td>Hard brake</td>
<td>0.0040(0.0014)**</td>
</tr>
</tbody>
</table>

Multiple R-squared: 0.58

Sample size= 5,032,529, ('): p-value < 0.1, (*): p-value < 0.05, (**) : p-value < 0.01

Preliminary analysis reveals a significant correlation between UBI score and key variables such as mileage driven and the number of hard brakes. The results show that both mileage driven and hard brakes are significantly negatively correlated with daily UBI score. More importantly, just these two factors alone can explain about 57% of the variation in daily UBI score observations in our dataset which means mileage and number of the hard brakes are two key factors in determining the UBI score based on the company's policy.

**Long term effect of UBI adoption on renewal insurance score improvement after one and two years.**

We model the changes in insurance score after one year (first renewal) and two years (second renewal) for customers who adopt UBI as compared to those who do not to estimate the effect of UBI adoption on long term improvement of insurance score.

\[ \Delta IS_i = \alpha + \text{state}_i + \beta_1 \times \text{age}_i + \beta_2 \times \text{male}_i + \beta_3 \times \text{UBI acceptance}_i + \epsilon_{it}, \quad A-2 \]

\[ \Delta IS_i: \text{Changes in insurance score of customer } i \text{ after 1 (or 2) year,} \]

\[ \text{UBI acceptance}_i: \text{Whether the customer } i \text{ adopts the UBI policy or not.} \]
Table A.2 Regression analysis results for long term effect of UBI adoption.

<table>
<thead>
<tr>
<th>Variables</th>
<th>First renewal</th>
<th>Second renewal</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Intercept</strong></td>
<td>5.08 (0.15)**</td>
<td>8.59 (0.21)**</td>
</tr>
<tr>
<td><strong>Age</strong></td>
<td>-0.08 (0.01)**</td>
<td>-0.12 (0.01)**</td>
</tr>
<tr>
<td><strong>Gender (male)</strong></td>
<td>-0.312 (0.11)**</td>
<td>-0.21 (0.1)*</td>
</tr>
<tr>
<td><strong>UBI acceptance</strong></td>
<td>0.28 (0.08)**</td>
<td>0.41 (0.11)**</td>
</tr>
<tr>
<td>State dummies</td>
<td>Included</td>
<td>Included</td>
</tr>
<tr>
<td><strong>Multiple R-squared</strong></td>
<td>0.39</td>
<td>0.41</td>
</tr>
<tr>
<td><strong>Sample size</strong></td>
<td>61,358</td>
<td>20,435</td>
</tr>
</tbody>
</table>

(*) : p-value < 0.1, (*) : p-value < 0.05, (**) : p-value < 0.01

Comparison of eight Fault and No-Fault states

Table A.3 Data summary of Fault and No-Fault states (UBI customers)

<table>
<thead>
<tr>
<th>States</th>
<th>No Fault</th>
<th>Fault</th>
<th>Significant difference at 0.05 level</th>
</tr>
</thead>
<tbody>
<tr>
<td>States</td>
<td>Michigan</td>
<td>Connecticut</td>
<td></td>
</tr>
<tr>
<td>Minnesota</td>
<td>Michigan</td>
<td>Connecticut</td>
<td></td>
</tr>
<tr>
<td>New Jersey</td>
<td>Michigan</td>
<td>Connecticut</td>
<td></td>
</tr>
<tr>
<td>Pennsylvania</td>
<td>Michigan</td>
<td>Connecticut</td>
<td></td>
</tr>
<tr>
<td><strong>Average Monthly Premium</strong></td>
<td>130.7</td>
<td>107.59</td>
<td>**</td>
</tr>
<tr>
<td><strong>Number of customers</strong></td>
<td>38487</td>
<td>32892</td>
<td></td>
</tr>
<tr>
<td><strong>Average UBI score (26 weeks)</strong></td>
<td>65.74</td>
<td>64.12</td>
<td>**</td>
</tr>
<tr>
<td><strong>Average age (Std.error)</strong></td>
<td>46.8(0.18)</td>
<td>45.1(0.16)</td>
<td>**</td>
</tr>
<tr>
<td><strong>Fraction male</strong></td>
<td>0.53</td>
<td>0.52</td>
<td></td>
</tr>
<tr>
<td><strong>UBI acceptance rate</strong></td>
<td>0.312</td>
<td>0.301</td>
<td>**</td>
</tr>
</tbody>
</table>
Comparison of Michigan (No-Fault) drivers versus Wisconsin (Fault) drivers

Table A.4 Fixed effects regression analysis results for UBI Score for Wisconsin vs. Michigan.

<table>
<thead>
<tr>
<th>Variables</th>
<th>weekdummies(Wisconsin)</th>
<th>Michigan*weekdummies(Std. Error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Week dummy2</td>
<td>0.78(0.14)**</td>
<td>0.69 (0.22)**</td>
</tr>
<tr>
<td>Week dummy3</td>
<td>1.38(0.14)**</td>
<td>0.72(0.22)**</td>
</tr>
<tr>
<td>Week dummy4</td>
<td>1.64(0.14)**</td>
<td>0.76(0.22)**</td>
</tr>
<tr>
<td>Week dummy5</td>
<td>1.92(0.14)**</td>
<td>0.78(0.23)**</td>
</tr>
<tr>
<td>Week dummy6</td>
<td>2.21(0.15)**</td>
<td>0.83 (0.23)**</td>
</tr>
<tr>
<td>Week dummy7</td>
<td>2.36(0.15)**</td>
<td>0.91(0.23)**</td>
</tr>
<tr>
<td>Week dummy8</td>
<td>2.32(0.15)**</td>
<td>0.96(0.23)**</td>
</tr>
<tr>
<td>Week dummy9</td>
<td>2.37(0.15)**</td>
<td>1.02(0.23)**</td>
</tr>
<tr>
<td>Week dummy10</td>
<td>2.41(0.16)**</td>
<td>1.35 (0.24)**</td>
</tr>
<tr>
<td>Week dummy11</td>
<td>2.54(0.17)**</td>
<td>1.47 (0.24)**</td>
</tr>
<tr>
<td>Week dummy12</td>
<td>2.49(0.17)**</td>
<td>1.59 (0.24)**</td>
</tr>
<tr>
<td>Week dummy13</td>
<td>2.53(0.17)**</td>
<td>1.55 (0.25)**</td>
</tr>
<tr>
<td>Week dummy14</td>
<td>2.50(0.17)**</td>
<td>1.64 (0.25)**</td>
</tr>
<tr>
<td>Week dummy15</td>
<td>2.56(0.18)**</td>
<td>1.68 (0.25)**</td>
</tr>
<tr>
<td>Week dummy16</td>
<td>2.63(0.18)**</td>
<td>1.59 (0.25)**</td>
</tr>
<tr>
<td>Week dummy17</td>
<td>2.73(0.18)**</td>
<td>1.67 (0.26)**</td>
</tr>
<tr>
<td>Week dummy18</td>
<td>2.71(0.19)**</td>
<td>1.75 (0.26)**</td>
</tr>
<tr>
<td>Week dummy19</td>
<td>2.77(0.19)**</td>
<td>1.79 (0.27)**</td>
</tr>
<tr>
<td>Week dummy20</td>
<td>2.86(0.19)**</td>
<td>1.83 (0.27)**</td>
</tr>
<tr>
<td>Week dummy21</td>
<td>2.79(0.20)**</td>
<td>1.76 (0.27)**</td>
</tr>
<tr>
<td>Week dummy22</td>
<td>2.84(0.21)**</td>
<td>1.91 (0.27)**</td>
</tr>
<tr>
<td>Week dummy23</td>
<td>2.95(0.21)**</td>
<td>1.99 (0.28)**</td>
</tr>
<tr>
<td>Week dummy24</td>
<td>2.89(0.22)**</td>
<td>1.93 (0.28)**</td>
</tr>
<tr>
<td>Week dummy25</td>
<td>2.91(0.22)**</td>
<td>1.89 (0.28)**</td>
</tr>
<tr>
<td>Week dummy26</td>
<td>3.08(0.22)**</td>
<td>2.02 (0.28)**</td>
</tr>
</tbody>
</table>

Multiple R-squared: 0.535

Sample size= 92464, (')$: p-value < 0.1, (*)$: p-value < 0.05, (**)$: p-value < 0.01

**The second column interaction effect shows the difference between the changes in UBI score of Wisconsin and Michigan drivers.
**Comparison of Minnesota (No-Fault) drivers versus Wisconsin (Fault) drivers**

Table A.5 Fixed effects regression analysis results for UBI Score for Wisconsin vs. Minnesota.

<table>
<thead>
<tr>
<th>Variables</th>
<th>weekdummies(Wisconsin)</th>
<th>Minnesota*weekdummies(Std.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Week dummy2</td>
<td>0.84 (0.13)**</td>
<td>0.22 (0.19)</td>
</tr>
<tr>
<td>Week dummy3</td>
<td>1.29 (0.13)**</td>
<td>0.27 (0.19)</td>
</tr>
<tr>
<td>Week dummy4</td>
<td>1.58 (0.13)**</td>
<td>0.18 (0.19)</td>
</tr>
<tr>
<td>Week dummy5</td>
<td>1.96 (0.13)**</td>
<td>0.29 (0.19)</td>
</tr>
<tr>
<td>Week dummy6</td>
<td>2.15 (0.14)**</td>
<td>0.31 (0.20)*</td>
</tr>
<tr>
<td>Week dummy7</td>
<td>2.31 (0.14)**</td>
<td>0.25 (0.20)</td>
</tr>
<tr>
<td>Week dummy8</td>
<td>2.39 (0.14)**</td>
<td>0.34 (0.21)*</td>
</tr>
<tr>
<td>Week dummy9</td>
<td>2.30 (0.14)**</td>
<td>0.37 (0.21)*</td>
</tr>
<tr>
<td>Week dummy10</td>
<td>2.48 (0.16)**</td>
<td>0.32 (0.21)</td>
</tr>
<tr>
<td>Week dummy11</td>
<td>2.61 (0.16)**</td>
<td>0.40 (0.23)*</td>
</tr>
<tr>
<td>Week dummy12</td>
<td>2.57 (0.17)**</td>
<td>0.49 (0.23)*</td>
</tr>
<tr>
<td>Week dummy13</td>
<td>2.49 (0.17)**</td>
<td>0.43 (0.23)*</td>
</tr>
<tr>
<td>Week dummy14</td>
<td>2.58 (0.17)**</td>
<td>0.52 (0.23)*</td>
</tr>
<tr>
<td>Week dummy15</td>
<td>2.69 (0.17)**</td>
<td>0.47 (0.25)*</td>
</tr>
<tr>
<td>Week dummy16</td>
<td>2.61 (0.17)**</td>
<td>0.57 (0.25)*</td>
</tr>
<tr>
<td>Week dummy17</td>
<td>2.77 (0.18)**</td>
<td>0.46 (0.25)*</td>
</tr>
<tr>
<td>Week dummy18</td>
<td>2.82 (0.18)**</td>
<td>0.60 (0.25)*</td>
</tr>
<tr>
<td>Week dummy19</td>
<td>2.70 (0.18)**</td>
<td>0.53 (0.25)*</td>
</tr>
<tr>
<td>Week dummy20</td>
<td>2.81 (0.18)**</td>
<td>0.56 (0.25)*</td>
</tr>
<tr>
<td>Week dummy21</td>
<td>2.78 (0.19)**</td>
<td>0.49 (0.26)*</td>
</tr>
<tr>
<td>Week dummy22</td>
<td>2.86 (0.19)**</td>
<td>0.57 (0.26)*</td>
</tr>
<tr>
<td>Week dummy23</td>
<td>2.92 (0.20)**</td>
<td>0.63 (0.26)*</td>
</tr>
<tr>
<td>Week dummy24</td>
<td>2.92 (0.20)**</td>
<td>0.59 (0.27)*</td>
</tr>
<tr>
<td>Week dummy25</td>
<td>2.84 (0.20)**</td>
<td>0.52 (0.27)*</td>
</tr>
<tr>
<td>Week dummy26</td>
<td>2.96 (0.20)**</td>
<td>0.60 (0.27)*</td>
</tr>
</tbody>
</table>

**Multiple R-squared**: 0.502

Sample size= 85826, (*) p-value < 0.1, (**) p-value < 0.05, (***) p-value < 0.01
Appendix B - Chapter 3: Reduced-form Models

In this appendix we capture the important factors associated with the adoption and dropout decisions by considering the reduced-form choice models. Based on summary statistics in Tables 3.1 and 3.2, we know that 70% of customers don’t choose the UBI policy at the purchase time and also among the customers who enroll in the UBI program, around 15% of these customers drop out just after day 75 of monitoring and receiving the updated discount. We run two separate logit models to find the factors that affect the customers’ adoption decision and dropout decision when they received the updated discount.

To test the relationship between the UBI adoption and drivers’ characteristics, we estimate the logit model (B-1) in which the dependent variable is defined as whether or not a driver adopts the UBI policy. The independent variables include consumers’ age, gender and their regular premium. Urban is defined as a dummy variable that equals one if the driver lives in an urban area, and zero if he or she is in a rural area. In addition, new driver is a dummy which shows whether the driver had previous driving experience or not. The estimation results are summarized in Table B1. We also include the state fixed effects in the model.

\[ p(UBI \text{ acceptance}_i) = \text{logit}(age_i, \text{Premium}_i, \text{state}_i, \text{gender}_i, \text{urban}_i, \text{new driver}_i) \quad B - 1 \]

<table>
<thead>
<tr>
<th></th>
<th>Estimate (Std. Error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>0.4652 (0.004)**</td>
</tr>
<tr>
<td>Age</td>
<td>-0.0053 (0.00004) **</td>
</tr>
<tr>
<td>Premium</td>
<td>0.0008 (0.00004)**</td>
</tr>
<tr>
<td>Gender (Male)</td>
<td>-0.0014 (0.0013)</td>
</tr>
</tbody>
</table>
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 indicates the customers in urban areas and new drivers are more likely to adopt this policy. Finally, the coefficient for gender is not statistically significant, suggesting that males and females are equally likely to adopt the UBI policy.

Turning to the decision to drop out just after receiving their updated discount, we run another logit model for the UBI customers who stayed in the program for at least 75 days and received their update discount after 75 days of being monitored. In this case, we try to model the “informed dropout” decision to capture the factors associated with the UBI customers’ decision at this choice point. We look only at informed dropouts here because of the significant dropout rate in a short period of time (15% in about two weeks) and it’s just after receiving the updated discount and the opportunity to have a permanent discount even if they drop out. For late dropouts, it’s true that more than 17% of UBI customers cancel their UBI policy in this period, but they are dropping out over a longer period of time (approximately 3 months) so it’s less accurate to aggregate the data into one decision point to run the logit model for the late dropouts.
\[ p(UBI \text{ informed dropout}_i | \text{stayed in the program for at least 75 days}) = \text{logit}(\text{age}_i, \text{Premium}_i, \text{average UBI score}_i, \text{changes in UBI score}_i, \text{state}_i) \]

where the \text{average UBI score}_i is the average UBI score of customer \( i \) in the first 75 days and \text{changes in UBI score}_i is defined as the difference between the UBI score at day 75 and day 1 for customer \( i \).

\[ UBI \text{ informed dropout}_i = \begin{cases} 1 & \text{if UBI customer } i \text{ drops out in the period of 75 to 90 days of monitoring} \\ 0 & \text{keep the policy in the above period (75 − 90)} \end{cases} \]

Table A.7 Logit regression analysis results for UBI “informed dropout” decision

<table>
<thead>
<tr>
<th></th>
<th>Estimate (Std. Error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>0.3841 (0.032)**</td>
</tr>
<tr>
<td>Age</td>
<td>0.0424 (0.0167)*</td>
</tr>
<tr>
<td>Premium</td>
<td>-0.0092(0.0021)**</td>
</tr>
<tr>
<td>Gender (Male)</td>
<td>-0.0034(0.0027)</td>
</tr>
<tr>
<td>Average UBI Score</td>
<td>-0.0452 (0.0218)*</td>
</tr>
<tr>
<td>Change in UBI Score</td>
<td>-0.0194 (0.0072)**</td>
</tr>
<tr>
<td>State dummies</td>
<td><strong>Included</strong></td>
</tr>
</tbody>
</table>

(*) p-value < 0.1, (**) p-value < 0.01

Table A.7 shows the estimated coefficients of the logit model for “informed dropout” decision point. The positive and significant coefficient of age shows that the dropout rate of older drivers is higher, and the younger drivers tend to stay longer than 75 days in the UBI program.

Interestingly, the coefficient of premium is negative and significant which shows the UBI customers who pays higher initial premium stay longer in the UBI program to possibly save more by getting higher discounts. In addition, the UBI customers who show better driving
performance in terms of higher average UBI score and also more improvement in their UBI score, have significantly lower “informed dropout” rate.