DIGITAL CITIZENSHIP: THE ROLE OF INFORMATION, AUTOMATION, AND TRANSFROMATION

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ABSTRACT

Digitization has fundamentally changed businesses, segments of society, and individuals' life. There are two changing perspectives in the history of digital transformation. One is the expanding boundary of digitization, from a transformation within organizations, through innovations in interactions among businesses and customers, to societal changes at large. The other is the shifting focus of digitization, from digitizing production and delivery of goods and services, to digitizing all aspects of everyday life. However, extant research in digitization has not paid much attention to its impacts beyond the organizational boundary and the business relationships, and often adopted a technology-deterministic view of digitization. In this dissertation, I propose the notion, "digital citizenship", to reexamine the nature and impact of digitization from a human-centric perspective and embed digitization in a broader social context. To elaborate on the notion of digital citizenship, I study the informative, automate, and transformative roles of digitization, and why and how various types of digitization enhance overall welfare for all parties of digital citizens. These three studies, presented as separate essays herein, i) evaluate the effectiveness of Intelligent Transportation Systems adopted by local governments transforming urban traffic management, ii) explore enhancing drivers' traffic safety effort due to the deterrent potential of automated surveillance technology on the road, and iii) examine the mechanisms of information provision on customers decision making on churn and the implications for firms on the challenge of digital channel attribution. In regard to each, I discuss the relevant theory, the methodology, data sources, results, and implications. I conclude by highlighting the contributions of my work, and possible avenues for future research.

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CHAPTER 1

OVERVIEW

Digitization has fundamentally changed businesses, segments of society, and our everyday life. The first wave of digital transformation happened in manufacturing to automate the process of production, and coordinate goods and value creation via information exchanges. The second wave of digital transformation occurred after the introduction of World Wide Web, which connects everyone and everything through networks. Such a network economy has grown in an exponential way that transforms the traditional ways of doing business and interactions among businesses and customers. The third wave of digital transformation is featured as massively collecting, monitoring, analyzing human behaviors through digitization, which serve to understand human nature and pose both opportunities and challenges for businesses, public policies, and individuals' lives. All entities in the society, businesses, governments, individuals, are now involved in this great transformation.

There are two changing logics in the history of digital transformation. One is the expanding boundary of digitization, from a transformation within organizations, through innovations in interactions between businesses and customers, and to the societal changes at large. The other is the shifting focus of digitization, from digitizing production and delivery of goods and services, to digitizing all aspects of our everyday life. The nature and impact of digitization has changed in response to the changes in the logic of digital transformation. However, extant research in digitization have adopted a technology-deterministic view of digitization and often oversighted its impacts beyond the organizational boundary and business relationships.

In this dissertation, I propose the notion, “digital citizenship”, to reexamine the nature and impact of digitization from a human-centric perspective and to embed digitization in a broader societal context. A digital citizen is defined as a person leverages digital technology to engage in every aspect of life, while digital citizenship stresses the status and experience of being a citizen in the digital state. The primary aim of this dissertation is to develop a better understanding of how digital citizens make decisions, what aspects of digitization influence the decision making processes and outcomes, and to what extent digitization enhances the overall welfare for all parties of digital citizens.

Information Systems (IS) literature suggests three general roles of digital technology –informative, automate, and transformative – in the business setting (Zuboff 1985, Chatterjee et al. 2001). In this dissertation, I study how different stakeholders in the digital state, individuals, businesses, and governments can leverage the informative, automate, and transformative potential of digitization to enhance overall social welfare. I argue that these roles are generalizable to a broader business and societal setting of our everyday life. Specifically, I focus on a particular group of population, drivers, to study digital citizenship and the roles of digitization. From drivers’ lens, I investigate how government-supported programs of intelligent transportation systems (i.e., traffic sensors, speed checkers) affect their decision making on travel schedule and risk-taking behaviors while driving, which in turn may offer solutions to grand societal challenges in traffic congestion and traffic safety. In addition, I examine the contract renewal pattern of drivers after they initially purchase auto insurance from different marketing channels, digital or traditional, that are endowed with distinct levels of information transparency, which provides implications for firms on how to allocate resources on customer acquisition channels as a long-term customer retention strategy.

I propose three essays to study the informative, automate, and transformative roles of digitization, and why and how digitization enhances overall social welfare. Each of the three essays deals with major stakeholders in the digital transformation: drivers, governments, and for-profit firms, with each piece adding a different component and context on fully understanding the nature and impacts of digitization.

In the first essay, I study a major societal and public policy problem, traffic congestion, and how Intelligent Transportation Systems (ITS) can be an effective solution. ITS digitize traffic monitoring and management, but its effectiveness on traffic congestion remains unclear in both research and practice. Drawing upon research in IS and transportation economics, I develop two theoretical explanations on the roles of ITS: (i) ITS play an informative role for drivers and local governments to balance traffic supply-and-demand, and (ii) ITS play a transformative role for local governments to develop an urban traffic management capability. To empirically test the theoretical predictions, I consolidate a unique dataset on road traffic and the implementation of a large federally-supported ITS program in the United States (U.S.)—511 Systems—in 99 urban areas in 1994-2014. I find that the adoption of 511 Systems is associated with a substantial decrease in traffic congestion, which has been both economically and statistically significant. I also show that ITS help drivers to schedule travel more efficiently, choose better navigation routes, and optimize their work-trip transportation mode. Besides, ITS help local governments to better manage traffic by coordinating road expansion and public transit services.

In the second essay, I focus another important societal challenge in the transportation sector, traffic safety, and examine whether and how automated enforcement in the form of surveillance technology (e.g., speeding checkers, red light cameras) is a cost-effective approach to mitigating traffic accidents. To investigate these questions, I leverage police accident reports of a major metropolitan in southern China and exploit the temporal and geographical variations in the installation of over 2,000 traffic surveillance cameras in 3 years. I find a disproportionate decrease in vehicular damages and occupant injuries at the road segments installed with surveillance cameras. To understand the observed effect, I develop a stylish analytical model for drivers' safety efforts under surveillance. The theoretical prediction on the effect of surveillance technology can be decomposed into two parts: a positive impact on safe driving efforts that deters careless or reckless behaviors (a "Stick" role reflecting the Deterrent Hypothesis in the criminology literature) and a negative impact that facilitates a safer traffic environment and compensates accident risks (a "Carrot" role reflecting the Risk Compensation Hypothesis in the economics of traffic safety). The direction of surveillance effect depends on the relative magnitude of these two countervailing impacts. I find supportive evidence for deterrent effect but not for the risk compensation effect, implying that "Stick" prevails "Carrot" in traffic safety regulation using surveillance technology.

In the third essay, I concentrate on a thorny business challenge, customer churn (not renewing term contracts), in the service industry where market information is highly transparent on the Internet, and I investigate whether and how such transparent information affects customer churn. I collaborate with a major European Insurance company to answer these questions by leveraging a large-scale dataset that contains rich information of drivers, their vehicles and contract status. Contrary to common belief, I find that information transparency actually reduces customer churn. Specifically, customers acquired from a channel with high information transparency (a third-party quote comparison website) are less likely to churn. Existing IS, marketing and economics literature offers two countervailing predictions on the role of information transparency: (i) either high price informedness (consumers' awareness of price information), which intensifies customers' price sensitivity and induces customer churn or, (ii) high product informedness (consumers' awareness of product information), which mitigates the uncertainty of product quality and reduces churn. I show that product informedness prevails price informedness in explaining the net negative effect of information transparency on customer churn.

CHAPTER 2

MITIGATING TRAFFIC CONGESTION: THE ROLE OF INTELLIGENT TRANSPORTATION SYSTEMS

ABSTRACT

Despite massive investments in transportation infrastructure, traffic congestion remains a major societal and public policy problem. Intelligent Transportation Systems (ITS) have been proposed as a potential solution to this challenge, but their effectiveness has remained unclear in both research and practice. To understand whether and how ITS affect traffic congestion, we consolidate a unique longitudinal dataset on road traffic and the implementation of a large federally-supported ITS program in the United States (U.S.)—511 Systems—in 99 urban areas in 1994-2014. The difference-in-differences estimates show that the adoption of 511 Systems is associated with a significant decrease in traffic congestion, saving over $4.7 billion dollars and 175 million hours in travel time annually in U.S. cities. 511 Systems also reduce about 53 million gallons of fossil fuel consumption and over 10 billion pounds of CO_2 emissions. We offer two theoretical explanations for the effect: (i) ITS help individual commuters to make better travel decisions, and (ii) ITS help local governments to develop an urban traffic management capability. Suggestive evidence supports the underlying theoretical mechanisms and shows that ITS help commuters to schedule travel more efficiently, choose better navigation routes, and optimize their work-trip transportation mode. Second, the effect of ITS is contingent upon road supply and public transit services. We also find that the traffic-reducing effect of ITS is larger with more actual usage of the online services and

when state and local governments incorporate more informative functionalities into the system. This study contributes to the research on IT capabilities, public sector IT value, and the societal impact of IT, while also extending the transportation economics to IT-enabled traffic interventions. Finally, we inform policymakers of ITS as a cost-effective means to mitigating traffic congestion.Type the text of your chapter here.

2.1 Introduction

According to the 2015 Annual Urban Mobility Scorecard, the average American spends over 41 hours stuck in traffic jams, resulting in almost $1,000 in congestion cost per person each year. These figures are more pronounced in large metropolitan areas (e.g., New York City, Los Angeles, Chicago) with 60-hour delays and $1,376 in congestion cost per person every year. Not only does traffic congestion cause economic losses to commuters, but it generates excessive greenhouse gas emissions (Barth and Boriboonsomsin 2008). Nationwide, traffic congestion results in an estimated $159 billion in costs annually and accounts for 7 billion travel hours, 3 billion gallons of fossil fuel, and 210 billion pounds of CO_2 in 471 U.S. urban areas. This poses a major challenge to transportation policymakers and city planners to reduce traffic congestion. In the last several decades, state and local governments in the U.S. have made major infrastructure investments in physical construction and road expansion, but these massive and often expensive investments in physical transportation infrastructure have not been shown to be effective in mitigating traffic congestion (e.g., Downs 1962, 2001, Arnott and Small 1994, Duranton and Turner 2011).

In addition to transportation infrastructure investments, policymakers have begun leveraging information technology (IT) to reduce traffic congestion, most commonly Intelligent Transportation Systems (ITS) (Figure 2.1). ITS are defined by the U.S. Department of Transportation (USDOT) as "an integrated system of advanced communications technologies embedded in the transportation infrastructure and in vehicles to improve transportation safety and mobility."[i] Since 2001, a number of U.S. state governments have made substantial investments in ITS with financial grants from the USDOT. These governments rely on ITS to leverage traffic data collected from sensors and video cameras installed in roads and bridges. For instance, the State of Washington uses real-time data from ITS in the Seattle metropolitan area to operate managed-lane highways, dynamically change speed limits, and inform drivers of traffic conditions via overhead traffic signs.[ii] ITS enable many state governments to make the real-time traffic information available through multiple channels (e.g., telephone services, websites with interactive traffic maps, TV and radio broadcasts). With the aid of ITS, state and local governments can effectively manage day-to-day traffic operations and devise long-term traffic-mitigation policies and future construction plans.

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[i] http://safety.fhwa.dot.gov/its/, retrieved on January 5, 2019. By definition, navigation and route guidance systems, such as Google Maps, are also classified as ITS. Albeit this, our study mainly focuses on government-adopted ITS that help traffic management not only on the demand side (i.e., commuters) but also on the supply side (i.e., road). Google Traffic have mainly served commuters, and their data, to our knowledge, has rarely been shared with state or local transportation agencies for traffic management.

[ii] http://www.wsdot.wa.gov/Operations/Traffic/ActiveTrafficManagement/, retrieved on January 5, 2019.

Figure 2.1.
The Intelligent Transportation Systems

Notes: The following is how ITS work. Real-time traffic is monitored by sensors and cameras on the roads. Then the data are collected and forwarded to a traffic control center for analysis. Interventions (e.g., merge signal) are sent back to roads and other channels (e.g., telephone services, government websites with interactive traffic maps, TV and radio broadcasts) to better manage traffic (Photos from the Washington State Department of Transportation).

The U.S. federal, state, and local governments spent $318.2 billion in transportation in 2018, amounting to $972 per capita.[iii] By comparison, annual investments in intelligent transportation only amount to $100 million (*Government Technology* 2010), which accounts for 0.3% of the total transportation investments. Given the considerable economic and societal costs of traffic congestion (Winston and Langer 2006, Winston 2013) and the potential of ITS to help mitigate traffic congestion, this study asks the following research questions: (1) *Do intelligent transportation systems*

[iii] https://www.usgovernmentspending.com/year_spending_2018USbn_18bs2n#usgs302, retrieved on January 5, 2019.

help mitigate traffic congestion? And if so, (2) *How do intelligent transportation systems help mitigate traffic congestion*?

To answer the questions, we draw upon long-held debates on traffic congestion in the transportation economics (e.g., Downs 1962, Cervero 2002, Duranton and Turner 2011). One central tenet in this literature involves “induced traffic” (Goodwin 1996, Cervero 2002), which challenges a taken-for-granted assumption that increasing road supply with physical infrastructure investments reduces traffic congestion. On the contrary, it contends that a decrease in driving costs followed by road expansion induces more traffic, and it does not necessarily reduce traffic congestion. One related question this raises is: Do ITS have a similar “traffic-inducing” effect? The transportation economics literature suggests that it may not necessarily be the case and proposes that traffic congestion can only be tackled by dealing with traffic supply-and-demand simultaneously (Cervero 2002), a solution that ITS could offer to traffic management.

Although the Information Systems (IS) literature has developed an extensive body of knowledge regarding how IT creates value in both the private and the public sectors (e.g., Melville et al. 2004, Pang et al. 2014a), it has not paid much attention to transportation, which is an integral part of everyone’s life. By integrating the transportation economics with the IS literature on the value of IT, we offer two theoretical explanations on the roles of ITS in reducing traffic congestion: (i) ITS help commuters to make better travel decisions, and (ii) ITS help local governments to develop an urban traffic management capability.

To empirically assess the impact of ITS on traffic congestion, we consolidate a panel dataset of the road stock, traffic volume, congestion costs, and delay hours for 99 urban areas (metropolitan statistical areas or MSA) in the U.S. from 1994 to 2014. We focus on the 511 Traveler Information Systems, the largest federally-supported ITS program in the U.S. history dedicated not only to collecting massive real-time traffic data and providing public access to this information, but also to monitoring and analyzing urban mobility patterns and using them to make strategic transportation plans (Auer et al. 2016). To estimate the impact of 511 Systems on traffic congestion, we exploit the deployment pattern of 511 Systems, which is staggered temporally and geographically across 46 U.S. states since 2001, utilizing a difference-in-differences approach. A battery of robustness tests helps to establish the validity of such an identification strategy, including a leads-and-lags model to test the parallel trend assumption and a discrete time hazard model to evaluate the potential correlates with the 511 Systems implementation.

Econometric analyses yield key findings. First, we find ITS to significantly reduce traffic congestion. Specifically, the adoption of 511 Systems is associated with a decrease in unnecessary travel time and congestion costs. The average commuter in a metropolitan area that adopted 511 Systems saves approximately 2.57% of her commuting time and 2.86% in extra costs due to traffic congestion. Multiplying those figures by the number of commuters in U.S. urban areas, we find that 511 Systems lead to annual total savings of about 175 million hours in travel time and $4.72 billion in travel costs. Second, the adoption of 511 Systems is associated with a decrease in excessive fuel consumption by about 53 million gallons of gasoline and over 10 billion pounds of CO_2 in greenhouse gas emissions due to traffic congestion each year nationally, demonstrating a compelling environmental impact of ITS. Further, our back-of-the-envelope calculation shows that the annual economic savings from 511 Systems (≈$4.72 billion) are 35 times that of their total investment over 10 years (≈$135 million), representing a substantial return on investment. These findings not only demonstrate the significant impact of ITS but also highlight its cost-effectiveness in managing traffic and mitigating road congestion.

Moreover, we take a further step to examine the underlying mechanisms by which ITS help to mitigate traffic congestion, providing unique insights into the critical roles of IT in the transportation sector. Utilizing a wide range of additional fine-grained administrative datasets (i.e., American Community Survey Public Use Microdata Samples, National Household Travel Survey, National Transit Data), we obtain a rich spectrum of supportive evidence on the roles of ITS in traffic management on both supply and demand sides. On the traffic demand side, we find that the adoption of 511 Systems is associated with changes in (i) individual travel patterns (e.g., daily trip frequency and distance), (ii) navigation routes choices, (iii) travel time uncertainty, and (iv) work-trip transportation modes. On the traffic supply side, we find that the effect of 511 Systems on traffic congestion is stronger with larger road supply and more rail transit services (See Section 7). In addition, we examine the impact of the usage of ITS on traffic congestion. We provide empirical evidence that the traffic-reducing effect of ITS is enhanced with more 511 website visits and with more information provision functionalities in 511 Systems (See Section 8).

This study makes important contributions to the IS and the transportation economics literatures. First, by focusing on the long-lasting public concern of traffic congestion, this study contributes to the emerging work on the societal impacts of IT. Second, we contribute to the literature on IT value creation by demonstrating the roles of ITS in traffic management and congestion mitigation. We substantially push the boundary of the IS literature, not only by identifying the significant impact of ITS on traffic congestion, but by unraveling the underlying mechanisms with a range of supportive evidence. Third, we contribute to the "Green IT" literature (e.g., Melville 2010, Malhotra et al., 2013) by documenting that ITS help to reduce fuel consumption and carbon emissions by mitigating traffic congestion. Fourth, we contribute to the transportation economics by stressing the role of ITS as a cost-effective traffic intervention. Finally, by integrating the information systems with the transportation literature, we propose a new interdisciplinary approach that sheds light on the increasing role of IT in transportation, an approach that, to our knowledge, few extant studies have attempted in either literature.

This research also provides practical implications for both policymakers and also for commuters. Providing transportation infrastructures is considered a primary responsibility of governments and a crucial factor for economic development (Winston 2013). This is why transportation spending is one of the largest public-sector expenditures. We seek to influence policy debates on transportation spending by empirically demonstrating that IT can be a cost-effective intervention for managing traffic and mitigating congestion. We also explain how policymakers can leverage ITS to develop traffic management supply-and-demand coordination. Commuters also benefit from ITS and other emerging traffic management technologies through reduced daily travel times and costs. Furthermore, we show that ITS increase social welfare not only in terms of economic savings but also environmental sustainability.

2.2 Intelligent Transportation Systems

Transportation planners in the U.S. have applied technologies to manage traffic since the 1980s, such as navigation routing, electronic toll collection, and traffic measurement (Auer et al. 2016). In 1994, the USDOT officially coined a term “ITS” to recognize the significant potential of IT-enabled interventions in tackling traffic problems. In 2000, upon a USDOT petition, the U.S. Federal Communication Commission (FCC) designated “511” as the single traffic information telephone number across the country.[iv] In 2001, the USDOT started to provide federal grants to U.S. state governments for implementing 511 Traveler Information Systems. By 2011, 70% of the U.S. population (i.e., over 233 million) was being served by 511 Systems. By 2014, 46 states implemented 511 Systems with federal grants totaling $135 million.

While 511 Systems started as a simple telephone service for traffic information, they now represent a broader set of sophisticated, intelligent systems for both commuters and state/ local governments. Table 2.1 provides a list of the functionalities and features of a typical 511 System. It aims to help both commuters and local governments to make

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[iv] https://www.fhwa.dot.gov/trafficinfo/511what.htm, retrieved on January 5, 2019.

better decisions with real-time traffic information obtained from cameras and sensors on roads and bridges and intelligent processing of said traffic data. Commuters can have access to such real-time traffic data via cellphones, websites, and even smartphone apps recently.[v] State and local governments can use such information to devise real-time and long-term interventions, such as dynamic toll pricing, lane adjustments, and rescheduling public transit in response to traffic demands.

Table 2.1.
The Functions, Infrastructure, and Instances of ITS

ITS Functionalities	ITS Infrastructures	Instances
Traffic data collection	Traffic monitoring systems Road weather monitoring	CCTV cameras, crowdsourcing traffic data from GPS-equipped cell-phones
Traffic analytics	Data analytics for planning and performance evaluation	Real-time simulation, network prediction
Traffic management	Active traffic management	Speed harmonization, queue warning, temporary shoulder use, dynamic merge control, dynamic lane markings, dynamic routing
	Driver information provision	Information provision through smartphone apps, websites, or telephone call services
	Ramp management and conventional lane management	Ramp metering, ramp closure, lane controls
	Diversion management	Divert traffic to avoid incidents, construction, weather, and events
	Integrated systems to assist other forms of traffic interventions	Electronic road pricing systems, smart parking, regional transit management systems

We choose 511 Systems as our research context for three reasons. First, 511 Systems encompass comprehensive IT functionalities and services that integrate traffic

[v] For instance, according to a traffic report (https://www.udot.utah.gov/main/f?p=100:pg:0:::1:T,V:4254, retrieved on January 5, 2019) by the Utah Department of Transportation, its 511 System had received 20,049 calls and 178,658 sessions of 511 website visits in January 2015. Besides, Utah has 191 variable message signs (VMS) across its roads, and it displayed 41,793 VMS messages with its 511 data in the same month. Such evidence illustrates that drivers do utilize the information from 511 Systems, either proactively via 511 calls and website visits or passively from road signs and TV/radio broadcasts.

data collection, intelligent analytics, and proactive, real-time traffic management. In addition, the infrastructure, IT functionalities, and IT services provided by 511 Systems are relatively standardized and thus have similar effects on traffic congestion across locations, allowing us to regard the adoption of 511 Systems as an identical or quasi-identical treatment for local traffic congestion once adopted. Second, 511 Systems have gradually been adopted across locations for more than a decade, providing us with a source of variance to compare the differences in traffic congestion between not only MSAs that adopted 511 Systems and those that did not, but also before and after such an adoption in a specific MSA. Third, some potential confounding factors (e.g., demographic and socioeconomic status) can be accounted for by using census data, and some MSA-specific (e.g., geographical location and climate) and year-specific heterogeneities (e.g., nationwide common macroeconomic trends) are arguably fixed or quasi-fixed. This research context, therefore, helps us to develop an identification strategy to uncover the effect of ITS adoption on urban traffic congestion.

Note that while our research subject is the 511 Systems developed and deployed by state and local governments since early 2000s, navigation apps such as Google Maps have recently become popular among drivers for travel planning and navigation. To stress the importance of our focus on 511 Systems, it is necessary to compare government-adopted ITS and privately-developed navigation systems. First, 511 Systems are a comprehensive ITS project that have provided information to and facilitated decision making on both the traffic supply and demand sides since as early as 2001, while navigation apps (e.g., Google Maps) have mainly served individual commuters with real-time traffic information on the demand side since 2009.[vi] Second, although navigation apps become prevalent now, drivers are still influenced directly and indirectly by the information provided by 511 Systems in the U.S,, whether or not they are aware of their existence.[vii] Third, while drivers choose to use or not use navigation apps, they are required to follow the direction of electronic signs and signals on the roads that are empowered by 511 Systems (Figure 2.1).

Having said that, in addition to the government-adopted 511 Systems, we also examine the impact of navigation applications developed by the private sectors, particularly Google Maps, on traffic congestion in Section 6.7. Specifically, we estimate how the search intensity of Google Maps is associated with traffic congestion, an exercise that reinforces our theorization on how real-time information provision helps manage traffic demand. In addition, we offer suggestive evidence on the joint effect of Google Maps and 511 Systems in mitigating traffic congestion.

2.3 Theoretical Development

To investigate how ITS influence traffic congestion, we draw upon two main bodies of research: (i) the nature of traffic congestion and conventional interventions in

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[vi] https://electronics.howstuffworks.com/how-does-google-maps-predict-traffic.htm, retrieved on January 5, 2019.

[vii] According to a report on Kentucky's 511 Traveler information Systems (Van Dyke et al. 2016), while 28% of the drivers obtain information from Google Maps or Waze and 5% from in-car navigation systems, up to 62% drivers directly and indirectly obtain traffic information from 511 Systems: Among them, 42% from TV and radio broadcasts which use 511 data for traffic news reports, 13% directly from 511 services, and 7% from social media accounts of state or local transportation agencies (e.g., @511SFBay, a twitter account for 511 traffic information in San Francisco Bay Area).

the transportation economics, and (ii) the IT and value creation in the IS literature. The transportation economics provides a theoretical foundation for the economic account of traffic congestion and traffic supply-and-demand, while the IS literature helps us to understand how ITS facilitate effective traffic management.

2.3.1 Traffic Congestion and Conventional Interventions for Traffic Congestion

Traffic congestion has been discussed in the transportation economics for over half a century (e.g., Downs 1962, Vickrey 1969, Arnott and Small 1994, Duranton and Turner 2011). Transportation economists view traffic congestion as a negative externality that arises when drivers do not bear the full costs of the impact (i.e., traffic congestion) from driving (Small and Verhoef 2007). Therefore, one ideal solution for traffic congestion from an economics perspective is to price these negative externalities (Jones 1998). If drivers do not pay for the time loss they impose on others, they make socially-inefficient driving choices (Arnott and Small 1994). Extensive research in the past few decades (e.g., Vickrey 1969, Arnott et al. 2005) has examined how to price traffic congestion. However, congestion pricing as a tool to improve urban mobility has received little attention from policymakers (e.g., Jones 1998).

Instead, policymakers have been in favor of an alternative intervention, namely "build our way out" for the past half a century (Arnott and Small 1994). Merely expanding the road supply, however, is generally considered ineffective or even counter-productive (e.g., Goodwin 1996). This is attributed to the phenomenon of "induced traffic," which occurs when latent travel demands are induced due to a decrease in driving costs after road expansion (Goodwin 1996, Cervero 2002). Downs (1962, 2001) calls induced traffic "the Fundamental Law of Highway," later generalized by Duranton and Turner (2011) to a broader class of major urban roads. This literature thus argues that the "build our way out" approach is not effective at all since it only considers the supply side and lacks the foresight to coordinate supply and demand in tandem (e.g., Cervero 2002). In this study, we propose ITS as a cost-effective intervention for traffic congestion as they enable coordination of traffic supply and demand simultaneously, a new theoretical perspective in transportation economics.

A small stream of transportation economics studies has discussed traffic information provision as a potential intervention for better allocating road traffic (e.g., Emmerink et al. 1996, Verhoef et al. 1996). This line of work adopts a microeconomics perspective and builds analytical models on how information provision by navigation systems for drivers affects both their travel decisions and overall traffic congestion (Arnott et al. 1991). However, simulation findings have been mixed on whether navigation systems help to reduce congestion (Small and Verhoef 2007). On the one hand, information from navigation systems can help drivers to make informed route choices and thus reduce excess travel (Ben-Akiva et al. 1991). On the other hand, if many drivers receive the same information, they might choose similar routes and departure times, exacerbating traffic congestion (Arnott et al. 1991). In this study, we expand and contribute to this literature in three ways: (i) unlike navigation apps for drivers (e.g., Google Maps), the focus of this study is a comprehensive ITS program (i.e., 511 Systems) that informs both drivers and state/local governments; (ii) we offer empirical evidence to reconcile the tension on whether information provision eases or exacerbates traffic congestion to complement extant analytical work (e.g., Arnott et al. 1991); and (iii) we examine how the effect of information provision on traffic congestion interact with conventional interventions (e.g., road-supply adjustment) for traffic management.

2.3.2 Information Technology and Value Creation

To theorize how ITS can be utilized for traffic management, we draw upon the IS literature to understand the role of IT for organizations, societies, and individual lives.

The first and foremost role of IT is to collect, transmit, store, process, and utilize information (Shapiro and Varian 1998, pp. 8). IT creates value as its generated information reduces different types of costs associated with economic activities, such as search cost (Goldfarb and Tucker 2019). IT can be leveraged to inform first-line workers and managers and decentralize decision making in an organization (Bloom et al. 2014). IT enables the exchange of unbiased, complete, and accurate information in the electronic markets for better firm and consumer surplus (Granados et al. 2006). The role of information has also been stressed in the nascent but growing literature of IT impact in a broader economic and societal setting. This line of work has touched upon a few concerning topics, such as the spread of HIV (Chan and Ghose 2014) and alcohol-related motor vehicle homicides (Greenwood and Wattal 2017). The key mechanism in these studies is that IT-enabled platforms (e.g., Craigslist, Uber) reduce information asymmetry and decrease search and transaction costs to citizens. In our setting, ITS make traffic information more accessible and transparent, lowering costs for drivers to optimize travel decisions and for local governments to improve traffic conditions. Our study thus extends the research on the societal role of IT to managing traffic.

Another role of IT is the technological changes that advanced technologies and information infrastructures contribute to effective management (Brynjolfsson and Hitt 2003). Information systems literature mainly focused on IT in the private sector and discussed the business value of IT (e.g., Pavlou and El Sawy 2006, Rai et al. 2012). The main theoretical perspective stresses that IT resources can improve organizational performance by developing relevant IT capabilities. Bharadwaj et al. (2002) define IT capabilities as the "firm's ability to acquire, deploy, and leverage its IT resources to shape and support its business strategies and value chain activities." In the recent development of IT capabilities, *coordination capabilities* stress the role of IT to co-create relational value within a firm (Bharadwaj et al. 2007) or within a value chain (Rai et al. 2012), while *reconfiguration (dynamic* or *improvisational) capabilities* stress the ability of IT to pro-actively or spontaneously, respectively, reconfigure existing resources to build operational capabilities in response to turbulent environments (Pavlou and El Sawy 2010). Beyond IT capabilities in the private sector, a burgeoning literature has begun to theorize IT value in the public sector (e.g., Pang et al. 2014a, 2016). This literature argues that IT resources help create societal value by developing public-sector IT capabilities. Drawing on the IT capability literature, our study argues that ITS help local governments to develop an *IT-leveraging traffic management capability*, which we define as the ability of local transportation agencies to leverage ITS infrastructure and functionalities (Table 2.1) to deliver value-added services to the public. Our perspective on IT-leveraging traffic management capabilities deepens our understanding of how ITS can be integrated with existing traffic interventions to better manage traffic and to mitigate congestion.

2.3.3 Intelligent Transportation Systems and Traffic Congestion

Integrating the IS literature with transportation economics, we develop two theoretical explanations by which ITS mitigate traffic congestion. First, ITS inform commuters of traffic conditions and facilitate their decision making on travel planning and navigation. Without ITS, drivers may make such decisions based on their own intuitions or experiences, which are unlikely to be accurate. With ITS, drivers can schedule their travel beforehand by obtaining real-time traffic information via 511 calls or 511 websites with interactive traffic maps. In addition, they can read roadside variable message signs and be aware of traffic situations ahead of them on the roads on a real-time basis. All reliable traffic information disseminated via various channels from ITS facilitates the individual travel decisions on departure times, transportation modes, and navigation routes (Small and Verhoef 2007). The changes in the micro-level commuting decisions can shift the pattern of overall traffic demand to be more temporal and geographical dispersed, thereby mitigating traffic congestion (Arnott and Small 1994).

Second, ITS inform local governments and transportation agencies of real-time traffic conditions and help them develop an urban traffic management capability. *First*, ITS enable local governments to adjust road supply proactively in response to potential traffic congestion. For instance, on the busiest stretch of Interstate 5, Washington State Department of Transportation manages traffic with overhead high-tech gantries that display speed limits and automatically adjust the onsite traffic conditions, with yellow arrows to merge, green arrows to show open lanes, and red X to mark closed lanes (*Government Technology* 2011a). Such VMS help adjust the road supply and allocate traffic demand more efficiently. *Second*, ITS enable local governments to develop IT-leveraging traffic management capabilities that (i) integrate the strengths of existing traffic interventions and (ii) facilitate proactive supply-side solutions for traffic management. Conventional interventions, such as road expansion and pricing, are often individually and independently designed and deployed to manage traffic (Papageorgiou et al. 2003). As with IT-enabled *coordination capabilities* (Bharadwaj et al. 2007), we argue that ITS can coordinate existing traffic interventions to maximize their joint effects. For instance, in 2009, New York City (NYC) Department of Transportation collected GPS data from 13,000 taxis to identify the most congested roads. Based on these data, NYC closed off the Times Square and Herald Square sections of Broadway Avenue to traffic to eliminate the confusion from the diagonal trajectory of Broadway Avenue. The speed of taxis in both directions has improved by 15% after this intervention (*Government Technology* 2011b). Besides, ITS can reconfigure existing resources (e.g., road supply, toll stations) to help local governments to develop a dynamic traffic management capability in response to traffic shocks. We argue that such IT-enabled *reconfiguration capabilities* enhance local governments' competence in urban traffic management. Specific ITS-enabled traffic solutions include dynamic fare adjustment in public transportation,[viii] dynamic High-Occupancy Vehicle (HOV)/managed lanes,[ix] and

[viii] https://ops.fhwa.dot.gov/atdm/approaches/adm.htm, retrieved on January 5, 2019.

[ix] HOV lanes (also known as carpool lanes) are restricted lanes reserved at peak hours for exclusive use by vehicles with a driver and one or more passengers. Managed lanes can dynamically change the qualifications for driving in an HOV lane.

dynamic pricing of toll roads and highways. These examples illustrate how ITS can help to enhance the traffic management capability of local governments.

In a nutshell, we argue that ITS can help mitigate traffic congestion by (i) assisting commuters to make better travel decisions, and (ii) enabling local governments to develop a traffic management capability.

2.4 Data and Methodology

2.4.1 Data

To empirically assess the impact of ITS on traffic congestion, we consolidate a longitudinal dataset of 99 U.S. Metropolitan Statistical Areas (MSAs) (Figure 2.2) over a period of 21 years from 1994 to 2014 by integrating several data sources. The unit of analysis is an MSA as designated by the U.S. Census Bureau.

The main analysis relies on the traffic data from the Annual Urban Mobility Scorecard (AUMS) maintained by the Texas A&M Transportation Institute. The AUMS is a comprehensive dataset that integrates highway performance data from the Federal Highway Administration (FHA), and traffic speed data collected by INRIX[x] on 1.3 million miles of U.S. urban streets and highways. The AUMS data have been widely used in transportation economics research (e.g., Fagnant and Kockelman 2015). To incorporate road network information, we matched AUMS dataset with the Highway Performance Monitoring Systems (HPMS) data for each MSA. The HPMS data, also widely used in

[x] INRIX is a global company which provides Internet services and mobile applications of road traffic and driver services.

transportation economics (e.g., Duranton and Turner 2011), contains administrative and roadway system information (e.g., road miles, vehicle miles traveled) on all public roads, including interstate highways, freeways, arterials/collectors, and local roads.

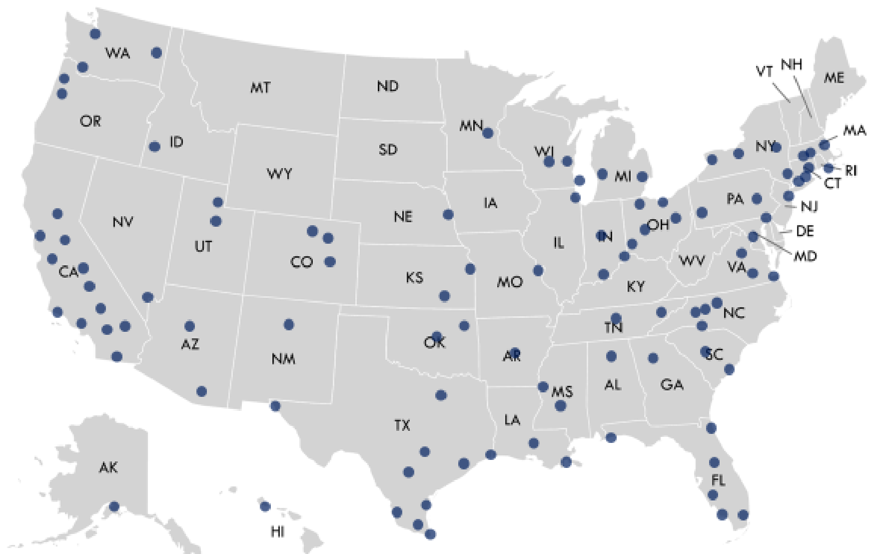

Figure 2.2.
Metropolitan Statistical Areas (MSAs) in the Sample

Notes: 99 MSAs are in the sample due to the availability of traffic congestion data (Annual Urban Mobility Scorecard, AUMS) and road network data (Highway Performance Monitoring Systems, HPMS). AUMS dataset covers 101 MSAs. Two of them, Indio-Cathedral City CA, Lancaster-Palmdale CA, cannot be matched with HPMS, and thus dropped out.

Our sample is restricted to 99 MSAs, as the AUMS only provides traffic congestion data for 101 U.S. urban areas[xi] (See Table A-1 in Appendix A). Albeit unavailable for other MSAs, to our knowledge, the AUMS is the only publicly accessible source covering most comprehensive congestion information of U.S. cities. Our timeframe begins at 1994, which allows us to capture at least 7 years of pre-intervention

[xi] We dropped two MSAs (Indio-Cathedral City-Palm Springs, CA, Lancaster-Palmdale, CA) as they fail to match HPMS data.

traffic trends for each MSA, as 2001 is the first year that an MSA (Omaha, NE-IA) started to adopt 511 Systems.[xii] The timeframe ends at 2014 after which up-to-date information on 511 Systems adoption is not available. The main dependent variable is *CONGESTION*, measured by the log of the annual congestion costs per commuter (*COST*) and the annual hours of delay per commuter (*TIME*) for each MSA from the AUMS dataset. As standard measures for traffic congestion in the transportation economics (Dewees 1979), *COST* and *TIME* indicate the amount of extra time and costs, respectively, incurred due to traffic congestion. *COST* is calculated based on delay costs and fuel costs during idling, while *TIME* is based on the difference between actual travel speeds and congestion-free speeds. For an MSA, we use average congestion *per commuter,* instead of aggregate measures (e.g. total congestion costs), in the main analysis for the ease of interpretation and comparison across MSAs. Besides, we use extra greenhouse gas emission (CO_2) and fuel consumption (*FUEL*) due to congestion as alternative dependent variables (e.g., Rothenberg 1970, Chen and Whalley 2012). We also use aggregate traffic volume, measured by Vehicle-Miles Travel[xiii] (*VMT*) from the HPMS data to measure MSA-level traffic demand (Duranton and Turner 2011).

[xii] We do not incorporate data earlier than 1994 for the following reasons. First, different data sources, such as employment and transportation, have various degrees of availability in the early 1990s and before, causing numerous missing values if we combine the datasets. Second, most relevant datasets before 1994 were not well-documented or well-archived, creating difficulties to obtain reliable data points. Last and importantly, the long pre-intervention period suffices to capture most variations between MSAs.

[xiii] VMT is calculated by multiplying the amount of daily traffic on a roadway segment by the length of the segment and then summing all the segments' VMT for an MSA.

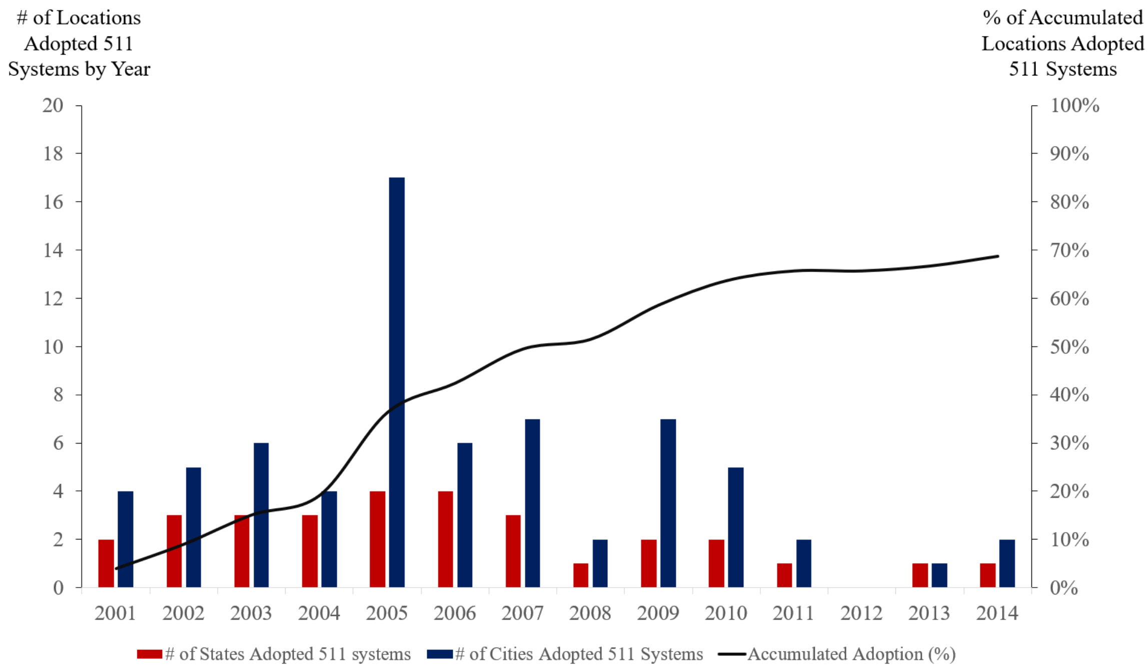

Figure 2.3.
Implementation Years by Location

Notes: Figure 2.3 shows the 511 Systems implementation pattern over years. The red bars indicate the number of states that adopted for each year, while the blue bars refer to the number of cities. The black line describes the cumulative adoption rate in 41 states (99 MSAs) over the years. By the end of 2014, 69% MSAs in our sample had implemented 511 Systems.

The independent variable of interest is the indicator *ITS*, which represents whether 511 Systems have been implemented and operated given a specific MSA and year (as determined by Table 2.2). The data for *ITS* is directly retrieved from the website of the FHA. Note that 511 Systems have mostly been adopted by state governments only with a few exceptions (e.g., local governments in California such as San Francisco made independent decisions). We match 511 Systems adoption data with our main AUMS dataset to each MSA and each year. Generally, most urban areas in our sample (77 out of 99) are bounded within a single state; however, some span across two or more states (e.g., Philadelphia-Camden-Wilmington, PA-NJ-DE-MD, MSA), where drivers can benefit from 511 Systems from different states. For such cross-state MSAs, we calculate the road miles-percentages of MSA in each state as weights and created weighted-average *ITS* measures.[xiv] Table 2.2 and Figure 2.3 show the 511 Systems adoption year by locations. By 2014, 68 out of the 99 MSAs (69%) in our sample had adopted 511 Systems. Setting the remaining as untreated MSAs throughout our timeframe allows us to compare congestion across treated and untreated MSAs over the same timeframe using a difference-in-differences framework (Angrist and Pischke 2008, pp. 227).

Table 2.2.
ITS Adoption Timing

State	Year	Month	State	Year	Month
Nebraska	2001	10	Tennessee	2006	8
Utah	2001	12	Wyoming	2006	9
Arizona	2002	7	Nevada	2006	11
Minnesota	2002	7	Louisiana	2006	12
Iowa	2002	11	San Diego, CA	2007	2
Kentucky	2002	11	Eastern Sierras, CA	2007	5
South Dakota	2002	11	Missouri	2007	5
San Francisco, CA	2002	12	Georgia	2007	8
Montana	2003	1	New Jersey	2007	8
North Dakota	2003	2	New Mexico	2007	12
Alaska	2003	4	Wisconsin	2008	12
Maine	2003	5	New York	2009	2
Washington State	2003	7	Pennsylvania	2009	7
Vermont	2003	10	San Luis Obispo, CA	2009	6
Oregon	2003	12	Inland Empire, CA	2010	4
Kansas	2004	1	Massachusetts	2010	5
North Carolina	2004	8	Los Angeles-Orange-Ventura, CA	2010	10
Sacramento, CA	2004	9	South Carolina	2010	12
Colorado	2004	12	Maryland	2011	8
Virginia	2005	2	West Virginia	2012	12
Rhode Island	2005	3	Hawaii	2013	11
Florida	2005	11	Mississippi	2014	2
Idaho	2005	11	Dallas, Texas	2014	5

[xiv] For example, in the Philadelphia-Camden-Wilmington MSA in the year of 2008, the percentage of roadway miles in Pennsylvania, New Jersey, Maryland, and Delaware is 63.39%, 26.63%, 0.6% and 9.34%, respectively. In 2008, only New Jersey adopted a 511 system, and therefore ITS for this cross-state MSA is calculated as 0.2663.

Table 2.3.
Main Variables, Definitions, and Data Sources

Variable		Description	Sources
Dependent Variables			
CONGESTION	COST	*ln* (annual congestion cost per commuter)	AUMS
	TIME	*ln* (annual hours of delay per commuter)	AUMS
TRAFFIC	VMT	*ln* (annual daily vehicle miles traveled)	HPMS
Independent Variable			
ITS	511 Systems deployment status		FHA
Control Variables			
POPULATION	*ln* (population)		BEA
PERSONINCOME	*ln* (average personal income)		BEA
ROAD	*ln* (total road miles)		HPMS
DIVERRATIO	% of drivers in the population		AUMS
GASOLINE	$ per gallon		AUMS
UNEMPLOYMENT	Unemployment rate (%)		BLS
PUCLICTRANSIT	# of vehicles operated for maximum service		NTP
COMMERCIAL	# of commercial truck drivers in the transportation sector		CBP
MANUFACTURE	Share of manufacturing industries in total employment (%)		CBP
TRANSPORT	Share of employment for the transportation-intensive sector (%)		CBP
INFORMATION	Share of employment for the IT-intensive sector (%)		CBP
EDUCATION	Share of employment for the educational sector (%)		CBP
SCIRESEARCH	Share of employment on science and R&D (%)		CBP

Notes: Table 2.3 displays the key variables for our main analyses at the MSA-year level. AUMS represents Annual Urban Mobility Scorecard; HPMS represents Highway Performance Monitoring Systems; FHA represents Federal Highway Administration; BEA represents Bureau of Economic Analysis; BLS represents Bureau of Labor Statistics; NTP represents National Transit Database; CBP represents County Business Patterns.

To account for potential confounding factors that might be correlated with both ITS adoption and traffic congestion, we incorporate a rich set of time-varying MSA-level covariates, including population, personal income, total road miles, commuter proportion, fuel costs, public transit, commercial traffic, unemployment rates, and employment distribution in related sectors (Table 2.3) for each MSA over our study period, following extant transportation studies (e.g., Duranton and Turner 2011, Hsu and Zhang 2014). Data for these covariates are collected from multiple sources. We use population and personal income from the Bureau of Economic Analysis (BEA), road supply data from HPMS, and public transit and commercial traffic using National Transit Data (NTD) and County Business Patterns (CBP) data. We measure unemployment rates using data from the Bureau of Labor Statistics (BLS) and employment shares in related sectors (i.e., manufacture, transportation, information, education, science and research) using CBP data. These variables account for time-variant heterogeneity across years and MSAs. Data sources, measures, summary statistics, and correlation matrix are shown in Tables 2.3, 2.4, and A-2 in Appendix A, respectively.

Table 2.4.
Summary Statistics of the Main Variables

		Mean	Std. Dev	Min	Max
		(1)	(2)	(3)	(4)
[1]	COST	6.773	0.386	4.625	7.635
[2]	TIME	3.588	0.363	1.792	4.466
[3]	VMT	9.907	1.017	12.647	7.225
[4]	ITS	0.278	0.440	0	1
[5]	POPULATION	5.551	0.327	4.744	8.607
[6]	PERSONINCOME	10.399	0.360	1.099	11.569
[7]	ROAD	8.190	0.888	5.700	10.707
[8]	DRIVERRATIO	0.473	0.045	0.234	0.550
[9]	UNEMPLOYMENT	0.060	0.025	0.015	0.199
[10]	GASOLINE	2.172	0.921	0.930	4.350
[11]	MANUFACTURE	0.115	0.060	0.008	0.671
[12]	TRANSPORT	0.037	0.023	0.007	0.229
[13]	COMMERCIAL	8.519	1.133	2.303	11.225
[14]	PUBLICTRANSIT	6.189	1.451	0	10.180
[15]	INFORMATION	0.029	0.013	0.002	0.140
[16]	EDUCATION	0.026	0.020	0.002	0.218
[17]	SCIRESEACH	0.063	0.041	0.003	0.325

Notes: 2,079 observations for 99 MSAs in 1994-2014. To reduce possible multicollinearity due to a correlation between population and road miles, POPULATION is a weighted measure, that is, the average population per road mile in an MSA in a given year.

2.4.2 Empirical Strategy

As our empirical design relies on the staggered implementation of 511 Systems across years and MSAs, we adopt a *difference-in-differences* (DID) approach. As such, we estimate the change in traffic congestion for treated MSAs before and after the adoption of 511 Systems, compared to that in untreated MSAs over the same timeframe. We also incorporate time-varying covariates and year- and MSA-specific fixed effects to account for unobserved invariant heterogeneity across time and locations. We model the traffic congestion ($CONGESTION_{it}$) in MSA *i* at year *t* using the following specification:

$$CONGESTION_{it} = \beta ITS_{it} + X_{it}'\gamma + u_i + v_t + \varepsilon_{it} \qquad \text{(Eq. 1)}$$

The variable ITS_{it} indicates the deployment status of 511 Systems in MSA *i* as of year *t*. *COST* and *TIME* are our primary measures for *CONGESTION*. u_i is a vector of 99 MSA fixed-effects; v_t is a vector of year fixed-effects, accounting for common trends in macroeconomic and transportation dynamics; X_{it} is a vector of time-varying covariates (Table 2.3). ε_{it} is the error term, clustered at the MSA level to account for autocorrelation within MSAs over time (Bertrand et al. 2004). We expect the coefficient on ITS (β) to be negative if the 511 Systems adoption helps to mitigate traffic congestion.

It is noteworthy that most decisions of 511 Systems adoption were made by state governments, while our analysis is at the MSA level. States may choose to implement ITS by considering traffic conditions across more than one MSA. For instance, Florida has seven MSAs, but traffic congestion at one MSA alone (e.g., Jacksonville, FL) might be unlikely to drive the state-wise adoption decision. In addition, many MSAs are located across states (e.g., Kansas City, MO-KS), and traffic congestion in such MSAs are unlikely to lead multiple states to adopt ITS in tandem. These two features in our empirical context suggest that reverse causality might not be as serious as the situation that all ITS implementation decisions were made by local governments. This does not, however, imply that ITS adoption is completely exogenous to traffic congestion. We further tackle the remaining validity concerns with a variety of robustness tests, such as the leads and lags model and instrumental variables analysis. Besides, we deepen our inquiry into the usage of ITS and its impact on traffic congestion by exploiting data on 511 functionality deployment and 511 telephone calls and websites visits below.

2.5 Results

2.5.1 Main Results

Table 2.5 reports the main results from the DID estimation. In Columns 1 and 2, the coefficients on ITS are negative and significant, representing a 2.86% decrease in traffic congestion costs and a 2.57% decrease in traffic delays. This indicates that on average, a commuter at a metropolitan area that adopted a 511 System saves approximately $28 and 63 minutes per year.[xv] By multiplying the number of commuters in U.S. urban areas, we estimate the total annual savings to be $4.72 billion at the national level, emphasizing the substantial impacts of ITS in mitigating traffic congestion. This finding supports our proposition that ITS reduce traffic congestion. Moreover, our estimation examines whether ITS induce traffic. In Column 5 with traffic volume (*VMT*) as a dependent variable, the coefficient of *ITS* is insignificant, failing to show that ITS induce more traffic. Consistent with the transportation economics studies (e.g., Duranton and Turner 2011, Hsu and Zhang 2014), the coefficient of road supply (*Road*) is positive and significant (Column 5), indicating that road expansion does induce traffic. By comparing the coefficients of *ITS* and *Road*, we find that ITS can be more

[xv] The cost and time savings are estimated by multiplying 2.86% by $968 (average congestion cost per commuter in 2014) and multiplying 2.57% by 41 hours (average delay hours per commuter in 2014).

effective in mitigating traffic congestion than building more roads.

Table 2.5.
Effects of 511 Systems Adoption on Congestion and Traffic Volume

	COST	TIME	FUEL	CO2	VMT
	(1)	(2)	(3)	(4)	(5)
ITS	-0.029***	-0.026***	-0.017***	-0.049***	0.019
	(0.006)	(0.006)	(0.006)	(0.014)	(0.023)
POPULATION	1.023***	0.021	0.902***	-0.107	0.367***
	(0.037)	(0.035)	(0.033)	(0.104)	(0.114)
PERSONINCOME	0.003	0.001	0.003	0.266*	0.002
	(0.009)	(0.009)	(0.009)	(0.147)	(0.006)
ROAD	1.032***	0.033	0.912***	-0.021	1.146***
	(0.037)	(0.035)	(0.032)	(0.101)	(0.121)
DRIVERRATIO	1.740***	0.415**	1.552***	-2.959***	0.133
	(0.212)	(0.209)	(0.202)	(0.848)	(0.516)
GASOLINE	0.067**	0.053**	0.043*	-0.160**	-0.063
	(0.026)	(0.026)	(0.023)	(0.080)	(0.049)
UNEMPLOYMENT	-1.370***	-1.287***	-1.163***	-2.435***	-0.220
	(0.249)	(0.234)	(0.215)	(0.641)	(0.402)
COMMERCIAL	0.016***	0.015***	0.015***	0.064***	-0.004
	(0.003)	(0.003)	(0.003)	(0.022)	(0.007)
PUBLICTRANSIT	0.028***	0.025***	0.015***	0.022	0.028
	(0.006)	(0.005)	(0.005)	(0.028)	(0.020)
MANUFACTURE	-0.011	-0.009	0.041	0.453*	0.047
	(0.088)	(0.084)	(0.076)	(0.248)	(0.177)
TRANSPORT	-0.498	-0.406	-0.506*	-3.063**	0.030
	(0.330)	(0.311)	(0.299)	(1.211)	(0.910)
INFORMATION	0.426	0.347	0.338	2.010***	-0.288
	(0.261)	(0.255)	(0.234)	(0.751)	(0.541)
EDUCATION	-0.473**	-0.442**	-0.377*	0.130	0.572
	(0.223)	(0.224)	(0.204)	(0.823)	(0.595)
SCIRESEARCH	-0.823***	-0.777***	-0.564***	-0.178	-0.093
	(0.090)	(0.080)	(0.077)	(0.384)	(0.185)
MSA FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
# of Observations	2,079	2,079	2,079	1,089	2,079
# of MSAs	99	99	99	99	99
Adj. R-squared	0.956	0.954	0.970	0.919	0.986

Notes: Table 2.5 reports results from difference-in-differences regressions on road congestion measured COST, TIME, FUEL, CO2 (data available for 2001-2014) and road traffic demand measured by VMT. Heteroskedasticity-adjusted standard errors, clustered at the MSA level, are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

2.5.2 The Parallel Trend Assumption of Difference-in-Differences Estimation

While DID estimates are compelling, it is important to note that they are subject to critical assumptions. The primary one is the parallel trend assumptions that require no heterogeneity in traffic congestion prior to 511 Systems adoption between treated and untreated MSAs (Bertrand et al. 2004, Angrist and Pischke 2008, pp. 231). This assumption could not be satisfied if unobservable factors, idiosyncratic to individual MSAs, cause pre-treatment heterogeneity in traffic congestion. For example, if 511 Systems have been treated as a pilot project that was adopted early in MSAs with light traffic (e.g., Salt Lake City), we may assume different trends in traffic congestion in MSAs that adopted and did not adopt 511 Systems. To rule out this possibility, we execute the leads-and-lags model proposed by Autor (2003). Specifically, we incorporate pre- and post-adoption dummies into DID model to capture inter-temporal effects:

$$CONGESTION_{it} = \sum_j \tau_j PreITS_{it}(j) + \beta ITS_{it} + \sum_k \omega_k PostITS_{it}(k) + X_{it}'\gamma + u_i + v_t + \varepsilon_{it} \quad \text{(Eq. 2)}$$

$PreITS_{it}(j)$ and $PostITS_{it}(k)$ are pre-treatment placebos and post-treatment variables, which are equal to 1 if the temporal distance between the year *t* and the year that 511 Systems are adopted by MSA *i* are *j* (or *k*) years. Intuitively, this model allows us to capture the trend of traffic congestion and to observe the relative effects before and after the treatment on an annual basis.

Results are shown in Table 2.6 and Figures 2.4-2.6. We find no significant difference between treated and untreated MSAs before the adoption (i.e. $PreITS_{it}(j)$ are not significant for $j \leq -10$ to j=-2), supporting the parallel trends assumption and

Table 2.6.
DID Estimation on Leads and Lags of 511 Systems Adoption on Traffic Congestion and Traffic Volume

	COST	TIME	VMT
	(1)	(2)	(3)
Pre-ITS (<=-10)	0.020	0.021	-0.043
	(0.033)	(0.031)	(0.033)
Pre-ITS (-9)	0.026	0.025	-0.035
	(0.025)	(0.024)	(0.025)
Pre-ITS (-8)	0.018	0.017	-0.039
	(0.022)	(0.021)	(0.025)
Pre-ITS (-7)	0.017	0.018	-0.028
	(0.019)	(0.018)	(0.022)
Pre-ITS (-6)	0.017	0.017	-0.029
	(0.016)	(0.016)	(0.023)
Pre-ITS (-5)	0.008	0.009	-0.033
	(0.014)	(0.013)	(0.022)
Pre-ITS (-4)	0.010	0.013	-0.027
	(0.011)	(0.010)	(0.020)
Pre-ITS (-3)	0.009	0.008	-0.024
	(0.008)	(0.008)	(0.019)
Pre-ITS (-2)	0.007	0.009	-0.009
	(0.005)	(0.005)	(0.011)
Pre-ITS (-1)		Omitted Baseline	
ITS (adoption year)	0.000	0.002	-0.002
	(0.004)	(0.004)	(0.007)
Post-ITS (1)	-0.007	-0.002	-0.001
	(0.009)	(0.008)	(0.010)
Post-ITS (2)	-0.014	-0.011	-0.009
	(0.011)	(0.011)	(0.013)
Post-ITS (3)	-0.018	-0.016	-0.002
	(0.014)	(0.014)	(0.017)
Post-ITS (4)	-0.026	-0.024	0.000
	(0.016)	(0.015)	(0.024)
Post-ITS (5)	-0.035*	-0.032*	-0.008
	(0.018)	(0.018)	(0.025)
Post-ITS (6)	-0.058**	-0.056***	0.007
	(0.022)	(0.021)	(0.030)
Post-ITS (7)	-0.063***	-0.057**	0.013
	(0.024)	(0.023)	(0.034)
Post-ITS (8)	-0.075***	-0.068***	0.015
	(0.026)	(0.025)	(0.034)
Post-ITS (9)	-0.072**	-0.063**	0.030
	(0.030)	(0.028)	(0.039)
Post-ITS (>=10)	-0.092**	-0.086**	-0.011
	(0.037)	(0.036)	(0.040)
# of Observations	2,079	2,079	2,079
# of MSAs	99	99	99
Adj. R-squared	0.956	0.955	0.986

Notes: All covariates, year and MSA fixed effects are included but omitted here for brevity. Heteroskedasticity-adjusted standard errors, clustered at the MSA level, are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

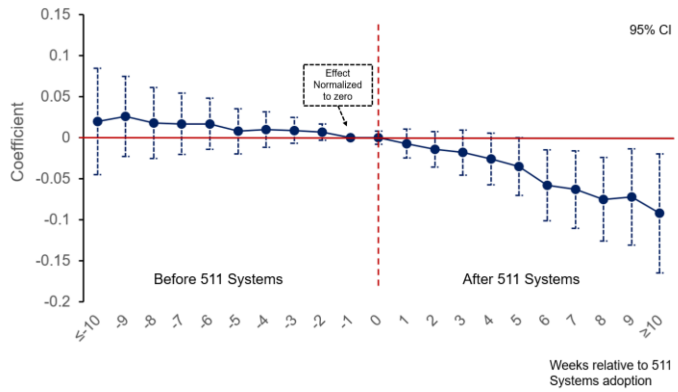

Figure 2.4.
Effects of 511 Systems adoption on COST (congestion cost) over years

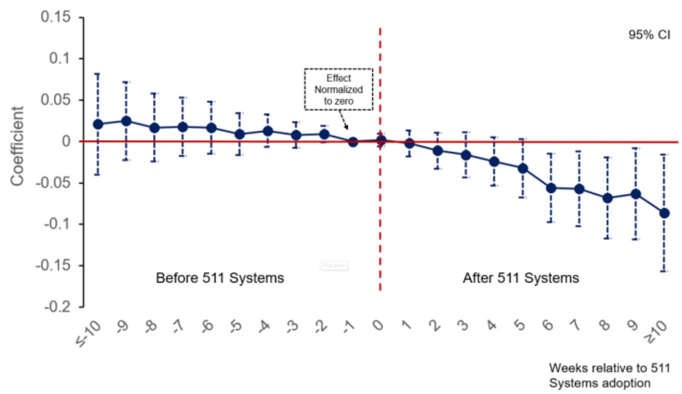

Figure 2.5.
Effects of 511 Systems adoption on TIME (delay hours) over years

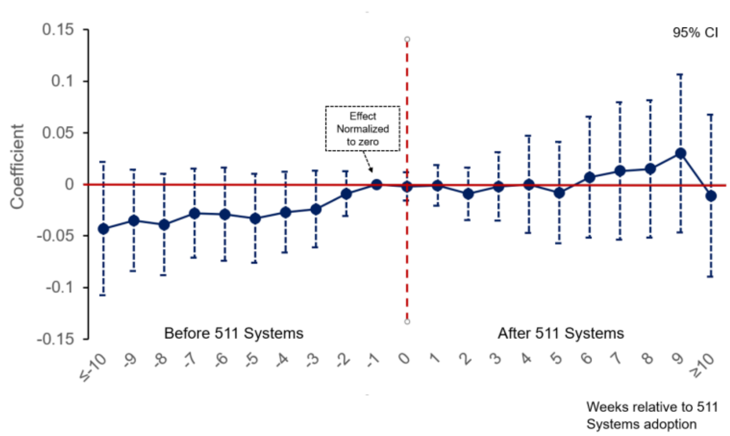

Figure 2.6.
Effects of 511 Systems adoption on VMT (traffic volume) over years

validating our DID estimates. We also observe a significant decrease in congestion cost and time 5 years after 511 Systems adoption, and such negative relative effects remain statistically significant until the end of our timeframe. This shows compelling evidence that the congestion-mitigating effects of ITS persist and grow after their implementation.

2.6 Robustness, Sensitivity, and Falsification Checks

Having identified the congestion-mitigating effect of 511 Systems, we next subject our baseline analysis to several robustness, sensitivity, and falsification checks.

2.6.1 Determinants of 511 Systems Adoption

One concern is a potentially endogenous adoption of 511 Systems. While the results from leads and lags models do not suggest heterogeneity in pre-treatment congestion trend, it is possible that there is stable variation in congestion across treated and untreated MSAs. Specifically, a reverse causality concern may be possible. We first use simple t-statistics to compare the congestion status and traffic volumes between treated and untreated MSAs in 1998, 1999, and 2000 before any U.S. states or cities adopted 511 Systems. In Table B-1 in Appendix B, we find that while MSAs that later adopted 511 Systems had, on average, higher congestion costs and delay hours than untreated MSAs did, such differences are not statistically significant conditional on the covariates (e.g., population) we accounted for in the main DID estimation.

Second, given the staggered pattern of 511 Systems adoption across locations and times, we systematically assess the determinants of 511 Systems adoption by leveraging our panel dataset. Specifically, we use a discrete-time hazard model (Jenkins 1995) to predict 511 Systems adoption as a function of MSA-level demographics, socio-economic factors, transportation-related factors (i.e., public transit, commercial traffic), and past congestion status. We measure past congestion levels using lagged traffic congestion (*COST* and *TIME*) for one, two, and three years. In Table B-2, we find while population and unemployment are significant predictors, past congestion status does not significantly determine 511 Systems adoption, implying that simultaneity between ITS and traffic congestion may not be a serious concern.

2.6.2 Instrumental Variable Analysis: Historical Routes within Cities

Next, we further address a concern that ITS may be adopted by MSAs in response to contemporaneous shocks to traffic by utilizing an alternative identification strategy. Specifically, we conduct instrumental variable analysis with two IVs about historical routes within MSAs: *railroad route miles in 1898* and *major road expansions between 1835 and 1850* (Figure B-1 and B-2). We choose such IVs for three reasons: First, both IVs are strong predictors for current road networks, throughout which the 511 Systems were installed (i.e., the independent variable of interest), and these IVs that characterize the U.S. historical road systems more than 100 years ago are unlikely to correlate with contemporaneous congestion status in 1994-2014. Second, even if there might exist associations between historical routes and current congestion besides ITS and roads, we already account for such confounding effects using a rich set of time-varying covariates, MSA-specific factors, and year-specific trends, which strengthens the validity of the IVs. Third, these IVs are commonly-used in the transportation economics (Duranton and

Turner 2011). Baum-Snow (2007), Michaels (2008), and Duranton and Turner (2011) also use historical routes as valid IVs for features of the interstate road system. We use Duranton and Turner (2011)'s data for the historical routes to execute a 2SLS estimation. Results shown in Table B-3 indicate qualitatively similar estimates with our baseline ones. The post-estimation diagnostic tests support that the IVs are not weak (KP F-test) and are exogenous (Hansen *J* test). In sum, the congestion-reducing effects of 511 Systems remain robust in the IV analysis.

2.6.3 Sample Selection

Another concern is that our estimation may be sensitive to the selection of MSAs in our sample. To check this possibility, we conduct a series of subsample analyses. First, we consider the complexity introduced by MSAs that span across states. Technically, cross-state MSAs are less comparable to intra-state ones since the former are more complex with respect to transportation mixtures and congestion status of neighboring states. Therefore, we exclude 22 cross-state MSAs and check if our estimation is sensitive to sampling. Second, we consider whether the decision of 511 Systems adoption is made by a state or a city government. Such decision types and corresponding implementation processes may introduce heterogeneity that possibly biases our estimation. We accordingly conduct two distinct analyses, one that is restricted to MSAs where state governments decided to adopt 511 Systems and the other on California MSAs where local governments made 511 decisions. Last, we consider temporal heterogeneity in our sample timeframe. It is noteworthy that traffic congestion had dropped after Financial Crisis in 2009. While year fixed-effects account for this nationwide event, the impacts of 511 might differ across time and MSAs and may drive down traffic congestion in the post-Financial Crisis period. Thus, we exclude this period and restrict our sample to 1994-2008. Using subsample until 2008 can also avoid some noises from the prevalent usage of navigation apps after 2009. For example, Google Maps has gained popularity since 2009 when it started to provide real-time traffic information by crowd-sourcing GPS data from cellphones. Table B-4 reports the results from subsample analyses and indicates that our main findings remain robust.

In addition to analysis on the sampled MSAs, we also examine the generalizable potential of our estimates to other MSAs in the U.S.[xvi] Following extant transportation studies (e.g., Couture et al. 2018), we compare the statistics of individual trip and aggregate traffic between in-sample MSAs (N=99) and out-of-sample MSAs (N=191) prior to 511 Systems adoption (in 1995 and 2001, separately).[xvii] In Table B-5, we find that individual trip statistics do not significantly differ between in-sample and out-of-sample MSAs. Moreover, while aggregate traffic statistics (i.e., daily *vehicle miles traveled* and *vehicle travel time*) of in-sample MSAs are larger than that of out-of-sample MSAs, the differences are not statistically significant after conditional on the covariates in Table 2.3. We conducted a similar analysis that compares treated and untreated MSAs in both in-sample and out-of-sample (Table B-6) and obtained a similar result. In sum,

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[xvi] Recall that the main analyses build on the 99-MSA sample due to the availability of congestion data in the AUMS dataset.

[xvii] National Household Travel Survey (NHTS) provides individual trip statistics aggregated to an MSA, including *mean trip distance*, *mean trip duration*, *mean trip speed* and *mean trip number per driver* on a random day. HPMS and Census provide MSA-level traffic statistics, including *mean daily vehicle miles traveled* and *mean daily vehicle miles traveled*.

the findings suggest that the sampled MSAs do not differ much from other MSAs on individual travel and aggregate traffic statistics conditional on observables, and we have confidence to extrapolate the identified effects of 511 Systems to elsewhere in the U.S.

2.6.4 Coarsened Exact Matching

The next concern is that while there is little heterogeneity between treated and untreated MSAs conditional on time-varying covariates and fixed effects, it is possible that untreated MSAs are not a representative counterfactual for (or not as good as comparable to) treated MSAs. To remedy this, we execute a Coarsened Exact Matching (CEM) procedure to limit the pre-treatment differences between the treated and untreated MSAs (Blackwell et al. 2009). In doing so, we match them based on several criteria: population, unemployment rates, lagged road miles, and traffic volumes. The CEM procedure generates a weight for balancing the heterogeneity across treated and untreated MSAs. We replicate DID regressions using the weight and find estimation adjusted by CEM are qualitatively similar to our main results (See Table B-7).

2.6.5 Random Implementation (Shuffle) Tests

A common concern for the DID estimation is a potential for false significance due to spurious relationships or serial correlations in our dependent variables. While the baseline estimates cluster standard errors within MSAs, it is useful to implement a falsification test suggested by Bertrand et al. (2004). Following extant literature (e.g., Greenwood and Wattal 2017), we execute a random implementation test by randomly generating and assigning dichotomous pseudo (or placebo) treatments to each MSAs. Using the pseudo indicator, we ran our baseline regressions, stored the estimates, and replicated the procedure for 1,000 times. This test allows us to identify more cleanly if correlation within MSA-year is unaccounted for and to check if our observed effect is merely driven by outliers. Table B-8 and Figure B-3 show the results. Comparing the estimates using ITS with that using pseudo treatments, the probability that the congestion-reducing effect of 511 Systems appears purely by chance is significantly low. Also, the placebo coefficients are not significantly different from zero, suggesting that autocorrelation might not be a serious issue.

2.6.6 Measure Operationalization

Another concern is that the estimation may be sensitive to our measurements. To mitigate the possibility, we first utilize alternative measures of *CONGESTION* – *FUEL* and CO_2 – and replicate the DID estimation. We observe a similar decrease in fuel consumption and GHS emission due to congestion after 511 Systems adoption (Table 2.5, Columns 3 and 4), which translated into annual savings of 53 million gallons of fuel and 10 billion pounds of CO_2 emission for the U.S. urban areas. In addition, we also use MSA-level aggregate congestion measures (i.e., total congestion cost, excessive time, fuel, and CO_2), instead of average congestion per commuter, as dependent variables. The results remain consistent (Table B-9)

Second, we vary the measures for *ITS*. Per extant platform-entry studies (Chan and Ghose 2014), we label those MSAs that implemented 511 Systems in the 4th quarter of a year (i.e., October, November, and December) as if they adopt them in the following year given that 511 Systems need time to materialize and their impacts on congestion may likely be manifested in the next year's statistics. We also use an alternative weight—

area-size proportional to each state—to construct the *ITS* measure for cross-state MSAs (e.g., New York-Newark NY-NJ-CT). The estimates using different *ITS* measures remain consistent (Table B-10).

2.6.7 Traffic Applications Developed in the Private Sector

Recently, technology companies in the private sector have developed traffic applications (e.g., Google Maps) that became popular among drivers thanks to the proliferation of mobile devices. Commuters use these applications to obtain real-time traffic information and plan their travels. While our study focuses on 511 Systems that have worked for both commuters and local governments for a relatively longer time (since 2001) prior to the prevalence of Google Maps (after 2009), we study the role of Google Maps in traffic congestion for the purpose of generalizability (Cheng et al. 2016).[xviii] While the Google Maps usage data is not publicly available, we obtained the search popularity of the term "*Google Maps*" from Google Trends as a proxy, and we used it as an independent variable and replicate the baseline estimation. In Table B-11, first, we observe that the search intensity of Google Maps is associated with a decrease in excessive travel time, similar to that from 511 Systems. This reinforces our theoretical claim that real-time information provision helps alleviate traffic congestion. Moreover, the effects of 511 Systems adoption are still statistically significant conditional on the

[xviii] Note that the baseline DID model has already accounted for the availability of Google Maps by using year fixed-effects as the initial launch and following updates of Google Maps in the US are one-time events for all Internet users regardless of locations. This means the congestion-reducing effect of 511 Systems still holds conditional on the Google Maps service (and any other Internet-based navigation applications that were launched and updated in the same fashion).

heterogenous Google Maps usage across locations and times. Last and importantly, 511 Systems and Google Maps usage complement to each other in reducing congestion.

2.7 Congestion-Mitigating Mechanisms

While we have shown consistent evidence of 511 Systems on mitigating traffic congestion, it is important to understand the underlying mechanisms. Accordingly, we empirically examine the questions: (i) How do ITS affect individual travel behavior? (ii) How do ITS interact with conventional traffic interventions?

2.7.1 Traffic Demand Mechanism

To understand the role of ITS in the traffic demand side, we examine how ITS help commuters to adjust their travel preferences and driving behavior patterns and to alter the traffic demand patterns over time.

Commute to Work: Travel Time, Departure Time, and Transportation Mode

A traffic demand changes led by ITS might be largely manifested at work-trip behaviors. With traffic information from ITS, commuters can optimize travel decisions on their departure times and transportation modes to save their travel time to work. These work-trip adjustments could be translated into a more efficient use of the transportation infrastructures (e.g., roads, railways), thereby easing traffic congestion. To empirically test this mechanism, we collect individual-level data from ACS Public Use Microdata

Samples (ACS PUMS) for 2000-2014[xix] on work-trip features, including "travel time to work," "means of transportation to work," and "time of departure for work – hour and minute" as well as personal information (e.g., personal income, employment). We matched the ACS PUMS data to our main dataset to study how 511 Systems adoption affects individual travel decisions across locations and over time.

First, we focus on changes in travel time for individual drivers after ITS adoption because the most direct implication of ITS is travel time. While we provide evidence that 511 Systems help to mitigate travel delays at an aggregate MSA level, it is useful to assess travel time changes at the level of individual drivers. Thus, we replace *CONGESTION* with *Travel Time to Work* as the dependent variable and replicate the baseline estimation. Table C-1 in Appendix C reports the results. We find that the adoption of 511 Systems significantly reduces travel time for drivers with commuting time within 60 mins. Moreover, this effect is significantly larger for drivers in heavy-traffic hours (7-10 am; 5-8 pm). This corroborates our main results and shows that ITS inform commuters and save their travel time.

Second, we examine departure time choice, an important element of the travel decision-making if peak-hour speed is of concern (Small and Verhoef 2007). We expect that based on traffic information from ITS, commuters can better optimize their departure timing to work in a way to avoid traffic congestion. To test this proposition, we examine

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[xix] The American Community Survey (ACS) is the largest ongoing nationwide survey by the U.S. Census Bureau, collecting household and personal information from 3.5 million people (1% of the U.S. population) annually.

the impact of 511 Systems adoption on the decisions to depart to work in the heavy-traffic hours or light-traffic ones. Table C-2 shows that drivers in locations that adopted 511 systems are less likely to depart at heavy-traffic hours. This supports our proposition that ITS help commuters make more informed travel decisions regarding departure timing to avoid traffic congestion.

Finally, we consider transportation mode choices (Train 1980, Arnott et al. 2005), another important work-trip decision by commuters who seek to minimize their travel costs. Like optimizing departure timing, a better modal choice could also be effective in alleviating traffic congestion (Arnott and Small 1994). To estimate the impact of ITS on work-trip transportation mode choices, we use the ACS PUMS data on the *means of transportation modes to work* (e.g., private car, taxi, public transit, bicycle, or walking). We use a dichotomous choice for each mode as dependent variables and replicate the baseline specification. Table C-3 offers an interesting finding that with 511 Systems, fewer commuters choose to travel to work by car, taxi, and bus, transportation modes that extensively occupy roads and exacerbate traffic congestion, while more commuters use rail-based transit, walking, or biking, which are environmentally-friendly. These findings support our proposition that ITS better inform drivers and help to distribute traffic demand across transportation modes (e.g., Mogridge 1997, Anderson 2014).

Frequency and Distance of Daily Travel

Next, we go beyond work-home travel decisions and study how ITS change the general pattern of individual daily trips. We expect that with transparent traffic information provided by ITS, drivers can schedule their travels more efficiently and reduce unnecessary trips with excess travel time. To test this, we retrieved census-tract level data on daily personal trips from NHTS. The latest two NHTS datasets provide travel information in 2001 and 2009-2011, respectively. These datasets show that while the number of family members and private-owned vehicles per household had increased from 2000 to 2011, the average trip distance had dropped significantly from 81.8 miles in 2000 to 63.3 miles in 2011. We match this census-tract-level trip data to the main dataset to study daily trip frequencies and distances before and after 511 Systems adoption. Table C-4 shows that in the census tracts in MSAs with 511 Systems, the average number of daily vehicle trips and vehicle mileages are lower by 1.6% and 4.9%, respectively, than that in untreated census tracts. This implies that information provided by ITS help individual drivers to reduce unnecessary personal and household travels, corroborating our theoretical proposition on the informative role of ITS.

Travel Time Uncertainty

Traffic congestion is often accompanied by travel time uncertainty (Becker 1965). The transportation economics literature points out that the absence of sufficient information increases travel time uncertainty, expected cost of commuting, and variability of queueing patterns, all of which cause traffic congestion (Small and Verhoef 2007). Hence, uncertainty around travel time can be reduced when the drivers are better informed about the traffic conditions (Noland 1997). We examine whether information provided by ITS reduces travel time uncertainty. Arguably, a major source of travel time uncertainty is extra travel time due to congestion. Thus, we measure this uncertainty using a deviation of the proportion (Z_{it}) of excess time to free-flow travel time. We use

Travel Time Index (*TTI*) and Commuter Stress Index (*CSI*) in the AUMS dataset to construct the uncertainty measure. TTI is calculated by the total travel time divided by free-flow travel time. TTI includes travel in all directions in the peak periods, while CSI only includes travels in peak directions. Based on TTI and CSI, we construct the travel time uncertainty measure ($\mathrm{U_{it}}$) as follows:

$$U_{it} = \frac{\left|Z_{it}-\frac{1}{t_0}\sum_1^{t_0} Z_{it}\right|}{\sigma_{Z_{it_0}}}$$

$$t_0 = \begin{cases} T_0 - 1994, & if\ 1994 \leq t < T_0 \\ 2014 - T_0, & if\ T_0 < t \leq 2014 \end{cases}$$

$$Z_{it} = TTI_{it}\ (or\ CSI_{it}) - 1 \qquad [3]$$

Where *i* and *t* indicate MSA and year, respectively, T_0 is the 511 Systems adoption year for an MSA, and t_0 is the number of years since 511 Systems have been adopted or during which they have not been adopted. $\sigma_{Z_{it_0}}$ is the standard deviation of Z_i in the period of t_0. We use U_i as the dependent variable derived from TTI and CSI and replicate the baseline regressions. Table C-5 reports the results that the average travel time became less uncertain after 511 Systems adopted, thus supporting our proposition.

Navigation Route Choices

Finally, we consider changes in navigation route choices as an important demand-side mechanism of ITS. As route choice is a travel decision that can be improved by better information (e.g., Ben-Akiva et al. 1991), we examine how ITS affect route choices by evaluating traffic allocation within existing road networks. Utilizing HPMS data, we assess three classes of roads – Highway, Major Road, and Local Road.[xx] Empirically we used traffic shares in each of these road types as dependent variables to examine how the 511 Systems alter traffic allocation among these roads. Table C-6 reports the results. We find that the adoption of 511 Systems is significantly associated with a decrease in the traffic share of Major Road. Major Road is the most congested road type, and the reduction in traffic volume on Major Roads after 511 Systems adoption explains the congestion-mitigating effect of ITS. Moreover, 511 Systems are not significantly associated with traffic shares in Highway and Local Road, possibly because these roads accommodate more traffic diverted from Major Road. These findings suggest that ITS inform drivers to optimize route choices, allocating traffic and reducing congestion more efficiently (Ben-Akiva et al. 1991).

In sum, we find that commuters benefit from the information from ITS to better schedule their trips, reduce unnecessary daily travels, mitigate travel time uncertainty, and optimize navigation routes. These illustrate that ITS improve the demand-side collective welfare. Not only do ITS allow a commuter to choose alternative transportation mode or driving times that increases her utility, but also getting her off from congested roads saves other drivers' driving time, improving the overall social welfare.

[xx] *Highway* is a measure by grouping "interstate highway" and "expressway/freeway", while *Major Road* is by aggregating "principal/minor arterial" and "major/minor collector".

2.7.2 Traffic Supply Mechanism

To test how ITS enhances traffic supply management, we study how the impact of ITS is affected by conventional interventions – road supply adjustment, and public transit services (Arnott and Small 1994).

ITS and Road Supply

First, we assess the interaction of ITS and road supply on traffic congestion. While the "Fundamental Law of Road Congestion" (Duranton and Turner 2011) suggests that solely increasing road supply does not reduce traffic, we argue that ITS help local governments to enhance the traffic management capability and to adjust the road supply towards better allocating traffic and reducing congestion. Table C-7 reports the results from the interaction effect of ITS and road supply. First, we find that road expansion exacerbates traffic congestion, consistent with extant transportation economics studies (e.g., Goodwin 1996, Duranton and Turner 2011). More importantly, the induced traffic by road expansion is attenuated by ITS. This beneficial effect of ITS is consistent with the anecdotal evidence that New York City reduced traffic congestion in 2009 by utilizing the Taxi GPS data to identify congested roads, block them, and distribute traffic effectively. This finding suggests that the impact of ITS on traffic congestion depends on the existing physical transportation infrastructures, and while expanding roads can make traffic congestion worse, the adoption of ITS could ameliorate such an adverse effect.

ITS and Public Transit Services

To further explore the joint effects of ITS and other traffic interventions, we examine the interaction of ITS and public transit services and its joint impact on traffic congestion. Public transit has attracted strong public support recently, especially in dense metropolitan areas (e.g., Los Angeles, New York City, Seattle), because of its capability to absorb flocks of commuters in peak hours (Anderson 2014). We incorporate public transit into our empirical assessment, focusing on two distinct service types – bus and rail. The former competes with private cars and trucks for limited road space, while the latter eases the burden of road transportation. Following extant transportation economics literature (e.g., Duranton and Turner 2011), public transit service is measured by the number of Vehicles Operated for Maximum Services (VOMS) for both bus and rail using the National Transit Data (NTD). Using these measures, we tested the effect of public transit and its joint effects with ITS on traffic congestion in urban areas.

Table C-8 reports the results. Interestingly, ITS decrease traffic congestion to a greater degree in MSAs with larger rail networks, but it is not the case with bus services. These findings illustrate that congestion is more relieved to a greater extent when ITS lead commuters to utilize rail transits more rather than buses in already traffic-heavy conditions. This is consistent with our finding that ITS could guide commuters to optimize their transportation mode (Table C-3). More importantly, these findings also suggest that ITS help local governments to improve public transit, especially rail transport, to accommodate more traffic and reduce congestion.[xxi] The above evidence

[xxi] For instance, similar to 511 Systems, ITS programs under the CIVITAS initiative are adopted by over 80 European cities for sustainable traffic mobility. By monitoring, collecting, and analyzing real-time traffic information, innovative ITS projects provide solutions for public transport enhancement, including fleet management, to optimize routing and schedule for buses and trams.

implies that local transportation agencies leverage ITS to coordinate traffic management with public transit services to ease congestion.

2.8 Empirical Extensions with Measures for ITS Use

While thus far we have provided a range of evidence on the impact of ITS on traffic congestion and its underlying mechanisms, the main analyses do not look into how *the use of ITS* by commuters and governments affects traffic congestion. It is also important to understand the impact of not only ITS adoption but also the extent of ITS use on traffic congestion, which would offer more practical implications for ITS stakeholders, such as which functionalities of ITS to implement. While empirical data on IT use is limited, we extend our empirical investigation with a few measures for ITS use.

First, we assess the effect of IT use on traffic congestion with the number of 511 calls and website visits. It is empirically challenging because only a few states report relevant statistics for a limited time in our study timeframe. We found data that contains 511 calls and website visits from Florida, Iowa, Kentucky, and Utah in 2010-2014. Thus, we classified 11 MSAs in these states (listed under Table D-1) into a treated group and MSAs that have never adopted 511 Systems into a control group and then replicate the DID estimation. The results are shown in Table D-1 in Appendix D. We find that the number of 511 website visits is associated with a significant decrease in traffic congestion, while the effect of 511 calls is not.

Second, we study the effect of the ITS functionalities that each state incorporates into their 511 Systems. While 511 Deployment Coalition requires consistency in 511

Systems adoption, a few variations in implemented functionalities exist across the states. We retrieve the functionality data from a report, titled "*Implementation and Operational Guidelines for 511 Services*", published by 511 Deployment Coalition. The functionalities include which information (e.g., about road condition, congestion status, incidents) each state 511 Systems made available to the public and through which channels (i.e., roadside variable message signs and 511 websites with interactive traffic maps). We interact these functionalities with ITS to examine the incremental effect of adding these functionalities to 511 Systems on traffic congestion. The results are shown in Table D-2. 511 Systems have greater impacts when road condition, congestion, and travel time information are provided. Moreover, the marginal value of incorporating a 511 website is larger than roadside variable message. The findings not only support that traffic information provision is critical to ease traffic congestion but also stress relative effectiveness of information provision ahead of travels.

Third, we explore another proxy for ITS use by examining the federal funding of 511 Systems across locations and years.[xxii] Following extant organization-level studies (e.g., Brynjolfsson and Hitt 2003), we used the amount of monetary investments in 511 Systems with federal aids to measure the degree and sophistication of ITS implementation, given that more funding is likely to allow states to develop more

[xxii] While the funding process for ITS could be affected by previous congestion levels, we argue that our previous analyses mitigate such a possibility: (i) We find that past congestion levels do not determine the adoption timing (thus grant effective date) of 511 Systems (see Table B-2); (ii) In all specifications, we account for location-related idiosyncrasies using time-varying variables and location and time fixed effects; (iii) With the instrumental variables (IVs) that are not correlated to contemporary confounders such as the funding process, we still see the consistent estimates of 511 Systems (see Table B-3).

advanced ITS (e.g., Pang et al. 2016). We retrieved funding data for 511 Systems from the Federal Aid Archive and matched it to our main dataset. We replicated the DID estimation using 511 funding as the independent variable. Table D-3 shows that 511 Systems adopted with larger federal subsidies have a greater impact on traffic congestion.

Lastly, the impact of ITS use may depend on the contexts where ITS are implemented. Particularly, we explore how the effects of 511 Systems vary by population size and congestion severity. We expect that ITS is more heavily used in MSAs with larger population or more chronic congestion. For population size, we create four dummy variables - very large MSAs (more than 3 million), large MSAs (1 million to 3 million), medium MSAs (500,000 to 1 million), and small MSAs (less than 500,000) - following the classification by the AUMS dataset. We then interact these variables with the ITS variable and replicate our estimation. Table D-4 shows that the impact of 511 Systems in traffic congestion is more pronounced in the large and the very large MSAs than in the small ones. Next, we assess the effects of 511 Systems at different congestion severity quantiles across MSAs. This helps understand how the effectiveness of ITS varies depending on congestion conditions. From Table D-5, we find that the congestion-heavier MSAs benefit more from 511 Systems adoption than congestion-lighter ones in saving more travel time and costs.

2.9 Discussion

2.9.1 Key Findings

In this study, we investigate the role of ITS in alleviating traffic congestion and quantify this effect by focusing on 511 Systems, a large federally-supported ITS program in U.S. urban areas. While policymakers hope that ITS can be a viable solution to traffic relief, our understanding of whether and how ITS can mitigate traffic congestion is limited. To fill this significant gap in research and practice, we compile a unique panel dataset of 99 urban areas over 21 years to empirically assess the effectiveness of ITS in mitigating traffic congestion. To our knowledge, this study is the first effort to theorize and quantify the roles of ITS in mitigating traffic congestion. We find that the adoption of 511 Systems is associated with a decrease in traffic congestion, an effect that amounts to an annual saving of $4.72 billion in congestion costs, 175 million hours of travel time, 53 million gallons of fossil fuel energy, and 10 billion pounds of CO_2 emissions. We also show ITS to help commuters to schedule travel more efficiently, choose better navigation routes, and optimize transportation mode. We also find that the functionalities and the usage level of 511 Systems are significantly associated with lower traffic congestion. Our finding is consistent with the theoretical explanations that ITS inform commuters and local governments and help the latter to develop urban traffic management capabilities to effectively mitigate congestion.

2.9.2 Theoretical Contributions

This study makes several key contributions to the information systems and the transportation economics literatures. First, we contribute to the research in societal impacts of IT by theorizing the IT-enabled traffic management capability in mitigating traffic congestion, a notorious societal problem in most developed and developing nations. Specifically, we quantify the significant economic and societal impact of ITS.

The extant work on societal impact of IT has paid limited attention to transportation. Although a few recent studies started to identify societal impact of the sharing economy (e.g., Greenwood and Wattal 2017, Ge et al. 2016), these studies have not discussed IT-enabled capabilities for local governments. Our study closes this gap by theorizing how IT helps local governments to develop effective traffic management.

Second, we contribute to the IT capability literature by offering new insight into how ITS enable governments to develop traffic management capabilities. The IS literature discusses IT capabilities mostly in the private sector (e.g., Pavlou and El Sawy 2006, Rai et al. 2012), whereas we draw upon and extend this literature to the public sector (Pang et al. 2014a). We argue that local governments can utilize information provided by ITS to cultivate a traffic management capability. To support the mechanisms, we show suggestive evidence that congestion-mitigating roles of ITS materialize in both the demand and the supply side of traffic management. Moreover, we contribute to the Green IT literature (Malhotra et al. 2013) by responding to the call to research in IT and environmental sustainability (Melville 2010). We show that ITS save fossil fuel and reduce CO_2 emissions by easing traffic congestion.

Third, we contribute to the transportation economics (e.g., Arnott et al. 2005, Wachs 2002, Small and Verhoef 2007) by providing empirical evidence that IT-enabled traffic interventions are effective in mitigating traffic congestion (Goodwin 1996, Cervero 2002). Moreover, by examining the effect of ITS on traffic volume at the census-tract level, we show that ITS can even decrease the number of daily trips and travel distance (Table C-4). Our finding that ITS help drivers to make informed decisions in routes, timings, and transportation modes complements extant transportation economics studies on information provision and traffic congestion (Arnott et al. 1991, Emmerink et al. 1996). These studies have used analytical modeling and simulation and set up a theoretical tension as to whether the information provided by driver navigation systems is welfare-inducing or welfare-reducing (Noland 1997). We show evidence to reconcile this tension by demonstrating the welfare-inducing role of ITS in mitigating congestion.

2.9.3 Practical Implications

This study provides policy implications for (1) transportation policymakers and urban planners, and (2) individual commuters and drivers. First, for transportation policymakers, we show that ITS could be a more cost-effective means to address traffic problems than costly infrastructure construction. Our estimation shows $4.72 billion annual cost savings for U.S. urban areas thanks to 511 Systems adoption, while the total investments in 511 Systems over 10 years are only about $135 million. More importantly, our study suggests that urban planners pay attention to the potential of IT (Wachs 2002, Glaeser 2011) to manage traffic. Within government agencies, IT has been shown to improve administrative efficiency (Pang et al. 2014b). However, its potential to create social welfare by tackling chronic societal issues needs to be more recognized by city planners and policymakers. We hope our study is a modest step toward this direction.

Second, this study has practical implications for individual drivers and commuters. When drivers anticipate traffic congestion, they had better to access to information provided by ITS to schedule their travel plan more wisely, adjust their departure times, and reduce travel time uncertainty on the road. Moreover, by checking traffic information from ITS, commuters could consider alternative transportation modes (e.g., rail-based public transit) and optimize their navigation routes to avoid traffic congestion during work-trip commuting at rush hours (Arnott and Small 1994).

2.9.4 Limitations

This study has a few limitations. First, we do not have complete congestion data for all MSAs due to data availability. The AUMS dataset only provides congestion information for 101 metropolitan areas. Albeit this, we find that individual travel and aggregate traffic patterns do not differ much between in-sample and out-of-sample MSAs after conditional on observed heterogeneities (Section 6.3). Even so, we still encourage further efforts in collecting more congestion data from more urban areas in the U.S. and other countries to improve the estimates of our study and generalize our findings.

Second, while we seek to rule out as many confounds and alternative plausible explanations as possible, our identification strategy does not rely on an ideal randomized controlled experiment. Thus, there might still be unaccounted factors that could bias our estimates. For example, although state governments implement standardized 511 Systems, how local governments use these systems may vary. Likewise, for drivers, the actual usage of 511 Systems may differ across MSAs. While we provide suggestive evidence on the use of ITS by examining the effect of 511 Systems functionalities, number of 511 calls and website visits (Section 8), we are conservative about the findings and encourage follow-up research along this line.

Finally, while our main analysis, supported by a series of robustness checks, seeks to carefully uncover the effect of ITS on traffic congestion, some of the underlying mechanisms have not been fully tested. These include development of traffic management capabilities and relative effectiveness of trip planning (ahead of travels) versus trip coordination (during travels). We cannot fully cover these directions due to empirical challenges in obtaining available, reliable, and comprehensive administrative data and measuring IT-leveraging traffic management capabilities at the city level. We encourage future work to advance our theoretical explanations with additional and rich empirical evidence.

2.10 Concluding Remarks

This work represents one of the first empirical attempts to assess and quantify the impact of IT-enabled interventions on traffic congestion by examining the deployment of 511 Systems, the largest federally-supported ITS program in the U.S. To the best of our knowledge, traffic congestion and its economic and environmental impacts are major societal problems that have seldom been investigated in the IS literature. Our study highlights the importance of IT in a broader economic and societal setting and identifies a new and promising avenue for IS research on how IT can improve the quality of life and create public value by tackling chronic urban problems. Future research can examine how ITS enhance traffic mobility and safety, how to facilitate the development of traffic management capabilities for local governments, and how to design effective transportation technologies. We hope our study sparks a new intellectual discourse around IT and transportation in the IS discipline.

CHAPTER 3

AUTOMATED ENFORCEMENT ON THE ROAD:
SURVEILLANCE TECHNOLOGY AND TRAFFIC SAFETY

ABSTRACT

Traffic safety has been a major society and public policy problem. Among various safety laws, regulations, and investments, automated enforcement in the form of surveillance technology (e.g., speeding checkers, red light cameras) is advocated to be a cost-effective approach to mitigating traffic accidents. However, there has been limited understanding of the impact of surveillance technology on traffic safety, its underlying mechanisms, and overall economic significance. To investigate these questions, we use police accident reports of a metropolitan in southern China and exploit the temporal and geographical variations in the installation of ~2,000 traffic surveillance cameras in 2014-2016. Our difference-in-differences estimates show a disproportionate decrease in vehicular damages and occupant injuries at the road segments installed with surveillance cameras. Second, we explore the underlying mechanisms of the observed effect and develop a stylized model for drivers' safety efforts under surveillance. The theoretical prediction on the effect of surveillance technology can be decomposed into two parts: a positive impact on safe driving efforts that deters careless or reckless behaviors (a "Stick" role reflecting the Deterrent Hypothesis in the criminology literature) and a negative impact that facilitates a safer traffic environment and compensates accident risks (a "Carrot" role reflecting the Risk Compensation Hypothesis in the economics literature). The direction of surveillance effect depends on the relative magnitude of these two

countervailing impacts. Suggestive evidence supports the deterrent effect but not the risk compensation effect, implying that “Stick” prevails “Carrot”. Finally, we estimate incremental economic savings of vehicular damages and human cost savings of occupant injuries to be ~¥ 41 Million ($ 6.5 Million) thanks to surveillance camera installation in the study city over a period of 3 years.

3.1 Introduction

According to *Global Status Report on Road Safety 2017* from the World Health Organization (WHO), nearly 1.3 million people die in road crashes each year around the world, and 20-50 million are injured or disabled. Strikingly, road crashes are the leading cause of death among young adults in 15-29 and the second leading cause of death among those in 5-14. Regarding the scale of economic loss, road crashes cost most countries 3% of their gross domestic product (WHO 2017). Enhancing traffic safety has thus been a timely and significant endeavor for policymakers.

Since the inception of Haddon Matrix (1970), the most commonly used framework for prevention of vehicular crashes that identifies preventable attributes on the human, vehicular, and environmental levels, various traffic safety interventions have emerged including, engineering innovations (e.g., safety belts, airbags), product design regulations (e.g., child restraint laws), and behavior mandates (e.g., speed limits, graduated driving licensing) (Ashenfelter and Greenstone 2004, Burris and Anderson 2013). However, the evaluations of their effectiveness have produced mixed results. For example, Peltzman (1975) proposed a controversial but profound risk compensation hypothesis that safety regulations compensate drivers' risks and reduce their own safety efforts. An illustrating case is that drivers in vehicles with better safety design (e.g., airbags) may perceive lower accident risks, drive more carelessly, and become more prone to crash. Such crashes may not cause death to the drivers but transfer the fatal risks to those who are not protected by safety designs, such as pedestrians or cyclists. Moreover, simply enforcing traffic safety regulations has challenges (Boyer and Dionne 1987), due to negative externality of unsafe driving on other drivers (Edlin and Karaca-Mandic 2006), the difficulty of monitoring traffic violations that lead to information asymmetry and moral hazard problems (Laffront 1976), and other issues.

In this study, we focus on automated enforcement in the form of surveillance technology (e.g., speed checkers, red light cameras; See Figure 3.1) and examine its impact on traffic safety. Surveillance technology differs from conventional safety interventions for several reasons. First, by monitoring and detecting reckless drivers and dangerous violations, surveillance technology resembles the presence of human police on the roads. However, it is advocated to be more cost-effective than police manpower because it is more durable and ubiquitous and can operate 24/7. To wit, surveillance technology improves drivers' compliance with the safety regulation (e.g., by moderating speeds). Second, surveillance technology operates in a real-time manner, making unsafe driving costly. For instances, speed checkers for highways or red light cameras at intersections are able to quickly detect violations and precisely capture license plate numbers even the car is at high speed (Retting et al. 2003). Last but not least, surveillance technology automates evidence gathering, reduces the uncertainty in violation recognition, and deters potential traffic violators. This can hardly be achieved by police manpower that subjects to human errors (Pang and Pavlou 2018).

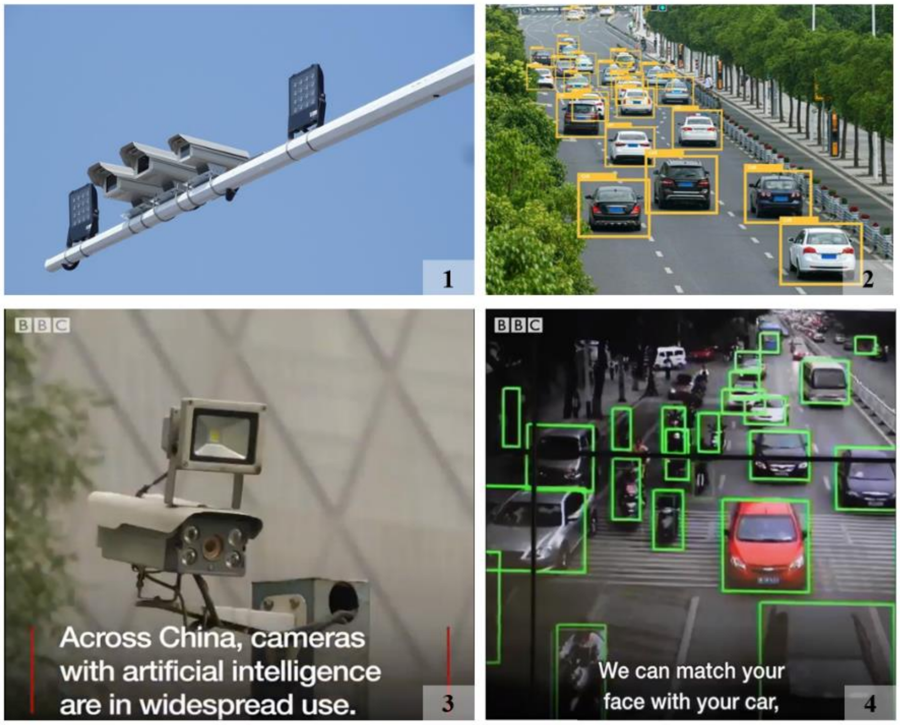

Figure 3.1
Surveillance Technology on the Road

Notes: As automated enforcement, traffic surveillance cameras can be triggered automatically if they identify a violation (e.g., running the red light, speeding), capture the image or video of violation behavior, store or send to a central server for prediction in a real-time manner and even without any human participation (Zhang et al. 2011). For instance, the AI algorithms embedded in surveillance cameras (or the automated license plate readers) can predict the license plate number within 0.1 seconds after the cameras detect a speeding car. Moreover, these algorithms can reach a high prediction accuracy of over 98% rate at daytime and above 95% rate at night (Du et al. 2013). In recent years, such AI-based surveillance cameras have been rapidly and widely installed on the roads in most Chinese cities for better traffic management. The sources for the above pictures are as follow.
1 and 2: https://baike.baidu.com/item/%E7%94%B5%E5%AD%90%E8%AD%A6%E5%AF%9F/8879897
3 and 4: https://twitter.com/bbcworld/status/939832896604565505?lang=en

While the role of surveillance technology in deterring crimes has been discussed in the criminology literature (Welsh and Farrington 2009, Priks 2015), there is little understanding of its role in the context of traffic safety. The context differs such that traffic violators, unlike potential criminals, face not only the risk of being captured and punished by traffic safety regulations but also the risk of road crashes. To close these research gaps, we aim to investigate the impact of surveillance technology on traffic safety and the underlying mechanisms of this effect.

We develop a stylized utility-maximizing model for drivers' safety efforts under surveillance. We posit that the optimal level of safety effort is at which the marginal value of safe driving just equals the marginal cost of additional safe-driving efforts. The former can materialize through a reduction in the probability of an accident, the size of the accident loss, the probability of apprehension due to a traffic violation, and the severity of the punishment. More importantly, our model predicts that the surveillance effect can be decomposed into two parts: a *positive* impact that *induces* safe driving efforts by deterring unsafe behaviors and a *negative* one that *reduces* drivers' own safety efforts by facilitating a safe traffic environment and compensating accident risks. The former reflects the *deterrent hypothesis* in the criminology literature (Becker 1968, Chalfin and McCrary 2017), while the latter reflects the *risk compensation hypothesis* in the economics literature (Peltzman 1975, Wilde et al. 2002). The overall surveillance effect depends on the relative magnitudes of these countervailing impacts. The competing hypotheses stress the dual influences of traffic surveillance on drivers' safety efforts.

To execute the empirical investigation, we exploit a unique dataset using police accident reports from the local police department of a large metropolitan in southern China. This dataset contains detailed information about every accident in this city from 2014 to 2016, including vehicular damage, occupant injury and fatality, and the accident site and timing, among others. We also collect information on more than 2,000 traffic surveillance cameras that had been gradually installed at different roads of this city during the same period. We match the camera installation to the accident data based on location and timing and aggregate the matched dataset into a balanced longitudinal panel with more than 800,000 observations at the road segment-week level. For an identification strategy, we exploit the camera installation pattern, which is staggered temporally and geographically, and execute a difference-in-differences approach. First, we compare the changes in the number of accidents, injuries, and fatalities, and economic cost of vehicular damage before and after the installation of surveillance cameras at treated road segments, compared to the changes at untreated segments over the same period. In addition, we conduct a series of robustness tests, including an event study to test the parallel trend assumption, different untreated segments as control groups to check if the baseline estimates are sensitive to sample selection, and negative binomial regressions for modeling count variables of accident outcomes.

Econometric analyses yield several notable findings. First, the presence of surveillance cameras is associated with a decrease in the number of persons injured by 0.53%, and the economic costs of vehicular damages by 6.42%. Moreover, by estimating the dynamics of the surveillance effects over time, we find that the occupant injuries and vehicular damage at road segments after camera installation have experienced a decrease until 5 months and remained at the same level afterward, suggesting a persistent effect of surveillance technology on traffic safety.

Further, we empirically examine the underlying mechanisms of the observed effect. To test the deterrent hypothesis, we estimate the effect of surveillance cameras installed at treated road segments on the accident outcomes at untreated neighbouring segments, following criminology studies (Draca et al. 2011). The intuition is that dangerous driving at focal road segments may be displaced to untreated neighbouring segments where drivers are not under deterrence, taking more risks and causing more accidents. This approach, together with the baseline estimates, corroborates that deterrent effect only picks up if surveillance is present. To test the risk compensation hypothesis, drawing upon the seminal work of Peltzman (1975), we test the pairwise differences between surveillance effects on the number of vehicle-to-vehicle, vehicle-to-pedestrian, and single-vehicle accidents. We expect that while surveillance technology decreases traffic violations (which mostly result in vehicle-to-vehicle accidents), it does not regulate non-violation accidents due to negligence (e.g., ones caused by unexpected obstacles or pedestrian behaviors on the road). Risk compensation would be observed if drivers are more likely to involve in vehicle-to-pedestrian or single-vehicle accidents because a safe traffic environment facilitated by surveillance technology encourages careless driving and non-violation accidents. Our suggestive evidence for the underlying mechanisms supports deterrent hypothesis but not for risk compensating.

Our study has several significant contributions. First, the deterrent role of surveillance technology is consistent with the economics literature on monitoring technology and moral hazards (Hubbard 2000, Pierce et al. 2015, Liang et al. 2018). We examine monitoring technology in a broader public sphere rather than that in a principal-agent relationship within organizations. Second and relatedly, the impact of surveillance technology on traffic safety adds to the studies on the societal impact of IT (Chan and Ghose 2014, Greenwood and Wattal 2017). Third, the evidence on the positive role of surveillance technology complements the recent public and scholarly debate on the dark side of surveillance (Marthews and Tucker 2017, Zuboff 2015). Finally, our model of drivers' safety efforts predicts that surveillance technology may exert both the deterrent effect and the risk compensation effect. This integrates economics of traffic safety (Peltzman 1975, Makowsky and Stratmann 2009) and criminology literature (Becker 1968, Chalfin and McCrary 2017) and suggests that "Stick" prevails "Carrot" as an effective intervention for traffic safety.

The research also offers significant implications for policymakers. Securing traffic safety is a primary responsibility of governments (Hansen 1997). We seek to influence transportation policy by theoretically justifying and empirically demonstrating that surveillance technology can be a cost-effective means to ensure traffic safety. In addition, our evidence shows the limitation of deterrent effect that drivers may take more risks when the surveillance switches off. Most importantly, savings in economic costs and human lives thanks to surveillance technology, though as conservative estimates, are compelling. Specifically, we estimate the savings of vehicular damages and occupant injuries to be ~ ¥ 41 Million ($ 6.5 Million) thanks to camera installation.

3.2 Related Literature

Our study builds on and contributes to several streams of research. First, our study adds to the economics literature on traffic accident and traffic safety interventions. In general, economists hold a view that traffic accidents are involved with not only personal costs related to vehicular damages, injuries, and fatalities, but also social costs as an individual driver's safety depends on other drivers' safe driving behaviors on the same road (Valavanis 1958, Vickrey 1963, Boyer and Dionne 1987, Dickerson et al. 1998, Edlin and Karca-Mandic 2006, Romem and Shurtz 2016). Traffic safety interventions are often designed either to decrease the personal and social costs during or after an accident (e.g., seatbelt, airbag), or to increase the actual or perceived costs of unsafe driving behaviors and those costs of an accident before it occurs (e.g., speeding tickets). The former serves as a "Carrot" to protect drivers and to compensate their driving risks, while the latter serves as a "Stick" to deter careless and reckless drivers and encourage their safe driving efforts. The economics literature has discussed a lot on "Carrot"- and "Stick"-like traffic safety interventions, including helmet, airbag, and seatbelt laws (Sass and Leigh 1991, Levitt and Porter 2001), restrictions on mobile use while driving (Redelmeier and Tibshirani 1997, Abouk and Adams 2013, Faccio and McConnell 2018), mandated speed limit (Ashenfelter and Greenstone 2004), alcohol advertising (Saffer 1997), incentive mechanisms such as violation fines (Goncalves and Mello 2017), experience rating (Dionne et al. 2011), and point-record licenses (Bourgeon and Picard 2007), as well as uniform mileage taxes and gasoline taxes (Parry 2004), and insurance premiums (Boyer and Dionne 1987).

However, anecdotal and empirical evidence on the effectiveness of these interventions on traffic safety has been mixed (Wilde et al. 2002, Cawley and Ruhm 2011). For example, Sam Peltzman (1975) questioned “Carrot”-like safety regulations and argued that they do not necessarily ensure driving safety but, on the contrary, may lift accident risks. This is the essence of the risk compensation theory that drivers will adjust their driving behaviors towards more risk-taking if they perceive a lower accident risk induced by a safety regulation (thus a safe driving environment). He provided evidence for the risk compensation hypothesis that while the regulation of safety device design in automobiles (e.g., penetration-resistant windshield) did not decrease the total highway deaths, savings of drivers’ lives have been at the expense of more pedestrian deaths and nonfatal accidents. The “Stick”-like safety regulation has also been criticized. For example, Boyer and Dionne (1987) discussed the challenges in enforcing such regulations because the existence of (1) negative externality of accidents, and (2) information asymmetry to monitor or detect unsafe drivers. The former problem lies on the common situation that unsafe driving is underpriced and therefore a driver will drive carelessly or recklessly, which increases the accident risks of other drivers on the same road (Romem and Shurtz 2016). The latter problem lies on the difficulty of observing and regulating drivers’ self-protection activities and their risks, which causes moral hazard (e.g., texting while driving) and thus low enforcement of safety regulations (Laffront 1976, Hoy 1982, 1984). To wit, these studies suggest that the key to ideal safety regulations is to avoid risk compensation and ensure enforcement and compliance.

Surveillance technology differs from the conventional safety interventions in several ways. First, as automated enforcement (NHTSA), surveillance technology can monitor and regulate unsafe driving behaviors and non-compliance to traffic safety regulations in a cost-effective manner. It is easier and cheaper to deploy surveillance cameras than to deploy police manpower. Second, as an evidence-gathering technology, surveillance cameras can detect unsafe driving behavior and traffic violations in a more accurate way, compared to the presence of police manpower that often subjects to human error (Pang and Pavlou 2018). Image an extreme case that surveillance cameras are equipped on every road of a city. In this scenario, drivers will be less likely opportunistic and correspondingly take more safe driving efforts. The negative externality of careless driving and moral hazard due to imperfect information can be mitigated by the ubiquitous presence of surveillance technology. Last, surveillance technology could play both "Stick" and "Carrot" roles in that it deters "dangerous" drivers from infringing the safety laws, and it also allows "honest" drivers to enjoy a safe driving and traffic environment.

Second, our study is related to the criminology and economics literatures on the effect of monitoring. This line of work focuses on the deterrent effect of monitoring (Polinsky and Shavell 1979, 1999, Ehrlich 1996, Draca et al. 2011, Nagin 2013). A fundamental economic theory behind this effect draws on a simple expected utility model introduced by Gary Becker (1968) on crime and punishment. The model envisions crime as a gamble undertaken by a rational individual, and it predicts that the aggregate supply of crime depends on the social investments in police and criminal justice systems (about the resource allocation to monitoring (thus change the probability that an individual is apprehended) and to the severity of punishment), as well as on labor-market opportunities (about the relative opportunity cost of time spent in illegal activities) (Chalfin and McCrary 2017). While Becker (1968) indicated the model should not be restricted to the analysis of criminal behaviors but intended to generalize to all types of violations (e.g., traffic violations, pp. 170), most empirical studies that build on this theoretical model are highly related to crime in the public sphere (Lochner 2007, Draca 2011) or employees' misconduct in the organizational environment (Olken 2007, Pierce et al. 2015).

Drawing upon Becker (1968)'s model, our study is related to a small and growing literature on deterrent effect in the context of traffic safety. For example, Hansen (2015) finds a positive and persistent effect of harsher punishments on driving under the influence (DUI). Goncalves and Mello (2017) estimates speeding punishments on the future driving behavior of cited drivers, and they found receiving a harsher fine reduces a driver's likelihood of receiving speeding tickets and that of accident rates in the following year, while receiving a lenient fine induces those risks. While these studies focused on the severity of punishment for traffic violations, to our knowledge, there has been no study examining the effect of monitoring (that changes the probability of apprehension) in the similar context. To close this gap, our study investigates the monitoring role of surveillance cameras on drivers' safety efforts and their accident risks.

Third and relatedly, our study also contributes to the information systems and operation management literatures on the monitoring technology. Most of the studies draw upon the labor economics on the impact of monitoring in a principal-agent relationship (Dickens et al 1989, Frey 1993, Nagin et al. 2002), and focus on how technologies that reduce monitoring costs can incentivize individual performance and improve productivity in a variety of contexts (reflecting the *automate* and *informate* roles of technology by Zuboff (1985)). For example, Hubbard (2000) examined onboard computers in the context of trucking and found this monitoring application not only raises individual drivers' productivity, and also increases the returns to managers by coordinating drivers' work. Miller and Tucker (2011) studied healthcare information technology, and they found that an increase in the number of hospitals that adopted Electronic Medical Records (EMRs) is associated with a significant decrease in neonatal mortality rate. They argue the reduction is mainly driven by the patient monitoring capability of EMRs. Pierce et al. (2015) focused on the restaurant industry and found that the firms' investments in monitoring technology (i.e., POS software services plus theft monitoring add-on) significantly reduce employees' misconduct and boost their productivity. Liang et al. (2018) looked at the online labor market and found positive evidence that the implementation of a monitoring system mitigates moral hazard in online platforms by providing direct information on worker's effort. Our study complements these studies and examines the impact of monitoring technology beyond the organizational barriers. In particular, we study the impact of surveillance technology on traffic safety, a critical inquiry that concerns our everyday life in a broader public sphere.

Our focus on monitoring technology is also related to the intellectual debate on the role of surveillance in political science, organization, and management science (Foucault 1977, Sewell and Barker 2006). Recent developments in digitization, which facilitate collection and repurposing personal data, heighten the concerns on digital surveillance (Lin 2014). Zuboff (2015) proposed the notion of “Surveillance Capitalism” (or “Big Other”) to illustrate the power of big technology companies and to provide implications (e.g., how to protect privacy) for “information civilization”. Marthews and Tucker (2017) discussed the detrimental effect of government surveillance on the profitability of internet firms across countries by examining a quasi-experiment setting of surveillance revelations in June 2013 by Edward Snowden and its influence on Internet search behaviors of personal and governmental-sensitive terms. In general, these studies discuss the dark side of surveillance and mostly focus on the digital surveillance. We argue the positive effect of surveillance technology cannot be underestimated. Our study, therefore, investigates it specifically in the context of traffic safety. Our consistent and conservative estimates on the economic and human cost savings associated with traffic surveillance camera installation may to some extent help dissolve public misunderstanding of mass surveillance systems deployed by the government.

Finally, our study contributes to the nascent literature on the socio-economic impact of Artificial Intelligence (AI). At a broader level, a number of studies have argued that AI reduces the costs of prediction, which facilitates decision making under uncertainty, automates tasks and processes to increase productivity, and helps to identify and gain competitive advantages (Agrawal et al. 2018, McAfee and Brynjolfsson 2017). Recent research on AI has discussed its impact in various contexts (Chalfin et al. 2016, Obermeyer and Emanuel 2016, Cowgill 2017, Kleinberg et al. 2017, Zhang et al. 2017). For example, Cowgill (2017) compared the advantages of human judgment and automated decision making in a context of resume screening. He provided experimental evidence that machine learning algorithms generate better performance than a human team on selecting workers for white-collar jobs. Kleinberg et al. (2017) looked at an AI application in bail decisions (i.e., make a jail-or-release decision based on a prediction of whether a defendant would commit a crime again if released) and they showed evidence that the judges' decisions assisted by machine learning algorithms can significantly reduce crime rate of a released defendant. Our study complements these studies by focusing on a particular AI application, traffic surveillance cameras, in a broader societal context. Recent anecdotal evidence shows surveillance cameras can be triggered automatically if they identify a traffic violation (e.g., running the red light, speeding), capture the violation image or video, store or send to a central server for prediction in a real-time manner without any human participation (Zhang et al. 2011). For example, the AI algorithms can predict the license plate number within 0.1 seconds after the surveillance camera (or the automated license plate reader) detects a speeding car. And these cameras can reach a high prediction accuracy of over 98% rate at daytime and above 95% rate at night (Du et al. 2013). To our knowledge, the study offers the first field evidence on the impact of AI-based surveillance cameras on traffic safety.

3.3 Empirical Setting

A major empirical challenge of this study is the identification of the causal impact of surveillance technology on traffic safety. An ideal experiment is to randomly assign surveillance cameras to distinct areas and compare the traffic accident rate in the areas installed with surveillance cameras with that in the areas without cameras. However, a local government may not have incentives to conduct such a costly and time-consuming randomized social experiment. It is more likely that the local police department selects areas for camera installation; however, doing so could cause biases to our analysis if the selection approach is unobservable and correlated with the traffic accident volume of the selected areas. We have to rely on some shocks into different areas that are as-if random and that could exogenously change the traffic accident in these areas.

To address these issues, we study the temporal and spatial patterns in traffic accidents across a metropolitan in Southern China over 3 years from 2014 to 2016. During the period, ~2,000 surveillance cameras had installed in this city. It is one of the largest and most developed cities in China with over 12 million population in 2016.

There are several features that make this city an appealing setting. First, we have access to the data of location and timing for each accident, as well as details of surveillance camera installation during the same period. Matching these two datasets allows us to compare traffic accident rates with and without surveillance cameras for a given location. Second, the number of accidents and cameras are aggregated to the level of week-and-road segment[1], a fine-grained unit of analysis to identify whether an accident occurs under effective surveillance. Third, the temporal and geographical variation in camera installation, together with the week and road segment fixed-effects, allows us to establish a causal relationship and rule out most confounding explanations. For example, it is possible that road segments already installed with cameras prior to 2014 are less likely selected for further installation. However, the history of past camera installation is time-invariant for a given road segment in our study period, and thus, can be accounted for by segment fixed-effects. Fourth, according to our interview with a police officer in charge of camera deployment, the selection of locations for camera installation is mainly based on the density of road network and population. This selection issue can be addressed by using segment fixed-effects given that the road network and population are quasi-fixed week by week. Fifth, the installation timings and locations are beyond drivers' anticipation and thus to some extent being exogenous with respect to drivers. In particular, the order of installation is affected by the application time for permits to use cameras, which vary substantially from a few weeks to half a year. Besides, drivers are aware of the presence of a camera only after its actual installation. Thus, it is unlikely that drivers take extra precautions in advance, a concern that perceived deterrence of surveillance in the future leads to the current decrease in traffic accidents (Lochner 2007). Sixth, by law, all surveillance cameras are clearly indicated by signs next to them. The *National Traffic Safety Regulation* in China requires that the signs be recognizable to all drivers. These features mitigate the concern that drivers do not notice cameras while driving. Last, the cameras look similar across roads in the city and required to operate 24/7 once installed, making it more straightforward to compare their effects by exploiting the temporal and geographical variation in camera installation.

3.4 Data and Methodology

3.4.1 Data

We collected data from two main sources. We obtained the accident-related information using the unique proprietary accident reports directly from the local police department of this city for the 2014-2016 period. We manually collected the date and location for each of more than 2,000 surveillance cameras from the announcements on the local government website. We matched the camera installation data to accident data based on location and timing and aggregated them into a balanced panel of 817,596 observations at the road segment-week level. Per extant studies using road-level panel data (Goncalves and Mello 2017, Faccio and McConnell 2018), we ensure that each road segment had at least one crash occurred within the 156-week sample period for a better comparison between road segments with surveillance cameras and those without. We use a week instead of a day as the time unit for two reasons. First, by narrowing the time interval of analysis, we reduce the possibility that a confounding event gives rise to the results. Second, we are able to tolerate some random measurement errors for the discrepancy between the actual installation date of a camera and its announcement date.

The dependent variables are the number of accidents, the number of persons injured, the number of fatalities, and the monetary loss of vehicular damage at the road segment-week level. These are standard traffic safety measures for accident rates, injuries, fatalities, and economic costs of accidents, respectively, all of which are widely used in the prior traffic safety research (Peltzman 1975, Cohen and Einav 2003, Abouk and Adams 2013, Faccio and McConnell 2018).

The main independent variable, Installationit, is a dichotomous variable that equals to 1 for all weeks during and after at least one surveillance camera is installed at the ith road segment and 0 otherwise. This variable essentially measures the presence of surveillance at the road segment i and the week t. Alternatively, we use Installation

Intensityit as an independent variable to capture the cumulative installations of multiple surveillance cameras. This intensity measure of automated surveillance resembles the measure of deployment changes in police manpower in the research in criminology (e.g., Draca et al. 2011) as well as in traffic safety (e.g., DeAngelo and Hansen 2014).

3.4.2 Summary Statistics

Figure 3.2 illustrates the distribution in installation timing of traffic surveillance cameras. The disproportionate installation pattern across locations and over time provides us more confidence in identifying the impact of surveillance technology by exploiting the temporal and geographical variation in the camera installation. Figure 3.3 shows the locations of over 2,000 surveillance cameras in the city. The cameras are located mostly in areas with high population density (e.g., the downtown or southwestern areas of the city), which is consistent with our interview accounts.

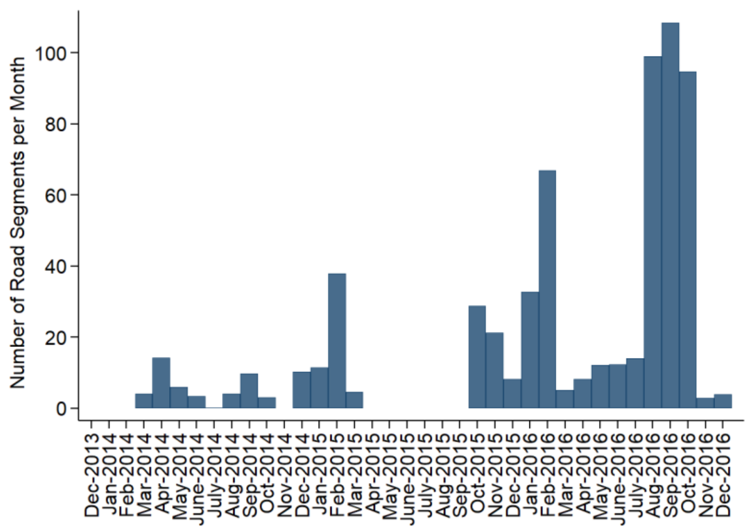

Figure 3.2
Number of Road Segments installed with Cameras per Month, Over Time

Notes: Figure 3.2 illustrates the distribution in installation timing of traffic surveillance cameras. The disproportionate installation pattern across locations and over time provides us more confidence in identifying the impact of surveillance technology on traffic accidents by exploiting the temporal and geographical variation in the camera installation.

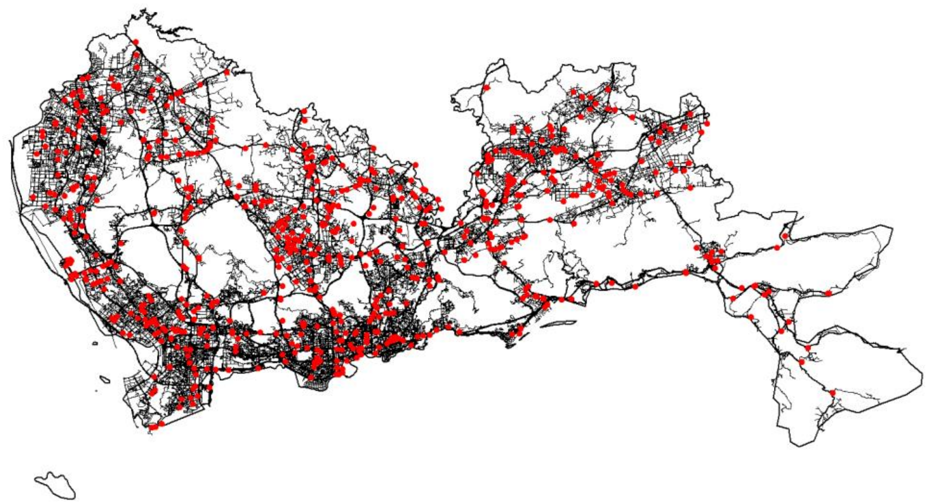

Figure 3.3.
Geographical Distribution of Surveillance Cameras

Notes: Figure 3.3 shows the geographic locations of ~2000 surveillance cameras in the study city. The cameras are concentrated in areas with high population and road density. For instance, downtown (the southwestern area of the city) has disproportionately installed with more cameras than elsewhere. This corresponds our interview with the police officer in charge of camera deployment that camera location selection is mainly based on the density of road network and population.

Table 3.1 reports the summary statistics for the main variables. Multiplying those mean values by the total number of observations, we find that 214,946 car accidents occurred for this city in the 2014-2016 period. Among them, 82,577 occupants were injured, and 1,553 died, taking up 38.4% and 0.7% of the total accidents, respectively. Moreover, the total economic loss due to vehicular damage amounts to ¥ 259,470,713 (or US $ 41,185,827).

Table 3.2 presents the comparison of summary statistics for main variables between treated and untreated road segments. From Columns 1 and 3, we find that, compared to the untreated segments, fewer accidents, fewer occupant injuries and fatalities, and lesser vehicle damages occurred at the treated road segments before camera installation. This finding suggests the importance of controlling for road segment fixed-effects in the regression analysis. When comparing these statistics before and after the installation for treated segments (Columns 3 and 4), we find they dropped in tandem. Multiplying them by the number of observations, we find a decrease in the total number of accidents by 69%, injuries by 63.8%, fatalities by 81.1%, and the total economic cost of vehicular damage by 76.9% at road segments after camera installation. To sum, descriptive evidence suggests that surveillance technology helps reduce traffic accidents.

Table 3.1.
Summary Statistics at Road Segment-Week Level (N=817,596)

	Mean	SD	Min	Max
	(1)	(2)	(3)	(4)
No. of Car Accidents (#)	0.2629	2.2788	0	205
No. of Persons Injured (#)	0.1010	0.6934	0	50
No. of Fatalities (#)	0.0019	0.0470	0	8
Damage to the Vehicles (¥)	317.3581	3,054.0356	0	645,000
Treated Road (0-1)	0.1252	0.3309	0	1
Camera Installation (0-1)	0.0363	0.1870	0	1
Installation Intensity (#)	0.0490	0.2986	0	8
Vehicle-To-Vehicle Accidents (#)	0.2166	1.9935	0	197
Vehicle-To-Pedestrian Accidents (#)	0.0206	0.1786	0	10
Single-Vehicle Accidents (#)	0.0244	0.3013	0	29

Table 3.2.
Summary Statistics for Treated and Control Segements

	Control Road Segments	Treated Road Segments		
		All Weeks	Pre-Installation Weeks	Post-Installation Weeks
	(1)	(2)	(3)	(4)
No. of Accidents (#)	0.2856	0.1042	0.1120	0.0851
No. of Persons Injured (#)	0.1070	0.0590	0.0610	0.0540
No. of Fatalities (#)	0.0020	0.0011	0.0013	0.0006
Damage to the Vehicles (¥)	335.8886	187.8423	214.8479	121.7239
Camera Installation (0-1)	0	0.2900	0	1
Installation Intensity (#)	0	0.3913	0	1.3494
Vehicle-To-Vehicle Accidents (#)	0.2356	0.0834	0.0903	0.0665
Vehicle-To-Pedestrian Accidents (#)	0.0219	0.0119	0.0123	0.0111
Single-Vehicle Accidents (#)	0.0267	0.0086	0.0091	0.0072
# of Observations	715,260	102,336	72,659	29,677
# of Road Segments	4,585	656	656	656

3.4.3 Identification Strategy

To identify the impact of surveillance cameras on traffic accidents, we utilize a difference-in-differences (DD) approach to capturing variation in traffic accident across locations and over time. The specification is of the following form:

$$y_{it} = \gamma_i + \lambda_t + \beta_1 Installation_{it} + \varepsilon_{it} \qquad \text{(Eq. 3)}$$

where y_{it} is one of the four dependent variables, i.e., number of accidents, number of persons injured, number of fatalities, and vehicular damage; γ_i represents the vector of road segment fixed-effects, and; λ_t represents the vector of week fixed-effects. The inclusion of road segment fixed-effects accounts for any time-invariant differences across road segments, and the week dummies control for contemporary shocks (e.g., newly enforced city-wide traffic safety regulations) that affect all drivers at all road segments. β_1 is the coefficient of interest. We expect β_1 to be negative if the presence of surveillance technology reduces accident outcomes. We cluster the error terms at both the road segment and the week levels to account for temporal and spatial autocorrelation across road segments and over time (Bertrand et al. 2004, Correia 2017).

Moreover, we conduct a series of robustness tests for our DD estimation. First, to test the parallel trend assumption, we estimate leads and lags models to check if traffic accidents in the pre-installation period are homogeneous between treated and untreated road segments. Second, given that several dependent variables (e.g., number of accidents) are count measures, we test negative binomial models. Last, we vary the operationalization of control groups using different untreated segments to check the sensitivity of the baseline DD estimates to sample selection.

3.5 Results

3.5.1 Effects of Surveillance Cameras on Traffic Accidents

Table 3.3 shows the baseline DD estimates of accident outcomes associated with the presence of surveillance camera. The result shows that while the number of car accidents and fatalities are not significantly affected, the number of injuries and damage to the vehicles are negatively and significantly associated with the camera installation (-0.0145, $p<0.05$ and -¥ 43.4356, $p<0.05$, respectively). The finding suggests that surveillance technology eases the severity of road crashes by reducing the risks of occupant injury and vehicular damage. In Table E-1 in Appendix E, we use the log-transformed dependent variables to account for skewness in the accident distribution. The results are consistent with those in Table 3.3.

Table 3.3.
Effects of Camera Installation on Accident-related Outcomes

	Dependent Variables:			
	No. of Accidents	No. of Persons Injured	No. of Fatalities	Damage to the Vehicles (¥)
	(1)	(2)	(3)	(4)
Installation (0-1)	-0.0029	-0.0145**	-0.0002	-43.4356**
	(0.0115)	(0.0061)	(0.0002)	(20.4269)
Road Segment FE	YES	YES	YES	YES
Week FE	YES	YES	YES	YES
# of Observations	817,596	817,596	817,596	817,596
# of Road Segments	5,241	5,241	5,241	5,241
Adj. R-squared	0.8323	0.5531	0.0532	0.4942

Notes: Tables 3.3 shows DD estimates of accident-related outcomes associated with camera installation. Robust standard errors (clustered at both road segment and week level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Tables 3.4 and Table E-2 use camera installation intensity measured by the number of installations for the given road segment and week, as an alternative independent variable, to examine the *intensity* of surveillance (rather than the *presence* of surveillance) on accident outcomes. The results from Tables 3.4 and E-2 are similar to those of Tables 3.3 and 3B. Columns 2 and 4 of Table 3.4 show that an increase in one camera installation is, on average, associated with a decrease in 0.0082 persons injured and ¥ 24.94 vehicular damage at a given segment and week.

Table 3.4.
Effects of Camera Installation Intensity on Accident-related Outcomes

	Dependent Variables:			
	No. of Car Accidents	No. of Persons Injured	No. of Fatalities	Damage to the Vehicles (¥)
	(1)	(2)	(3)	(4)
Installation Intensity (#)	-0.0029	-0.0082**	-0.0000	-24.9392**
	(0.0065)	(0.0038)	(0.0001)	(10.5356)
Road Segments FE	YES	YES	YES	YES
Week FE	YES	YES	YES	YES
# of Observations	817,596	817,596	817,596	817,596
# of Road Segments	5,241	5,241	5,241	5,241
Adj. R-squared	0.8323	0.5531	0.0532	0.4942

Notes: Tables 3.4 uses camera installation intensity measured by the number of installation for the given road segment and week, as an independent variable, to examine the intensity of surveillance (rather than the presence of surveillance in baseline models) on accident-related outcomes. Robust standard errors (clustered at both road segment and week level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

3.5.2 Dynamic Effect of Surveillance Cameras

Figures 3.4 and 3.5 illustrate the results from the event study using a DD model with leads and lags of camera installation (Autor 2003). The DD regression here replaces $Installation_{it}$ with a set of dummy variables, $Installation_{it}^{s}$, where $s \in \{\ldots, -2, -1, 0, 1, 2, \ldots\}$ indicates whether week *t* is the s^{th} week since the first surveillance camera is installed at the i^{th} road segment.

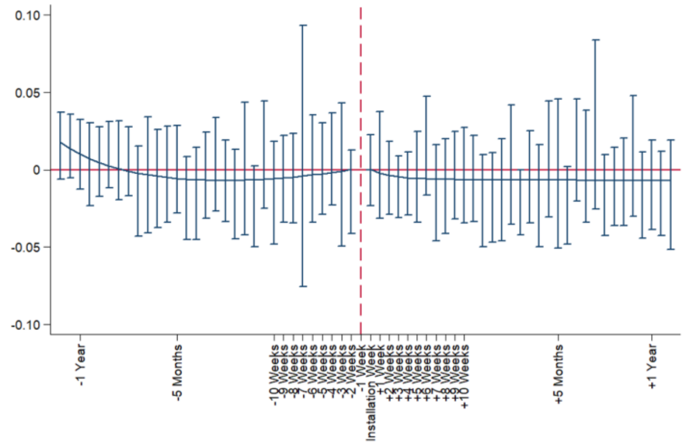

Figure 3.4.
Effects of Camera Installation on the Number of Persons Injured, Over Time
(Weeks relative to 1 week before camera installation)

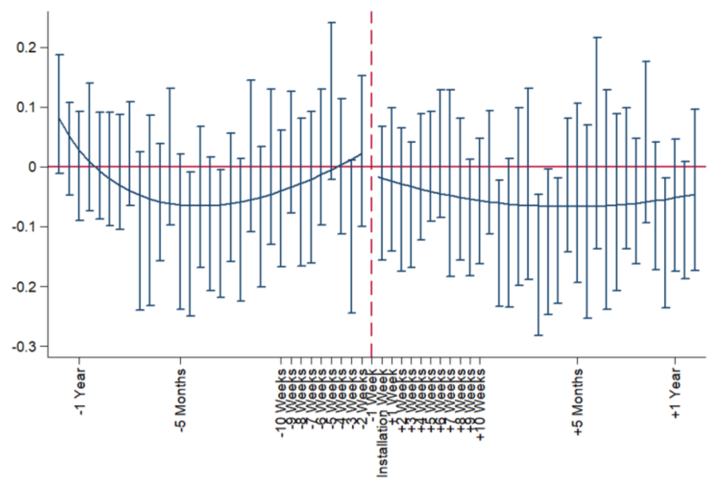

Figure 3.5.
Effects of Camera Installation on Damage to the Vehicles, Over Time
(Weeks relative to 1 week before camera installation)

The graphical evidence offers two insights – the pre-treatment homogeneity, and the persistence of surveillance effects over time. The pre-treatment trend is generally homogeneous, supporting the parallel trend assumption that treated and untreated road segments are indistinguishable in traffic accidents in the pre-treatment period. For the post-treatment dynamics, the occupant injuries and the vehicular damages have experienced a gradual decrease in the first five months and remain at the same level slightly below the one at the camera installation week. This suggests that the effect of surveillance technology on traffic accident persists over time.

3.5.3 Additional Robustness Checks

Table 3.5 reports the results from the negative binomial models, which indicate qualitatively similar findings to our baseline estimates. We find that the *number of persons injured* significantly drops by 14.73% (=1-$e^{-0.1477}$, p<0.01) followed by the camera installation at the treated road segments.

Table 3.5.
Effects of Installation on Accident-related Outcomes
(Negative Binomial Models)

	Count Dependent Variables:		
	No. of Accidents	No. of Persons Injured	No. of Fatalities
	(1)	(2)	(3)
Installation (0-1)	-0.0107	-0.1477***	-0.3143
	(0.0294)	(0.0399)	(0.2970)
Road Segment FE	YES	YES	YES
Week FE	YES	YES	YES
# of Observations	817,596	585,156	93,288
# of Road Segments	5,241	3,751	598

Notes: Table 3.5 reports the results from the negative binomial models. Such count model still adopts a difference-in-differences design with both road segments and week fixed-effects. However, to the best of our knowledge, for the negative binomial estimates, there exists no STATA package to allow for clustered standard errors at both temporal and spatial dimensions. We use robust standard error as default. The results show similar findings, indicating that the overall accidents and fatalities are not significantly affected, while the number of injuries drop significantly by 14.73% (=1-$e^{-0.1477}$) on average, ceteris paribus.Robust Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.6 compares DD estimates by varying untreated road segments as different control groups. Approach I is our baseline using all untreated road segments as a control group (identical to Table 3.3). Approach II restricts to the same roads within which some segments are treated but some are not, and the untreated segments are used as a control group. The benefit of Approach II is that treated and untreated segments are more

Table 3.6.
Comparison of Estimates across Models
Using Different Road Segments as Control Samples

Independent Variable: Installation (0-1)		*Dependent Variable:* No. of Accidents	No. of Persons Injured	No. of Fatalities	Damage to the Vehicles (¥)
		(1)	(2)	(3)	(4)
I. *All Untreated*		-0.0029	-0.0145**	-0.0002	-43.4356**
Road Segment as a Control Group		(0.0115)	(0.0061)	(0.0002)	(20.4269)
II. *Untreated Neighbouring*		-0.0155	-0.0083	0.0002	-57.7244
Road Segments as a Control Group		(0.0287)	(0.0094)	(0.0003)	(63.3146)
III. *Untreated Non-Neighbouring*		-0.0002	-0.0169***	-0.0003	-35.6291*
Road Segments as a Control Group		(0.0119)	(0.0063)	(0.0002)	(20.1235)
Comparison of Estimates (t-Stat):					
II vs. I		-0.4075	0.5533	1.1094	-0.2148
III vs. I		0.1632	-0.2737	-0.3536	0.2722
III vs. II		0.4924	-0.7600	-1.3868	0.3326
	Road Segment FE	YES	YES	YES	YES
	Week FE	YES	YES	YES	YES
Approach I:	# of Road Segments	5,241	5,241	5,241	5,241
	R-squared	0.8323	0.5531	0.0532	0.4942
Approach II:	# of Road Segments	1,159	1,159	1,159	1,159
	R-squared	0.8939	0.3586	0.0430	0.6176
Approach III:	# of Road Segments	4,215	4,215	4,215	4,215
	R-squared	0.7802	0.5817	0.0556	0.4352

Notes: Table 3.6 reports DD estimation using different sets of road segments as control groups and compares the estimates of average treatment effects on accidents using these different approaches (I, II, and III). Robust standard errors (clustered at both road segment and week level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

comparable as they are adjacent and share common in traffic and road characteristics. The caveat is that camera installation may exert an effect on untreated neighboring segments, which may also experience a decrease in accidents. Our baseline findings of the accident-reducing effect of surveillance could thus be underestimated. Approach III only uses the untreated non-neighboring road segments as a control group. This mitigates the limitation in Approach II but may decrease the comparability between segments. The results show that Approach II produces insignificant estimates of accidents, while the

Approach III produces slightly larger estimates than that using approach I. However, when comparing these estimates formally (Clogg et al. 1995), we find that they are not statistically distinguishable. In sum, the findings corroborate the baseline results and suggest that sample selection is not a serious concern.

3.5.4 Treatment Effect Heterogeneity: Where and When?

Having established robust evidence on the average treatment effect of surveillance technology on traffic accidents, we next explore treatment effect heterogeneity across different accident locations and timing. Table F-1 in Appendix F compares statistics across accident sites including *Freeway*, *Highway*, *Urban Expressway*, and *Urban Road*. The first two belong to suburban (or between-city) road system, while the remaining belong to urban (or within-city) road system. Table F-2 compares statistics across accident timing including *Daytime* and *Night* for the time in a day, and *Weekday* and *Weekend* for the day in a week.

Figure F-1 In Appendix F shows the heterogeneous treatment effect across accident location. Interestingly, the effects at Suburban roadways, especially for *Freeway*, are drastically different from those at roads within the Urban area. Evidence shows that camera installation could even induce more damages and at *Freeway*, while it is generally the reverse story for those at *Urban Road*. Recall that more accidents were located at *Urban Road*. Therefore, we believe that, generally, surveillance technology leads positive changes in traffic safety in the urban area. Figure F-2 shows the heterogeneous treatment effect across accident timings. In contrast to the findings on location effects, the analysis by stratifying accident timings does not show much heterogeneity. One plausible reason would be that surveillance technology exerts very similar effects regardless of when an accident occurs.

3.5.5 Economic Significance of the Main Effect

As the effect magnitude seems statistically small in terms of the estimates on saved occupant injuries (-0.0145, $p<0.05$) and vehicular damages (- ¥ 43.44, $p<0.05$) due to the presence of surveillance technology (Table 3.2), it would helpful to estimate the economic value of the effect that is more intuitive and direct for drawing policy implications. we herein do a conservative estimate on the incremental economic savings and human cost savings associated with the presence of surveillance. Economic savings are calculated using vehicular damage that could be avoided by the presence of surveillance technology and human cost savings are calculated using saved costs for body injuries and lost lifetime income thanks to the presence of surveillance technology.

For the economic saving, the total saved damage associated with camera installation for 656 treated road segments during the period of 3 years is ¥ 1,289,114 (¥ 43.4356 × 3.63% × 817,596; Due to the staggered installation, it is convenient to use 3.63% in Table 3.1 for the share of surveillance presence in total sample). For the human cost savings, we first calculate the saved number of persons injured, 430 (-0.0145 × 3.63% × 817,596) and then multiply it by the average claim for body injuries and average claim for lost lifetime income in this city in 2016. According to the *2016-2017 Local Traffic Accident Compensation Standard and Calculation Method*, the average claim for body injuries range from ¥ 89,267~¥ 892,666 (Level 1~ Level 10 based on the severity of body injury), we use most conservative average claim at Level 1, ¥ 89,267 ($14,169).

This number is comparable with that in the U.S. (According to the Insurance Information Institute[xxiii], the average claim for bodily injuries due to vehicular crashes in the U.S. during 2015–2016 was $16,427). The average claim for lost lifetime income seems not available for our setting. we use 1-month salary (¥ 3,719) as the conservative compensation for lost lifetime income assuming the work time loss is 1 month for an average accident involved with persons injured. Therefore, the total human cost savings associated with camera installation during the 3 years is ¥ 39,983,980. In sum, a conservative estimate of the total economic and human cost savings thanks to the surveillance cameras is ¥ 41,273,094 ($ 6,551,284) for the city within 3 years. Each surveillance camera (2,134 in total) gains social welfare about ¥ 19,341 ($ 3,070).

3.6 Mechanisms: Why Does Surveillance Technology Enhance Traffic Safety?

3.6.1 A Model of Drivers' Safety Effort Under Surveillance

We develop a model in an optimal fashion to determine how to incentivize driver safety behavior with surveillance technology. The model attempts to simplify the choices of driver safety effort under surveillance to maximize her utility and well-being. We assume that drivers have sufficient information for making decisions, and they are competent in making choices such that they can process information even when uncertainty is involved. For example, drivers realize accident risks increase with unsafe

[xxiii] https://www.iii.org/fact-statistic/facts-statisticsauto-insurance

behaviors such as speeding, be aware of the traffic regulation, and be able to find the surveillance technology whenever and wherever they are driving at.

In this model, a rational driver makes choices on the level of safety efforts subject to several costs in order to maximize her utility and well-being. The driver will experience one of the two states: either an accident does not occur, or it does occur over a period of time. The probability that a driver is involved in an accident (p) depends on the drivers' safety effort (e) and exogenous traffic safety regulation in the form of surveillance (s). The production function is specified by $p(e, s)$ with $p_e < 0$, $p_{ee} > 0$, $p_s < 0$, $p_{ss} > 0$, and $p_{es} > 0$, such that (1) the partial effect of an increase in drivers' own safety effort and traffic surveillance would reduce the probability of an accident (thus the first derivatives, $p_e < 0$, and $p_s < 0$), (2) further improvements bring a further, but diminishing reduction (thus the second derivatives, $p_{ee} > 0$, $p_{ss} > 0$), and (3) individual safety effort and exogenous regulation are similar and are substitutes in production ($p_{es} > 0$).

The driver is subject to a loss (L) given that the accident occurs. The loss includes human costs as body injury or fatality, and economic costs as vehicular damage, which is also influenced by the driver's own safety effort and exogenous traffic safety surveillance, thus the $L(e, s)$ with $L_e < 0$, $L_{ee} > 0$, $L_s < 0$, $L_{ss} > 0$ and $L_{es} > 0$. Notice that the expected loss from an accident (pL) is determined by the probability of the accident and the size of the loss.

The driver will receive a punishment in the form of a violation ticket if she violates the road safety regulation. The probability (q) that she will be caught depends on both her own safety effort and the level of exogenous safety surveillance, thus $q(e, s)$

with $q_e < 0$, $q_{ee} > 0$, $q_s < 0$, $q_{ss} > 0$, $q_{es} > 0$. Once the driver is caught, she will pay the ticket with T, the amount of which depends on her own safety effort but not on the probability of apprehension (q), and thus $T(e)$ with $T_e < 0$.

Finally, let there be disutility (D) associated with driver safety effort and exogenous traffic safety surveillance, thus $D(e, s)$ with $D_e > 0$, $D_{ee} > 0$, $D_s > 0$, $D_{ss} > 0$ and $D_{es} \geqslant 0$. Driver effort can involve time, inconvenience, discomfort, energy, and money, $D_e > 0$, and increases in effort can become increasingly distasteful, $D_{ee} > 0$. Disutility may depend on exogenous traffic safety surveillance, $D_s \geqslant 0$, and may interact with the driver's safety effort, $D_{es} \geqslant 0$.

If the driver has a resource constraint represented by income (I) and is risk neutral, then expected utility is

$$U = I - p(e, s)L(e, s) - q(e, s)T(e) - D(e, s) \qquad \text{(Eq. 4)}$$

Equation 4 shows that expected utility is the income (I) subtracted by expected loss from an accident (pL) and punishment for the traffic violation (qT), and disutility (D). In balancing the advantages and disadvantages of safety effort the driver increases effort through driving carefully, moderate speeds and keep vehicle-to-vehicle distance or similar activities until $\frac{dU}{de} = 0$, or

$$-D_e = p_e L + pL_e + q_e T + qT_e$$

$$\frac{d(-D)}{de} = \frac{d(pL)}{de} + \frac{d(qT)}{de} \qquad \text{(Eq. 5)}$$

Thus, the optimal amount of safety effort for the individual driver is the effort for which the marginal value of the utility cost (the left-hand side of Eq. 5) just equals the marginal benefit of the reduction in expected costs (the right-hand side of Eq. 5). The reduction in expected costs can occur through a reduction in the probability of accident (p), the size of the accident loss (L), the probability of apprehension if the driver violates the safety regulation (q), and the severity of punishment (T).

The condition for the optimal level of safety effort also indicates that general drivers will adjust their behavior (e) in response to a change in exogenous safety surveillance (s). To simplify the analysis, let us assume that exogenous safety surveillance does not affect disutility, $D_s = D_{es} = 0$. To determine the effect of a change in exogenous safety surveillance on driver safety effort, we treat Equation 5 as an implicit function, use the implicit function rule, and find $\frac{de}{ds}$:

$$\frac{de}{ds} = -\frac{-p_{es}L - p_eL_s - p_sL_e - pL_{es} - q_sT_e}{-D_{ee} - p_{ee}L - p_eL_e - p_eL_e - pL_{ee} - q_eT_e - 2q_eT_e - qT_{ee}} \qquad \text{(Eq. 6)}$$

The second order condition for utility maximization is that $\frac{d^2U}{de^2} < 0$ where $\frac{d^2U}{de^2}$ turns out to be equal to the denominator in Eq. 6. To make interpretation of Eq. 6 more intuitive, we group the numerator by accident loss and punishment cost, then find

$$\frac{de}{ds} = \underbrace{\underbrace{\frac{1}{\frac{d^2U}{de^2}}}_{<0} \underbrace{(p_{es}L + p_eL_s + p_sL_e + pL_{es})}_{= \underbrace{\frac{d(pL)}{de}}_{<0} \times \underbrace{\frac{d(pL)}{ds}}_{<0} > 0}}_{Risk\ Compensation\ Effect\ (<0)} + \underbrace{\underbrace{\frac{1}{\frac{d^2U}{de^2}}}_{<0} (\underbrace{q_sT_e}_{\underbrace{\frac{d(qT)}{de}}_{<0} \times \underbrace{\frac{d(qT)}{ds}}_{>0} < 0})}_{Deterrent\ Effect\ (>0)} \qquad \text{(Eq. 7)}$$

It follows that the sign of $\frac{de}{ds}$ (marginal effect of surveillance technology on driver safety behavior) depends on the relative magnitude of *a positive effect* of surveillance technology on accident loss to that of *a negative effect* of surveillance on punishment loss.

The former effect reflects the *risk compensation hypothesis* that an increase in safety regulation will induce drivers to decrease their own safety efforts (by compensating the risk of accidents) (Peltzman 1975, Wilde et al. 2002), while the latter reflects the *deterrent hypothesis* that an increase in probability and severity of punishment will incentivize drivers to increase their own safety efforts (by deterring the unsafe driving behaviors) (Becker 1968, Chalfin & McCrary 2017).

3.6.2 Suggestive Evidence on Deterrence versus Risk Compensation

We next offer suggestive evidence for the underlying mechanisms of this observed effect. To examine the deterrent effect, we restrict the data to roads within which some segments are installed with surveillance cameras while others are not. We use accident measures at the neighboring segments without cameras as dependent variables, and we regress them on the camera installation at focal segments of the same roads. The intuition is that dangerous driving at focal road segments may be displaced to untreated neighboring segments where drivers are not under deterrence. Table 3.7 shows a disproportionate *increase* in damages at the untreated neighboring segments close to the treated segments (Column 4 in Table 3.7). Together with the estimate on the average treatment effect of surveillance technology (Table 3.3), this finding on accident displacement effect supports the *deterrent hypothesis* that when the surveillance is no longer present, drivers immediately respond with less caution and drive more carelessly (Priks 2015, Chalfin and McCrary 2017).

Table 3.7.
Deterrent Effect of Camera Installation on Accident-related Outcomes at Neighbouring Untreated Road Segments (within the Some Roads)

	Dependent Variables: (Accident Outcomes at Untreated Neighbouring Road Segments)			
	No. of Accidents	No. of Persons Injured	No. of Fatalities	Damage to the Vehicles (¥)
	(1)	(2)	(3)	(4)
Installation (0-1)	0.1436	0.0307	0.0041	585.8368*
	(0.1641)	(0.0865)	(0.0037)	(316.4408)
Road Pair FE	YES	YES	YES	YES
Week FE	YES	YES	YES	YES
# of Observations	18,720	18,720	18,720	18,720
# of Road Pairs	120	120	120	120
Adj. R-squared	0.9032	0.7963	0.1934	0.7688

Notes: Robust standard errors (clustered at both road and week level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

To examine risk compensation effect, we follow Peltzman (1975) and replicate his test by comparing the surveillance effects on the number of vehicle-to-vehicle, vehicle-to-pedestrian, and single vehicle accidents. We expect that while surveillance technology detects and decreases traffic violations (which mostly result in vehicle-to-vehicle accidents), it does not regulate non-violation accidents due to negligence (e.g., ones caused by unexpected obstacles or pedestrian behaviors on the road). Risk compensation would be observed if drivers are more likely to involve in vehicle-to-pedestrian or single-vehicle accidents than in vehicle-to-vehicle accidents. Table 3.8 compares estimates and shows that the effects are statistically indistinguishable. Therefore, we do not find supportive evidence for the risk compensation effect.

Table 3.8.
Risk Compensation Effect of Surveillance Camera Installation on Accident-related Outcomes

	No. of Vehicle-to-Vehicle Accidents	No. of Vehicle-to-Pedestrian Accidents	No. of Single Vehicle Accidents
	(1)	(2)	(3)
Installation (0-1)	-0.0046	-0.0004	0.0024
	(0.0100)	(0.0013)	(0.0018)
Road Segments FE	YES	YES	YES
Week FE	YES	YES	YES
# of Observations	817,596	817,596	817,596
# of Road Segments	5,241	5,241	5,241
R-squared	0.8209	0.2561	0.6282
Pairwise comparisons of coefficients (t-Statistics)		(2)-(1): 0.4165 (3)-(2): 1.2616 (3)-(1): 0.6889	

Notes: Robust standard errors (clustered at both road & week level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

3.7 Discussion and Conclusion

In this study, we investigate the automated enforcement on the road, and we theorize and quantify the impact of surveillance technology on traffic safety. Using a unique matched panel dataset on all traffic accidents of a metropolitan in Southern China in 2014-2016 and traffic surveillance cameras installation during the same period, our difference-in-difference estimates show a disproportionate decrease in occupant injuries and vehicular damages at the road segments with the presence of surveillance cameras. we develop a simple theoretical model of drivers' safety efforts to further understand this empirical observation. The model predicts that the effect of surveillance technology can be decomposed into two parts: a positive impact on the safe driving effort by deterring unsafe behaviors ("Stick" role) and a negative one on drivers' own safety effort by facilitating a safer traffic environment and compensating accident risks ("Carrot" role). We offer suggestive evidence supporting the deterrent effect of surveillance technology and suggest that a “Stick” role prevails a “Carrot” role in explaining why surveillance technology enhances traffic safety.

Significant theoretical contributions stem from our findings. First, the observed deterrent role of surveillance technology in traffic safety contributes to the IS literature on monitoring technology and moral hazard to a broader socio-economic setting (Hubbard 2000, Liang et al. 2018, Pierce et al. 2015). Relatedly, our study we add to the research on the societal impact of IT (Chan and Ghose 2014, Greenwood and Wattal 2017, Pang and Pavlou 2018) to examine the impact of surveillance technology in the transportation sector. Third, our study seeks to influence the public and intellectual debate on the role of surveillance technology. The theoretical prediction on the coexistence of “stick” and “carrot” roles of surveillance technology is consistent with two “discursive formations (“coercive” and “caring”)” of surveillance in the organizational environment, expending the duality of surveillance to a broader social system. Finally, we incorporate both the deterrent effect and the risk compensation effect in a same expected utility model of driver’s safety effort, add to the long-lasting conversations on the economics of traffic safety (Valavanis 1958, Peltzman 1975) and deterrence (Becker 1968, Ehrlich 1996, Chalfin and McCrary 2017), and show that, “stick” seems better than “carrot” in enhancing traffic safety.

Important insights for policymakers and drivers can be derived from this research. First, our survey on the traffic safety interventions and our theoretical prediction shows the effective policy design for traffic safety should not focus on the perfection of an intervention itself but instead on whether drivers respond to this intervention by increasing their own safety efforts (Peltzman 1975, Boyer and Dionne 1987). Our empirical evidence suggests surveillance technology can be a cost-effective intervention as it deters unsafe driving behavior. For the drivers, we encourage them to use caution no matter whether surveillance technology is present because our evidence shows that drivers may be more opportunistic and take more risks when they are not under surveillance. Furthermore, our conservative estimate on the economic and human cost savings due to surveillance technology (i.e., ~ ¥ 41 Million ($ 6.5 Million) in the city over the 3 years) demonstrates a compelling economic significance that government surveillance can be beneficial for social welfare that cannot be underestimated.

Our study has a few limitations which direct the ongoing efforts on this research-in-progress. First, our identified effect is not based on an ideal randomized experiment, and there might be some unobserved confounding factors that bias our estimation. For example, the traffic volume for each road segments may change by time and it may predict both camera installation and traffic accident rate in tandem (Fridstrom et al. 1995, Edlin and Karca-Mandic 2006, Romem and Shurtz 2016). To remedy this, we are seeking ways to proxy such a variation in traffic flows across locations and over time.

Second, we do not find significant variation in the number of accidents before and after the presence of surveillance technology. One major concern would be the nature of our data at the fined-grained road segment and week level such that many roads have only experienced one accident over the 156 weeks. Next, we will try to aggregate geolocations or weeks to higher levels, such as blocks or months, replicate the DD estimation, and check if the results are sensitive to the choice for the unit of analysis.

Another related problem is the potential for redundancy in the accident data. Currently, we cannot tell visually if multiple road segments with similar names actually represent the same road segment. One plausible solution to reduce redundancy and identify unique road segments is to match and merge our current dataset to the reference GIS data and to locate road segments and cameras onto the GIS map.

Third, using GIS data can also help to gain more insights into how deterrent effect spills over to neighbouring road segments. One would-be implication is to identify which types of location-based surveillance technology allocation is more effective in both reducing traffic accident rate and saving the cost from unnecessary camera installation. This is consistent with the notion of "hot-spot" policing in the criminology literature for a substantial reduction in crime rate by precisely shifting sizable policy manpower to "hot-spot" areas with highest crime rate (Draca et al. 2011, Chalfin and McCrary 2017).

Forth, our theoretical model assume that drivers are risk neutral when they face the costs while driving following the extant traffic safety studies (e.g., Blomquist 1986). This may not always hold true if the cost is for the punishment of a traffic violation (e.g., a speeding ticket). Research in crime and punishment does discuss risk preference. Therefore, we need to include such discussion.

Fifth, we use road-level cumulative count of accidents to approximate the measure for driver's safety efforts with or without the presence of surveillance in the mechanism testing. While the changes in accident rate reveal the changes in safety efforts, a more direct and precise measure is to look at individual driving behaviors, at least focusing on the identified reasons for each accident. Perhaps accidents due to traffic violations reveal lower safe driving efforts compared to those due to a natural disaster (or force majeure). It is noteworthy that we haven't explored an available dataset on the accident-involved persons. In the next steps, we will dive into this dataset and see if we could measure safety effort at the individual driver level.

Last but not least, in this version we do not discuss the treatment effect heterogeneity of surveillance technology given the space limit. Next, we will explore more of the effect by considering heterogeneities in camera types (e.g., speed camera, red light camera), driver groups (e.g., driving ages, education, gender, age), accident timings (i.e., daytime and night), road types (e.g., local roads, urban expressways, highways). Understanding heterogeneous effects (Athey and Imbens 2016) will help us gain more insights on how to effectively allocate and leverage surveillance technology for better traffic safety performance on the road.

CHAPTER 4

INFORMATION TRANSPARENCY AND CUSTOMER CHURN: EVIDENCE FROM THE INSURANCE INDUSTRY

ABSTRACT

Customer churn (customers not renewing term contracts) has been a major headache for firms, especially in industries where market information is highly transparent due to the Internet. However, whether and how information transparency affects customer churn are poorly understood in both research and practice. In this study, we collaborate with a major European insurance company to answer these questions with a longitudinal dataset that contains rich information about customers and their contract status. First, surprisingly, we find that information transparency actually reduces customer churn. Notably, customers acquired from a highly transparent channel (a third-party quote comparison website) are less likely to churn by at least 4.6%. The observed effect remains significant across alternative econometrics estimates, using matching techniques, and exploiting a quasi-experimental setting where the comparison website was shut down for a period. Second, we explore the theoretical explanations of this observed counter-intuitive effect. The extant literature offers two competing predictions on the role of information transparency on customer churn: (1) either price informedness (customers' awareness of price information), which intensifies customers' price sensitivity and induces churn or, (2) product informedness (customers' awareness of product information), which mitigates product quality uncertainty and reduces churn. Third, leveraging another dataset from a major infomediary on insurance offerings for a

random sample of customers, we show that product informedness prevails price informedness in explaining the observed negative effect of information transparency on customer churn. Our findings bridge the information transparency and customer churn literatures and provide practical implications for pro-active churn management by emphasizing product (versus price) transparency on the Internet.

4.1 Introduction

Customer "churn" (not renewing term contracts) has been a major problem for firms in the service industries, such as financial services, utilities, telecommunications, and insurance (Neslin et al. 2006). Customer churn often occurs in industries where information is highly transparent. For instance, a car driver can easily access third-party quote comparison websites, also known as Shopbots (Smith and Brynjolfsson 2001, Smith 2002), to search and compare insurance policies across different car insurance providers and decide whether to renew an existing contract (or churn). Some car insurance firms have legitimate concerns about comparison websites because information transparency allows customers to learn about the competitors' product offerings and motivates them to churn if they find cheaper or more attractive options. In contrast, other insurance firms seem to embrace the concept of information transparency. For instance, a major US insurance firm, *Progressive*, has adopted a bold marketing strategy that displays both its own and also its competitors' insurance product and price information, even though Progressive does <u>not</u> always offer the cheapest insurance options (Granados et al. 2010). Information transparency may help Progressive increase its short-term revenues (i.e., by attracting new customers), albeit its long-term effect on churn is not clear. Our study is thus motivated by a fundamental question: *Does information transparency help firms retain their existing customers (reduce churn), or does information transparency drive customers to churn?*

To study this research question, we develop a theory by integrating the information transparency and customer churn literatures. First, information systems, marketing, and economics literatures on information transparency (e.g., Zhu 2004, Anderson and Renault 2006, Granados et al. 2010) have mostly focused on transparency of information elements (e.g., price, product) and the strategic use of such elements on market competition and customer behavior. Studies have examined the impact of information transparency on customer demand (e.g., Chevalier and Goolsbee 2003, Ellison and Ellison 2009). Price transparency increases price elasticity of demand (Granados 2012), while product transparency mitigates this effect (Gupta et al. 2004, Li et al. 2014). Our study extends this literature to the long-term effect of information transparency, specifically, how transparent information customers obtained at acquisition affects their churning behavior afterwards. Second, research on customer churn has centered on after-sales factors, such as customer satisfaction (Rust and Zahorik 1993), service experience (Gustafsson et al. 2003), service recovery efforts (Jamal and Bucklin 2006), or situational, reactional, and influential triggers (Roos et al. 2004). However, the effects of before-sales factors, specifically, customer acquisition channels, on customer churn have remained unclear. Note that the levels of information transparency vary across acquisition channels (a comparison website is arguably more transparent than other channels as the former offers comprehensive market information about prices and products, for example). Our study thus aims to extend the information transparency and customer churn literatures (e.g., Zhu 2004, Neslin et al. 2006, Granados et al. 2010, Huang et al. 2012, Ascarza et al. 2016) by incorporating information transparency as a key predictor of customer churn.

Integrating the information transparency with the customer churn literature, we offer two competing hypotheses. On the one hand, information transparency is proposed to increase price informedness (customers' awareness of price information in the market). As customers are sensitive to price changes, a transparent market exposes price information to customers, thereby increasing their likelihood to churn. Accordingly, information transparency *induces* customer churn. On the other hand, information transparency increases product informedness (customers' awareness of product information in the market). The rich information makes customers confident about their choices, and they would be unwilling to make additional efforts to churn afterwards. Hence, we also propose that information transparency *reduces* customer churn.

This study reconciles this theoretical tension by empirically assessing the effect of information transparency on customer churn in the insurance industry. Auto insurance firms typically acquire customers from both traditional (e.g., call centers, agents) and digital channels (e.g., websites, third-party quote comparison sites). The different levels of information transparency across acquisition channels provide the source of variation to uncover the role of information transparency in customer churn, given that the auto insurance product and service experience are relatively homogeneous across channels.

We leverage three unique datasets: First, we use a dataset from a major European insurance provider[xxiv] with 82,212 contract-level observations over eight years (2008 – 2015). The dataset provides rich information about where customers came from, when they signed, renewed, or terminated their insurance contracts, as well as customer characteristics, vehicle features, and detailed information of their insurance contracts. Second, for 1,200 randomly-selected customers, we simulate each of their "obtaining a quote" processes from a major third-party comparison website in the study using information about these customers and their vehicles and contracts. We manually collect information on insurance offerings from all available firms in the auto insurance market. We analyze this additional dataset to gain insights into the relative importance of product and price transparency in churn decisions. Third, we conduct a survey to assess preferences of insurance policy holders on information transparency, acquisition costs, pre- and post-acquisition information search behaviors across channels to better understand the impact of information transparency on customer churn.

We empirically examine the effect of information transparency by comparing the churn probability of customers acquired through channels with different levels of information transparency, conditional on customer heterogeneity, vehicles, and contracts. First, we employ a Linear Probability Model (LPM) as our baseline specification (Angrist

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[xxiv] The partner firm is a competitive provider in the insurance market, albeit it is not always the cheapest or the highest quality provider. Since insurance is a highly differentiated product, for different customers, the focal insurance firm stays at different positions of advantage / disadvantage relative to its competitors in terms of price and product quality (Section 5 for detailed discussion). The nature of the insurance product and market position mitigate the concern about generalizability (i.e., whether our findings could apply to other firms rather than our focal firm).

and Pischke 2008, pp. 94). We also include nonlinear models, including a Probit model and survival analysis, to cross-validate the LPM estimates. In addition, considering differences in overt characteristics across customers from different channels, we use matching techniques (Rubin 1997, Heckman et al. 1998) to attenuate potential selection bias. Moreover, it is possible that unobserved heterogeneity that (e.g., market price dynamics) drives both customers' channel selection and churn decision, which may confound the observed effect. To address this potential concern, we exploit a quasi-experimental disruption where customers could not access the focal third-party comparison website[xxv] (the most transparent channel) for a certain period. Specifically, we focus on repeat customers with a difference-in-differences (DID) approach to estimate the changes in churn rates of customers on the comparison website before and during the disruption period versus that of customers on other channels during the same timeframe.

Econometrics analyses yield notable results. First, customers who purchased insurance from a channel with higher information transparency (i.e., a third-party comparison website) are more likely to be retained, by at least 4.60%, compared to those from less transparent channels (i.e., firm's own quote website, online advertising, or telemarketing), implying that information transparency helps firms reduce churn. The effect remains qualitatively and quantitatively consistent using a variety of econometric specifications. Moreover, we did a back-of-the-envelope calculation, which shows the

[xxv] Note that the third-party comparison website is not the price comparison function of the focal insurance company, but an independent infomediary that has a dominant position in the country with 82.9% market share. We checked the robustness by using other independent comparison websites, and the results from our main analysis still hold.

identified effect is economically significant. Specifically, we predict that the overall churn rate in our study period would have been reduced by almost 4% if customers acquired from other channels have had purchased insurance from a comparison website. The reduced churn rate can be translated into retaining 1,077~1,521 more customers during the focal period, amounting up to over half a million Euro revenue gain had these customers never churned.

We also explore the underlying mechanisms to explain the effect of information transparency on customer retention. For a random sample of 1,200 customers, we manually collected product and price information offered to each of the customers by all available insurance providers from the largest third-party comparison website in the country. These data allow us to examine how product and price information affects customers' decisions to churn. We find that if a customer comes from a transparent channel (i.e., a third-party insurance quote comparison website), the effect of product information on reducing churn is statistically significant, while the effect of price information is not. This finding demonstrates the relative importance of product transparency to price transparency in enhancing customers' long-term retention, and it explains why information transparency exerts positive effect on customer churn.

Several contributions stem from this work. First, to our knowledge, this is the first study to theorize and quantify the relationship between information transparency and customer churn, extending the literature on information transparency (e.g., Granados et al. 2010) and customer retention (e.g., Neslin et al. 2006, Scheweidel et al. 2008). Second, we disentangle the effects of price transparency and product transparency, and we find product transparency to be mostly helpful to reduce churn, extending prior work on short-term demand effects of price/product information (e.g., Chevalier and Goolsbee 2003, Ellison and Ellison 2009), and extending the long-term effects on customer retention. Third, we shed light on the role of acquisition channels by exploiting their differences in terms of information provision, stressing the significance of the informational role of acquisition channels, which could be leveraged as a marketing strategy, not only for acquiring customers but also preventing customer churn (Ascarza et al. 2017, Blattberg et al. 2008).

This study offers practical implications to manage customer churn in increasingly transparent markets (Ascarza et al. 2017). First, our finding on the positive effect of information transparency on customer retention may explain the confidence of some quality-oriented insurance firms; notably, Progressive auto insurance openly compares insurance products on its own comparison website. Thus, the key insight for firms in the service industries is that taking advantage of the transparency strategy essentially retain more customers in the long run. Second, firms should acknowledge the relative importance of product transparency to price transparency, especially when fierce price competition is inevitable on the Internet. Finally, since firms face the challenge of strategizing which channels to invest and how much they should allocate their resources across multiple channels (Kannan et al. 2016), our findings imply that firms should prioritize highly transparent channels. More importantly, for each customer, a firm should customize transparency strategies based on the relative market positions of its product offerings regarding price and quality. Practically, transparent channels (e.g., comparison websites) significantly helps retain customers if the product offering has a quality advantage in the market, while it may be less effective if it has a price disadvantage.

4.2 Theoretical Background

4.2.1 Information Transparency and Customer Informedness

We build on the information transparency (Granados et al. 2010) and customer informedness literatures (Clemons 2008). The information transparency literature discusses how buyers and sellers react to different types of (e.g., price and product) transparency, and how firms or intermediaries use transparency strategies to transform market competition and buyer behaviors (Chevalier and Goolsbee 2003, Chen and Sudhir 2004, Ellison and Ellison 2009). Transparency strategies may vary on how electronic service providers reveal, conceal, bias, or distort market information (Granados et al. 2010). Extant research has discussed firms' transparency strategies by changing the level of availability and accessibility to market participants (Granados et al. 2012, Li et al. 2014). For example, online travel agencies are classified as either *transparent* if the search results include the airline name and itinerary (e.g., Expedia), or *opaque* if they do not (e.g., Priceline's name-your-own-price mechanism and Hotwire's opaque offerings).

This study seeks to extend the information transparency literature in three key ways. First, while extant studies have mostly focused on industries that provide relatively homogenous products or services, such as airline tickets and hotel bookings, we focus on a service industry that offers a highly customized and differentiated product, auto insurance. To purchase auto insurance, customers need to go through a lengthy process by typing information about themselves, their vehicles, and their coverage preferences. Our study focuses on the firms' transparency strategy on displaying information regarding customized product, extending the boundary of applicability of information transparency theory (Ellison and Ellison 2009, Granados et al. 2010). Second, consistent with prior literature on transparent/opaque channels on information transparency (Granados et al. 2012), our empirical setting allows us to examine a set of customer acquisition channels that are associated with different levels of information transparency. Specifically, we extend channel-related studies (e.g., Jamal and Bucklin 2006) to third-party comparison websites that provide the highest level of transparency for market information on products and prices. Third, how to leverage multiple channels to develop transparent strategies remains elusive. Firms offer various channels to satisfy different information needs for different customer segments, but how to allocate resources among these channels remains an open question. This study attempts to connect the transparency literature with the omnichannel marketing literature on attribution challenges (e.g., Abhishek et al. 2015, Kannan et al. 2016, Xu et al. 2014).

Beyond the firm's transparency strategy, for the effect of information transparency on the customer's side, the literature examines how customer informedness, "*the degree to which customers know what information is available in the marketplace, including the precise attributes of different product and service offerings*" (Clemons 2008), has changed customer behavior. Li et al. (2014) found that product informedness helps customers to value and find a best possible product that fits their needs, and thus the negative impact of price informedness on customer purchase decision attenuates.

Gupta et al. (2004) also found that product information makes customers less price sensitive so to focus their search on product characteristics and quality and less on price. Similarly, Granados et al. (2012) suggested that product information via transparent channels mitigates pressures from head-to-head price comparisons on the Internet.

While this line of work stresses the effect of product and price informedness on customer short-term decisions to purchase a product or subscribe to a service, there has a limited understanding of whether customer informedness has a long-term effect on customers' loyalty, manifested by the customer retention or churn rate. To close this gap, this study examines customer lifetime tenure and churn rate in response to different levels of product and price transparency across various types of acquisition channels.

4.2.2 Determinants of Customer Churn

This study also relates to research in customer churn (Ahn et al. 2006) and customer retention (Bolton 1998). This stream of research aims to understand what drives customers to churn or stay. Schweidel et al. (2008) suggested the determinants of service retention in a contractual setting includes contract term duration and customer tenure, customer heterogeneity, and seasonal effects. Service experience and satisfaction is also a major factor that determines customer churn (Gustafsson et al. 2003). Bolton (1998) found that satisfaction increases the duration of service tenure; in contrast, such an effect is larger for customers who subscribe to the service longer. Relatedly, service quality has received much attention (Boulding et al. 1993). In addition, the customer retention literature has identified other factors, including customer commitment and loyalty (e.g., Bolton et al. 2000, Verhoef 2003), plan recommendations (Ascarza et al. 2016), and payment equity (Jamal and Bucklin 2006). Situational, reactional, and influential triggers also affect customers' switching among service providers (e.g., Roos et al. 2004). For instance, Godinho de Matos and his colleagues (2018) found customer churn to be driven by social influence or peer effect in the telecommunication industry.

We also seek to extend the literature on the determinants of customer churn to information transparency. While studies (e.g., Verhoef and Donkers 2005) found differences in customer tenure across acquisition channels, they argue that they are mainly explained by the heterogenous price offerings and psychological bonds across channels. However, in our setting, insurance firms do not differentiate their pricing strategies across acquisition channels. Besides, customers barely interact with their insurance providers unless they make claims for car accidents, thus, the perceived distinction in psychological bond across acquisition channels, arguably, make little difference to customers' churn decision in our setting.

Another stream of customer churn research has applied statistical learning (e.g., Lemmens and Croux 2006) and data mining (Berry and Linoff 2004, Hung et al. 2006, Hadden et al. 2007) to predict customer churn (Verbeke et al. 2012). Huang et al. (2012) built churn prediction models using different techniques (e.g., Classifications, Naïve Bayes, Decision Trees, Neural Networks, and Support Vector Machines) and conducted a series of comparative experiments to evaluate the performance of these models.

We build on the identified predictors of churn, add a critical determinant, *information transparency*, and enrich the customer churn literature by empirically uncovering the effect of information transparency on customer churn. Though not intending to build a model for predictive accuracy, we pursue consistency of our estimation across different econometrics specifications. Specifically, we vary estimates using LPM, Probit model, survival analysis, matching techniques, and difference-in-differences in a quasi-experiment setting. All analyses identify and cross-validate the observed empirical effect of information transparency.

4.2.3 Effect of Information Transparency and Customer Churn

Integrating the information systems, marketing, and economics literatures on customer churn and information transparency, we offer two competing explanations for the potential effect of information transparency:

On the one hand, information transparency increases *price informedness* (e.g., Granados et al. 2012). In a highly transparent environment, customers are in a state of high price informedness. Information about market prices allows customers to search and find lower prices for a given product or similar differentiated substitutes (Stigler 1961). The ability to effectively present and compare prices for similar products makes customers more price sensitive since they have a relatively larger consideration set of substitutes from which to choose. To maximize utility and minimize cost, customers are sensitive to price changes and price differentials in pursuit of a better deal (Brons et al. 2002). A transparent market makes customers available to dynamic price changes frequently adjusted by the focal insurance provider and diverse price differentials presented by other insurance providers. Customers can thus alter their decisions more frequently, increasing their likelihood to switch or churn. In our setting, compared to other channels (e.g., call centers), a third-party quote comparison website is arguably more transparent by providing information from alternative insurance providers. This highly transparent channel increases customers' likelihood to find a better alternative offering, thus increasing their likelihood to churn. Accordingly, we propose:

H1a: ***Customers acquired from channels with higher information transparency are more likely to churn.***

On the other hand, information transparency also raises *product informedness* (e.g., Li et al. 2014). In a highly-transparent environment, customers are well informed of products, and they can easily search, compare, and find better options in terms of quality, as signaled by product information (e.g., Akerlof 1970, Alba et al. 1997). Prior literature on price and product information suggests that, a decrease in search costs of acquiring product-related (and thus quality) information helps offset the increasing price sensitivity induced by more transparent price information (e.g., Kaul and Wittink 1995, Mitra and Lynch 1995, Lynch and Ariely 2000). Customers are also often more satisfied with the price/product combination based on transparent market information. After choosing their product, customers show higher confidence in their informed decision, less motivated to take additional efforts to search for and compare among alternatives and are more likely to stick with what they chose, which may reduce their churn likelihood in the long run (Gupta et al. 2004, Johnson et al. 2004). In our setting, customers acquired from a third-party quote comparison website are well-informed of insurance products and the quality signals offered by all available providers in the market. Recognizing the quality, customers make better choice up front, lowering the likelihood to churn later, which is manifested as a low churn rate in the long term. Accordingly, we propose:

H1b: ***Customers acquired from channels with higher information transparency are less likely to churn.***

Before moving to the empirical investigation, we note that the two opposite hypotheses are not necessarily mutually exclusive, albeit they are competing. Price informedness increases churn likelihood by raising the customers' price sensitivity, while product informedness may mitigate this effect and decrease their churn rate. However, the objective of this study is to understand which effect dominates, i.e., whether price or product informedness has a larger effect on customer churn in the long term.

4.3 Research Setting and Data

4.3.1 Research Context

We examine the role of information transparency in the auto insurance industry. To empirically study customer churn in this context, we collaborate with a major European insurance firm that is interested in gaining insights into their customers and, based on that, efficiently managing customer retention. Consumers of insurance products typically go through the following process: they search insurance offerings through different channels, such as inbound telemarketing (i.e., call center), online advertising, the firm's own quote website, and third-party comparison websites. Next, they make purchase decisions based on their preferences and all available price and product information of the offerings. Once they purchase an insurance product, they can decide to renew or terminate their contracts at any time afterwards. Their decisions on renewal or termination take effect after the expiration of the existing contract period (e.g., a month).

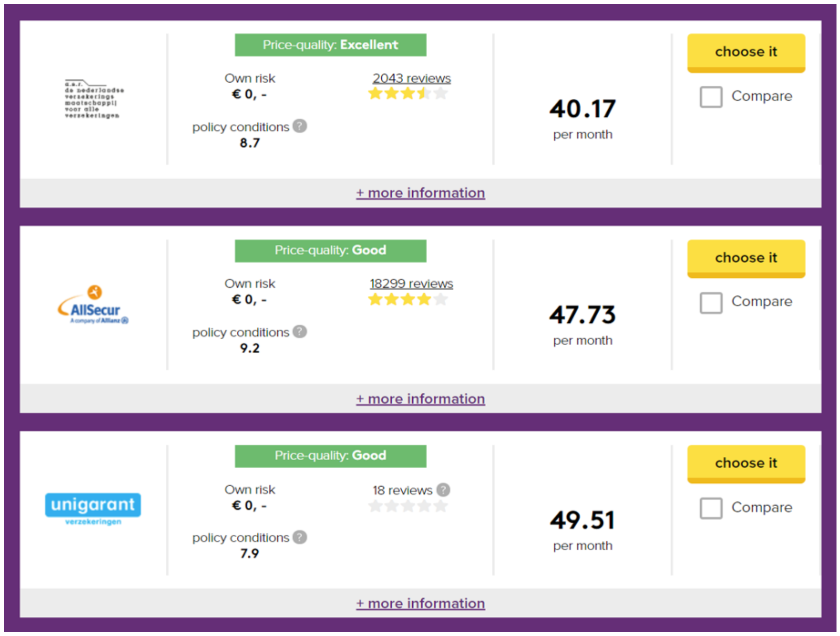

Figure 4.1.
A Typical Comparison Website

Our research context has several advantages to examine the impact of information transparency. First, we use the multi-channel setting to explore variations in information transparency as different acquisition channels are associated with different levels of information transparency. Customers acquired from a call center, online advertising, or the firm's website can only access price and product information of the focal insurance firm. These acquisition channels do not offer sufficiently transparent information for customers to make decisions on staying or switching to another insurance provider. However, customers acquired from a third-party comparison website have access to more transparent information, not only of the focal provider's product and price, but most importantly about the product and price offerings by other insurance providers in the market. Figure 4.1 shows a typical third-party comparison website. Within a few clicks, customers can search premium offerings and rating scores, infer product quality, and compare them in tandem. In sum, the different levels of information provision across acquisition channels provide us the source of variation to examine the effect of information transparency on customer churn (see Table 4.1).

Table 4.1.
The Level of Information Transparency across Channels

Acquisition Channels	Focal insurance provider's product information	Focal insurance provider's price information	Focal insurance provider's and its competitors' product and price information
	(1)	(2)	(3)
Online advertising*	√	√	×
Call center	√	√	×
The firm's website	√	√	×
Third-party comparison website	√	√	√

Notes: this includes display advertising, search engine advertising and affiliate marketing.

The insurance industry offers a clean setting to empirically estimate the effect of acquisition channels on customer churn. The reason is that customers seldom interact with their service providers after purchase, unless making claims for damage or theft, which is less frequent. For most other service industries, such as telecommunication and financial services, the interactions after purchase are more frequent and intimate as customers use their product and services (e.g., cellular data, credit cards). Post-acquisition use brings in unobservable noise and creates difficulties to identify the variation in churn solely from acquisition channels. However, such usage is relatively low in the insurance industry. Besides, customer perceptions of service quality are often homogeneous across acquisition channels and even across insurance providers. Hence, the low level of after-acquisition heterogeneity in the insurance industry teases out considerable confounders, which allows us to better identify the effect of transparent channels on customer churn.

4.3.2 Data

The dataset consists of 82,212 auto insurance contracts for customers with signup dates ranging from October 2008 to February 2015. "Churn" indicates that the status of an insurance contract becomes and remains inactive within our time frame. The data are thus right censored, and we cannot observe contract status after March 1st, 2015. Right censoring is reasonable and very common in customer retention research in contractual settings as we cannot track all customers until they churn (Ascarza et al. 2017). Moreover, this dataset contains information about acquisition channels, including third-party insurance comparison website, the firm's own website, inbound telemarketing, and online advertising, through which the customers are acquired by the firm. The dataset also covers detailed information about customer (e.g., age, gender, past purchase history), their insured vehicles (e.g., production year, original list price, engine power, total kilometers driven, and accident-free years), and their contracts, including contract signed date, and termination date (if so), duration, coverage types (e.g., liability, comprehensive coverage), monthly premium, and total damages. This allows us to account for churn predictors other than information transparency, such as customer heterogeneity and seasonality, per extant customer churn research (e.g., Schweidel et al. 2008). Table 4.2 shows the variable definitions, while Table 4.3 presents the descriptive statistics.

From Table 4.3, we find that the overall average churn rate until March 2015 is 48.3% for all customers in the sample, while customers acquired from a comparison website is 48.6%, which provides a balanced number of customers in the treated group (those acquired from a third-party comparison website) and the control group (those

Table 4.2.
Main Variables

Variables	Descriptions
Dependent Variable	
Churn	Status of contract (=1 if churn, otherwise 0)
Independent Variable	
Comparison	Purchased via comparison websites? (=1 if yes, otherwise 0)
Customer Characteristics	
Gender	=1 if female, otherwise 0
Age	The age of the customer
Past purchasing history	= Customer lifetime – current contract duration (days)
Vehicle Characteristics	
Car age	The age of the insured vehicle
Car value	The original value of the insured vehicle (€)
Engine power	The engine power of the insured vehicle (kw)
Total kilometers driven	Total kilometers driven (km)
Damage free years	# of years without car damage
Contract Characteristics	
Coverage type (liability)	Liability? (=1 if yes, otherwise 0)
Coverage type (limited comprehensive)	Limited comprehensive? (=1 if yes, otherwise 0)
Coverage type (comprehensive)	Comprehensive (cover full risk)? (=1 if yes, otherwise 0)
Monthly Premium	Premium per month (€)
Total Damage	Total damage for the insurance claims (€)
Contract duration	# of months since a customer signed the contract
Other Insurances (from the same focal company)	
Also purchased travel insurance	Has travel insurance? (=1 if yes, otherwise 0)
Also purchased accident insurance	Has travel accident insurance? (=1 if yes, otherwise 0)
Also purchased legal aid insurance	Has legal aid insurance? (=1 if yes, otherwise 0)
Also purchased home insurance	Has home insurance? (=1 if yes, otherwise 0)
Also purchased other insurances	Have other insurances except for auto insurance and the above mentioned four? (=1 if yes, otherwise 0)

acquired from other channels) to ensure statistical power. The percentage of male customers is larger than female ones (32.3%). The customer age is around 45 years old. The demographic statistics of our sample is similar to that of the population of the country in our setting. New customers take up most of the sample, on average, giving a short prior purchase history. The characteristics of the insured vehicles vary in terms of age, value, engine power, total kilometers driven, and damage-free years. Also, customers chose different types of insurance coverage but with balanced shares, i.e., liability with 35.4%, limited comprehensive with 33.2%, and comprehensive with 31.3%.

The average monthly premium is €32.54, while the average contract tenure is about 20 months. Also, 15.5% of the customers also purchased other insurance products (e.g., travel insurance, home insurance) from the same focal insurance company.

Table 4.3.
Summary Statistics (N=82,212)

	Mean	SD	Min	Max
	(1)	(2)	(3)	(4)
Churn	0.478	0.500	0	1
Comparison	0.459	0.498	0	1
Driver gender	0.323	0.468	0	1
Driver age	45.53	14.200	21	94
Past purchasing history	58.908	211.844	0	5,719
Car age	12.150	5.464	0	46
Car value	24,206.708	14,299.253	1,050	157,008
Engine power	77.933	40.967	12	8,107
Total kilometers driven	14,119.058	13,793.999	0	99,000
Damage free years	6.565	7.465	0	57
Coverage type (liability)	0.354	0.478	0	1
Coverage type (limited comprehensive)	0.332	0.471	0	1
Coverage type (comprehensive)	0.313	0.464	0	1
Monthly premium	32.540	16.42	0	257.5
Total damage	289.750	1,670.498	0	50,000
Contract duration	19.540	15.940	0	78
Also purchased travel insurance	0.040	0.195	0	1
Also purchased accident insurance	0.003	0.058	0	1
Also purchased legal aid insurance	0.019	0.138	0	1
Also purchased home insurance	0.050	0.219	0	1
Also purchased other insurances	0.042	0.201	0	1

4.3.3 Model-Free Evidence

We provide a non-parametric comparison of the average customer churn rates by acquisition channels to initiate the empirical study. In Figure 4.2, we find customers acquired from the most transparent channel (third-party comparison website) show a significant lower overall churn rate (44.55%), when compared to those from other channels, i.e., online advertising, inbound telemarketing, and the firm’s own website. Also, we aggregate all the channels except the comparison website into a single category (thus the control group), and we compare the churn rate with the group of customers who are acquired by a third-party comparison website (treatment group). We find that customers acquired from less transparent channels, are 6.09% more likely to churn compared to the customers acquired from a third-party comparison website. It is noteworthy that this is a naïve comparison in the sense that customers may self-select their preferred channels to purchase insurance and make churn decisions, and such selection issues may bias our comparison results. In the following sections, we introduce formal econometrics models to properly address these concerns.

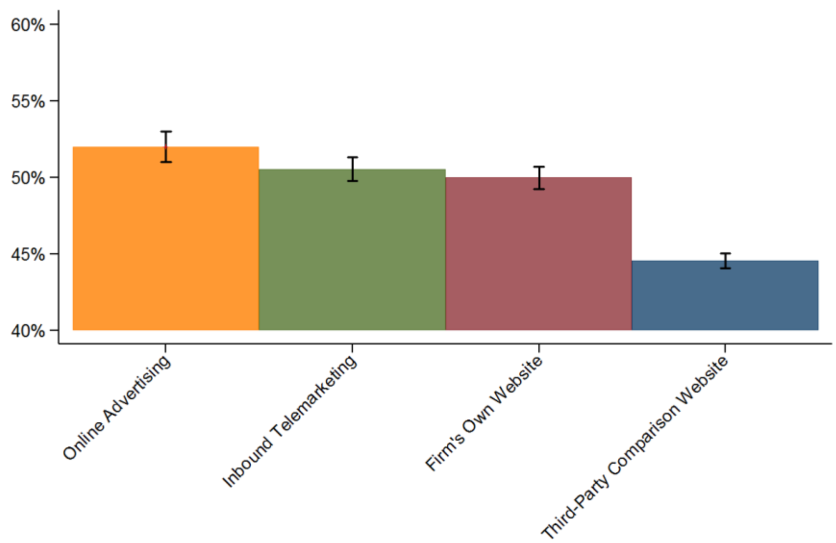

Figure 4.2.
Average Customer Churn by Channels

4.4 Empirical Models and Results

To empirically test the effect of using a transparent channel on customer churn, we use a threefold empirical approach. First, we analyze regressions with covariates under the Conditional Independence Assumption (CIA), which suggests that acquisition channels are as good as randomly assigned, conditional on the observed heterogeneity.

Second, we use matching to balance covariates between customers in the treatment and control groups and adjust the baseline regressions based on the matched pairs of customers. Third, to mitigate the concern that time-varying unobservable heterogeneity may bias our analyses, we adopt a difference-in-differences approach to exploit a quasi-experimental setting where customers could not access the comparison website for searching and purchasing insurance products for a long period of time (53 days).

4.4.1 Baseline Regression Analyses

First, we estimate the effect of transparent channels on customer churn using regression analyses under the CIA assumption. We use a dichotomous variable, $Churn_i$, to denote whether a customer terminated her contract (1=yes, 0 otherwise), drawing on customer retention (e.g., Ahn et al. 2006) and risk and insurance literatures (e.g., Brockett et al. 2008). For transparent channels, we use $Comparison_i$ (=1 if the customer i acquired via a comparison website; 0 otherwise), as our primary independent variable.

We employ LPM as the baseline specification to identify the effect of $Comparison_i$ on $Churn_i$. LPM interprets the probability changes more directly, and it allows for the coefficients to be comparable across models and customer groups. Besides, LPMs are unbiased and consistent estimates of a variable's average marginal effect (Angrist and Pischke 2009, pp. 107). In our empirical setting with dichotomous independent variable ($Comparison_i$), the marginal effect is the discrete change, i.e., how predicted probability churn likelihood changes if a customer changes her channel for purchasing insurance from other channels ($Comparison_i$ = 0) to a comparison website ($Comparison_i$ = 1). With this notion, our LPM is:

$$Churn_i = \alpha_1 + \rho_1 Comparison_i + X_i{'}B_1 + \varepsilon_{1i} \quad \text{(Eq. 8)}$$

where Xi is a set of covariates (Table 4.2), and ε_{1i} is an error term. As mentioned earlier, we assume that $E[\varepsilon_{1i}|Comparison_i, X_i] = 0$. In this setup, we use the OLS estimator (ρ_1) to uncover the effect of using a comparison website (transparent channel) on customer churn. Column 1 of Table 4.4 reports the results; consistent with the model-free evidence, customers acquired from a comparison website are less likely to churn than those from other channels by at least 4.60% ($p< 0.01$).

However, LPM has the following limitations: 1) it assumes a linear relationship between customer churn and acquisition channel, thus the model might be mis-specified and could be sensitive to data; and 2) LPM yields probability predictions outside the range of 0 to 1 by treating the dependent variable (i.e., churn or not) as continuous, thus understating (or overstating) the magnitude of the true effects. To address this potential concern, we use a Probit model (Equation 9) in which ρ_2 is the estimator of interest:

$$Prob(Churn_i = 1|Comparison_i, X_i)$$
$$= \varphi(\alpha_2 + \rho_2 Comparison_i + X_i{'}B_2 + \varepsilon_{2i}) \quad \text{(Eq. 9)}$$

Column 2 in Table 4.4 shows the result from the Probit regression. We find the estimation is consistent with that from LPM in terms of the coefficient sign and significance. After calculating the marginal effects, the estimated effect is 4.21% (p<0.01), consistent with 4.6% (p<0.01) in LPM, implying that potential underestimation or overestimation by LPM is not a serious concern in our study.

Table 4.4.
Effect of the Comparison Website on Customer Churn

Dependent Variable = Churn	Econometric Specifications OLS	 Probit	 Cox hazard: continuous time	 Collapse multiple purchases	 Proportional hazard: discrete time
	(1)	(2)	(3)	(4)	(5)
Comparison	-0.046***	-0.192***	-0.199***	-0.211***	-0.233***
	(0.008)	(0.029)	(0.025)	(0.027)	(0.049)
Past purchasing history	0.005***	0.014***	0.085***	0.147***	0.032***
	(0.001)	(0.003)	(0.003)	(0.004)	(0.005)
Driver gender	-0.005	-0.032**	-0.043***	-0.046***	-0.101***
	(0.003)	(0.013)	(0.012)	(0.012)	(0.021)
Driver age	-0.002***	-0.007***	-0.004***	-0.004***	-0.010***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Car age	0.012***	0.049***	0.031***	0.030***	0.045***
	(0.000)	(0.002)	(0.002)	(0.002)	(0.003)
Engine power	0.119***	0.488***	0.073**	0.095**	0.427***
	(0.010)	(0.042)	(0.034)	(0.038)	(0.070)
Car value	-0.133***	-0.557***	0.206***	0.215***	-0.648***
	(0.009)	(0.035)	(0.028)	(0.030)	(0.054)
Total kilometers driven	-0.055***	-0.306***	-0.145***	-0.147***	-0.302***
	(0.001)	(0.003)	(0.003)	(0.003)	(0.006)
Damage free years	-0.002***	-0.006***	-0.047***	-0.049***	-0.003
	(0.000)	(0.001)	(0.002)	(0.002)	(0.002)
Coverage1 (limited comprehensive)	0.012***	0.091***	-0.232***	-0.241***	0.025
	(0.004)	(0.018)	(0.015)	(0.016)	(0.025)
Coverage2 (comprehensive)	0.103***	0.467***	-0.038*	-0.029	0.294***
	(0.007)	(0.030)	(0.020)	(0.022)	(0.037)
Total damage	0.002***	0.010***	-0.079***	-0.082***	-0.016***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)
Average premium per month	-0.001***	-0.004***	-0.004***	-0.004***	0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Cross-buying other insurances	YES	YES	YES	YES	YES
Contract signed time	YES	YES	YES	YES	YES
# of Observations	82,212	82,212	80,140	72,244	1,584,679

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

The LPM and Probit models have not considered the non-linear effect of duration that customers hold the contracts. For instance, the probability to churn is quite different for customers who hold insurance policy for two months and for those who that for two years. Thus, such duration may have a complex probability distribution that Equation 9 has not assumed. In addition, our data are right-censored after which we do not know the customers' status (i.e., churn or not) of their contracts. Right censoring is inevitable as we cannot track every customer until they churn, but it can be considered empirically. We turn to a proportional hazard model (Cox 1972), and we rely on the following model:

$$\lambda(t|Z) = \kappa(\mathrm{Z})\lambda_0(t), \qquad \text{(Eq. 10)}$$

$$where\ \kappa(\mathrm{Z}) = \exp(\alpha_3 + \rho_3 Comparison_i + X_i{}'B_3 + \varepsilon_{3i})$$

$\lambda(t|Z)$ is the probability that customer churns on the next day, conditional on survival (i.e., not churned) until current day *t* and other factors such as $Comparison_i$ and X_i. Here, ρ_3 is the parameter of interest. We expect ρ_3 to be negative, indicating that a customer terminates her insurance contract slower when she used a comparison website to purchase insurance compared to that when she used other channels.

Column 3 in Table 4.4 reports the result from the Cox Proportional Hazard model. The estimator ρ_3 meets our expectation (-0.199, p<0.01), corroborating that customers from a comparison website stay longer with the insurance firm. To test the robustness of the findings, we replicate the analysis but collapse customers who purchased multiple times because they have repeat observations, and thus they could be over-weighted in our sample. The result remains consistent (Column 4). Unlike the continuous-time hazard models in Equation 10, we use a hazard model that treats time as discrete by month in Column 5. We expand observations into an unbalanced panel dataset for each customer who had a distinct number of active months until they churned or the end of study period. In spite of this, we prefer continuous-time survival analysis as it allows to observe if the customer signed or terminated their contracts at the day level. We use discrete-time hazard model functions as a robustness check. The estimates are consistent for both discrete-time and continuous-time survival analysis. Last, our results remain robust in models under different assumptions for the baseline hazard, i.e., Weibull, Gompertz, and Exponential distribution (Table G-1 in Appendix G).

4.4.2 Regression Analyses Adjusted Using Matching

The CIA assumption that $Comparison_i$ is exogenously determined might be violated if some sources of heterogeneity drive both channel selection and churn decision, i.e., $E[\varepsilon_i | Comparison_i, X_i] \neq 0$. Specifically, with idiosyncratic shopping preferences (e.g., price-driven), some customers may be more likely to self-select to use a comparison website to purchase insurance than use other channels. The selection issue may bias our estimation. To mitigate such a concern, we first employ the matching technique to mimic a randomized controlled trial. Matching allows us to reliably estimate the average treatment effect (e.g., Rubin 1997, Heckman et al. 1998, Austin 2011), even if the customers' selection to purchase from a comparison website had not been completely at random. In essence, matching attempts to remove the potential selection bias by generating balanced covariate-specific treatment-control groups. In our study, we mainly rely on propensity score matching, which is the conditional probability of purchasing insurance from a comparison website, i.e., $Prob\ (X_i) = E(Comparison_i \mid X_i) = Prob(Comparison_i = 1 \mid X_i)$. Based on the propensity scores, we match each customer in the treatment group to one or more customers in the control group who are similar (in terms of X_i). "Similar" here means that the propensity scores of matched customers in the treatment and the control groups differ by less than 5%.

Table 4.5.
Covariate Balance Summary for Matching Estimator

	Overall Customers			Propensity-Based Matched Customers		
	From a comparison website?		Standardized Difference	From a comparison website?		Standardized Difference
	YES	NO		YES	NO	
	(1)	(2)	(3)	(4)	(5)	(6)
Past customer relations*	0.153	0.457	24.6	0.153	0.165	0.8
Driver gender	0.310	0.334	5.1	0.310	0.308	0.5
Driver age	43.830	46.976	22.3	43.830	43.673	1.1
Car age	12.377	11.9	8.8	12.375	12.236	2.6
Engine power*	4.327	4.271	15.5	4.327	4.321	1.6
Car value*	9.999	9.881	22.0	9.999	9.995	0.9
Total kilometers driven*	8.050	7.073	24.5	8.052	8.167	2.9
Damage free years	5.622	7.409	24.2	5.623	5.633	0.1
Limited comprehensive	0.325	0.342	3.6	0.325	0.322	0.6
Comprehensive	0.257	0.366	23.7	0.257	0.257	0.1
Monthly premium	32.455	32.802	2.1	32.455	32.604	0.9
Total damage*	0.958	1.340	15.0	0.958	0.972	0.5
Travel insurance	0.022	0.055	17.2	0.022	0.024	1.0
accident insurance	0.001	0.005	6.8	0.001	0.002	0.6
Legal aid insurance	0.009	0.028	14.6	0.009	0.009	0.5
Home insurance	0.026	0.070	20.5	0.026	0.030	1.4
Other insurances	0.021	0.059	19.3	0.021	0.024	1.2

Notes: Standardized difference is the mean difference divided by the pooled standard deviation. Variables with * take a logarithm transformation in the regression analysis.

Table 4.6.
Effect of Comparison Website on Churn Using Matched Customer Pairs

Dependent Variable: Churn	OLS	Probit	Cox Hazard
	(1)	(2)	(3)
Comparison	-0.071***	-0.239***	-0.350***
	(0.016)	(0.050)	(0.040)
All Covariates	YES	YES	YES
# of Observations	75,480	75,480	73,311

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4.5 shows that covariates are more balanced (in terms of standardized differences) for customers between the treatment and control groups after using matching pairs. Also, Figure I-1 in Appendix I shows a substantial overlap of the propensity score densities for these two groups, which enables the matching technique to find control customers who are similar to treated customers, and vice versa. By comparing the estimates ($\rho_1, \rho_2,$ and ρ_3) with and without using matched customers, we find that the churn-reducing effect still holds (Table 4.6). We observe a slightly larger coefficient size when using matching (Column 2, Table 4.6). This implies that the estimate in Table 4.4 represents the lower bound of the effect of information transparency, and the effect might be more substantial when the potential selection issue is further mitigated.

4.4.3 Exploiting A Quasi-Experimental Setting (Disruption in Third-Party Comparison Website)

Matching is still a control strategy on observables, and it may subject to confounding effects from unobserved heterogeneity (Angrist and Pischke 2009, pp. 69). If the unobservables correlate with customers' channel selection and churn decision, the above estimates may be biased. To mitigate such a concern, we seek for some exogenous variation (Z_i) that is highly correlated with the treatment variable ($Comparison_i$) but not correlated with the unobserved factors (ε_i) that predict $Churn_i$. Analyzing the time series data on comparison website utilization by weeks (Figure 4.3), we observe a disruption that no customer purchased car insurance from any comparison websites over a period of 53 days from July 14, 2012 to September 5, 2012. Descriptive analysis suggests all the other channels remain accessible except for the third-party quote comparison websites. This disruption turns out to be a strategic decision exclusively made by the insurance firm that customers could not anticipate *ex ante*. Since disruption was <u>not</u> initiated by customers, it could be treated as exogenous to their channel selection, which provides us a quasi-experimental setting to re-estimate the effect of transparent channels on customer churn.

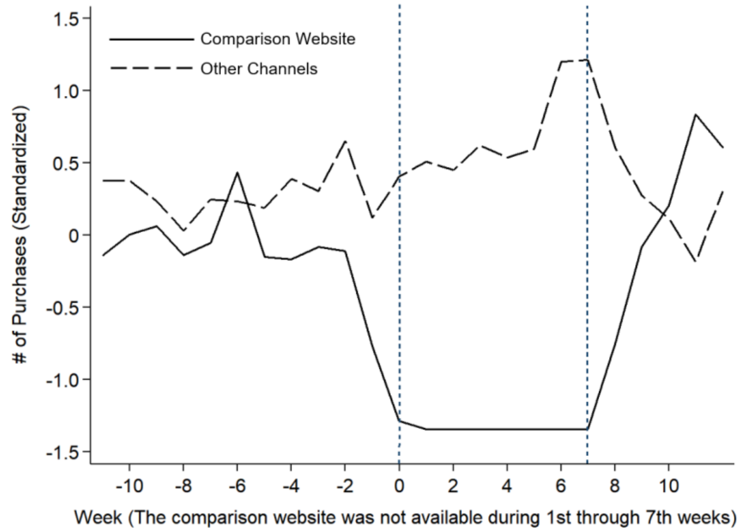

Figure 4.3.
A Time Series of Comparison Website Utilization
***Before* and *After* the Disruption**

We use two approaches to exploit this quasi-experiment. First, we compare the customers' churn rates before and during the disruption. Since customers could not anticipate the timing of the disruption on the comparison websites, there should be no systematic difference among customers within a rather short period (53 days) before the disruption. Therefore, we utilize the variance of whether or not a customer made a purchase during the disruption period to uncover the effect of the comparison website unavailability on her churn likelihood. Accordingly, based on Zhang and Zhu (2011), the specification is:

$$\mathrm{Churn_i} = \alpha_4 + \rho_4 \mathrm{Disruption_i} + \mathrm{X_i}'\mathrm{B}_4 + \varepsilon_{4\mathrm{i}} \qquad \text{(Eq. 11)}$$

We expect ρ_4 to be positive, as customers could not have access to the comparison website during the disruption, and they would have to use less transparent channels (e.g., firm's own quote website, call center) to purchase insurance. The lack of information transparency during acquisition made them more likely to churn later on. In addition, we check the robustness of the estimate by making equal-size pairs of customers (499 customers), instead of same duration of time period (53 days), before and during the disruption. Table 2.7 shows positive and statistically significant ρ_4 across Columns 1-4, which corroborates our main estimates that the transparent comparison websites help reduce customer churn, conditional on observed and unobserved heterogeneity.

Table 4.7.
A Comparison of Churn Rate between Customers Who Purchased Insurance *Before* and *During* the Period of Restriction on the Comparison Website

Dependent Variable: Churn	**Same number of days** (53 days) *before* and *after* the 1st day of disruption		**Same number of customers** (499 customers) *before* and *after* the 1st day of disruption	
	Overall customers	Propensity-based matched customers	Overall customers	Propensity-based matched customers
	(1)	(2)	(3)	(4)
Disruption (*=1 if comparison website was restricted for this customer, 0 otherwise*)	0.090** (0.022)	0.111*** (0.029)	0.092** (0.032)	0.171*** (0.043)
All Covariates	YES	YES	YES	YES
# of Observations	2,058	1,504	998	752
Adj. R-squared	0.288	0.260	0.241	0.250

Notes: In Column (1) and (2), we compare churn rate of customers same 53 days before and after the 1st day of disruption, while, in Column (3) and (4), we compare churn rate of the same number of customers before and after the 1st day of disruptions. The former ensures the same duration before and after the disruption, while the latter ensures the same number of customers. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Second, it is possible that customers who prefer comparison websites may not purchase at all during the disruption. In this case, the changes in the composition of customers before and after the disruption may bias our estimate. Evidence supports this possibility: there was an overall downward trend of customer acquisition after the disruption across all channels (1,498 customers 53 days before the disruption versus 560 customers 53 days after). Accordingly, we employ a difference-in-differences approach (DID) on a panel dataset of repeat customers who purchased car insurances multiple times, at least once during and another time before the disruption. Leveraging DID, we estimate the changes in the churn rate of customers acquired from the comparison website before and after the disruption, compared to the churn rate of customers acquired from other channels during the same period.

$$Churn_{it} = \alpha_5 + \rho_5 Comparison_{it} + X_{it}{}' B_5 + \delta_i + \gamma_t + \varepsilon_{it} \qquad \text{(Eq. 12)}$$

Where t=1 if a customer purchased the insurance in the period of disruption, 0 if she did it before the disruption. δ_i and γ_t are customer- and period-fixed effects. ρ_5 is the DID estimate of interest, capturing the changes in churn rate for customers who previously chose a comparison website for insurance purchase switched to a less transparent channel (because they had to) during the disruption.

Column 1 in Table 4.8 shows that the churn-reducing effect (ρ_5<0, p<0.05) still holds, but the magnitude is significantly larger (0.146>0.046, p<0.1). Columns 2 and 3 in Table 4.8 shows the DID estimates using Probit model and Cox Hazard proportional model. Similarly, we find the coefficient sign holds, albeit the magnitude is larger than those in our main analysis (Column 3 and 4 in Table 4.4). The reason for the larger effect size may be due to the advantage of DID estimation that could account for the within-variation of each customer across time, thereby teasing out time-invariant unobservables (e.g., inherent insurance purchase preference, habit), which, if not accounted for, may underestimate the true churn-reducing effect.

Table 4.9 formally compares the estimates from three identification strategies, namely, baseline regression, regressions adjusted using matching, and DID. We find, in general, the latter two identify larger effect; however, the increases in coefficient magnitude are not all statistically significant (Columns 4-6), suggesting that the potential self-selection issue may not be serious.

Table 4.8.
DID Analysis on the Effect of Comparison Website on Churn

Dependent Variable: $Churn_{it}$	OLS	Probit	Cox Hazard
	(1)	(2)	(3)
$Comparison_{it}$	-0.146**	-0.281***	-0.730**
	(0.055)	(0.102)	(0.307)
All Covariates	YES	YES	YES
# of Observations	760	760	760

Notes: The results are based on a DID estimate on a sample of repeat customers. Each customer purchased insurance in both two periods, during the disruption of comparison websites and before the disruption. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4.9.
Comparing Estimators from Regression, Matching, and Quasi-Experiment

Dependent Variable: Churn	Regression (R)	Matching (M)	Quasi-experiment (QE)	Difference between estimates (M)- (R)	Difference between estimates (QE)- (R)	Difference between estimates (QE)-(M)
	(1)	(2)	(3)	(4)	(5)	(6)
OLS	-0.046***	-0.071***	-0.146**	-0.025	-0.100*	-0.075
	(0.008)	(0.016)	(0.055)	(0.018)	(0.056)	(0.057)
Probit	-0.192***	-0.239***	-0.281***	-0.047	-0.089	-0.042
	(0.029)	(0.050)	(0.102)	(0.058)	(0.106)	(0.114)
Cox Proportional Hazard	-0.199***	-0.350***	-0.730**	-0.151***	-0.531*	-0.380
	(0.025)	(0.040)	(0.307)	(0.047)	(0.308)	(0.310)

Notes: Column (4)(5)(6) compare the estimates from different identification strategies, regression, matching and quasi-experiment using Z-test. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.5 Underlying Mechanisms: Price Transparency and Product Transparency

Thus far we have provided consistent evidence that information transparency reduces customer churn. Then, we explore the underlying mechanisms that drive this effect. Recall the two competing hypotheses: information transparency increases price informedness, which thereby induces customer churn (H1a); and information transparency increases product informedness, which then reduces customer churn (H1b). The identified churn-reducing effect represents the overall effect of information transparency. While our results suggest that H1b is more likely, we do not directly examine H1a and H1b, specifically the relative importance of product transparency and price transparency in customer churn decisions. We next explore the effect of price informedness and product informedness separately as plausible underlying mechanisms.

Disentangling and identifying the effects of price and product transparency has empirical challenges as our main dataset does not contain market information of all available product and price offerings for each customer. To empirically exploring the underlying mechanisms, we consolidate a new dataset by randomly selecting a sample of 1,200 customers from the main dataset. For each customer, we simulate her insurance shopping process as if she goes to a third-party quote comparison website, types in her own information, car and contract preferences, and then browses, compares, and purchases auto insurance. From a dominant comparison website (precisely, 82.9% auto insurance comparison is generated from this site) in the focal country, we execute this simulation and manually collected information about insurance products and price offerings from all providers in the market that are available to each customer. We also obtain data about brand names, price rankings, rating scores (on a 0-10 scale), and the number of ratings for all insurance providers available to the focal customer (as in Figure 4.1). The rich market information about available insurance products and price offerings for each customer allows us to take a closer look at the effect of both price transparency and product transparency on customer churn decisions. Table H-1 in Appendix H reports the details of this dataset and the variables we use in the mechanism testing.

We measure the effects of price and product informedness by examining how the effects of price and product quality depend on the information a customer obtains when they purchase insurance. In other words, even customers who were given the same product quality and price offerings, their churn rates would be different if they came from a more transparent channel (i.e., a third-party quote comparison website) rather than from less transparent channels. Hence, we test whether, in a channel with high information transparency, (1) price effect is stronger to induce churn or, (2) product quality effect is stronger to reduce customer churn.

Empirically, we examine the effect of price by focusing on price advantage and price differential and testing their effects on customer churn. Price advantage is a dichotomous indicator measuring whether the price premium offered by the focal provider (A) is lower than that of its lowest price competitor (B)xxvi in the market (=1 if Price(A)<Price(B), 0 otherwise). Price differential is a continuous variable measuring the difference between the price premium offered by the focal firm (A) and that by its lowest price competitor (B) (=Price(B) - Price(A)). Likewise, we examine product quality by focusing on quality advantage and quality differentials and their effects on customer

[xxvi] We identify the best competitor as the top insurance provider recommended by the dominant third-party comparison website, and we assume that best competitor offers the lowest price, even if a customer searches and compares price offerings from other channels (e.g., each insurance provider's own quote website).

churn. Rating score is a reasonable indicator of product quality. The quality advantage is a dichotomous indicator on whether the rating score of the focal firm (A)'s insurance product is higher than that of its best quality competitor (B)[xxvii] (=1 if Rating(A)> Rating(B), 0 otherwise), while quality differential is a measure of continuous difference between the rating score of the focal firm (A) and that of its best quality competitor (B) (=Rating(A)- Rating(B)).

Table 4.10.
Mechanisms: Price and Quality Advantage and Customer Churn

	Dependent Variable: Churn					
	OLS		Probit		Cox Proportional	
	(1)	(2)	(3)	(4)	(5)	(6)
Comparison	-0.043**	-0.001	-0.215**	-0.033	-0.356**	-0.120
	(0.020)	(0.048)	(0.096)	(0.278)	(0.163)	(0.478)
Price Advantage	-0.034	-0.022	-0.213	-0.142	-0.392	-0.243
(=1 if Price A < Price B)	(0.029)	(0.040)	(0.161)	(0.211)	(0.267)	(0.349)
Quality Advantage	-0.020	0.031	-0.101	0.143	-0.211	0.169
(=1 if Rating A > Rating B)	(0.021)	(0.030)	(0.101)	(0.137)	(0.165)	(0.223)
Comparison ×		-0.029		-0.166		-0.332
Price Advantage		(0.055)		(0.307)		(0.520)
Comparison ×		-0.108**		-0.553***		-0.913***
Quality Advantage		(0.043)		(0.201)		(0.331)
All Covariates	YES	YES	YES	YES	YES	YES
# of Observations	1,200	1,200	1,200	1,200	1,200	1,200

Notes: Robust standard errors in parentheses. *** <0.01, ** p<0.05, * p<0.1

Table 4.10 shows the results using price and quality advantage of focal firm (A)'s insurance product relative to that of its best competitor (B). We find that both price and quality advantages may lead to customer churn; such effects are not statistically significant (Column 1 in Panel A). However, if customers acquired from a comparison website, product quality advantage positively and significantly lowers their churn

[xxvii] As the lowest-price competitor, the best quality competitor has the best rating in the market (besides the focal firm).

likelihood (-0.108, p<0.05), while price advantage does not have such a significant effect (Column 2). The estimates hold consistent across different models (Columns 3-6). The finding supports the second rationale above that product quality effect (relative to price effect) is stronger to reduce churn in a highly transparent channel. This implies that product transparency prevails price transparency in explaining the overall churn-reducing effect of information transparency.

Table 4.11 shows further details of how price differentials and product rating differentials affect customer churn probability, and how such effects vary depending on information transparency. We find that customers are significantly less likely to churn if they face alternative offerings at a lower price (-0.046, $p<0.01$; Column 1). Interestingly, if the customer originates from a comparison website, the price effect is not statistically significant (0.031, $p>0.1$), while the product quality effect is (-0.036, $p<0.1$) (Column 2).

Table 4.11.
Mechanisms: Price and Quality Differential and Customer Churn

	Dependent Variable: Churn					
	OLS		Probit		Cox Proportional	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Price differential and *quality differential* are continuous variables measuring to what extent the price and the rating of the insurance product from the focal firm are lower or better than that of its best competitor. To put it simply, *Price differential* = Price(B) – Price(A), 0 otherwise; *Quality differential* = Rating(A) – Rating(B), 0 otherwise .						
Comparison	-0.044**	-0.043**	-0.216**	-0.203**	-0.361**	-0.369**
	(0.020)	(0.020)	(0.098)	(0.100)	(0.164)	(0.179)
Price Differential	-0.046***	-0.062***	-0.192***	-0.242***	-0.334***	-0.358***
(=Price B – Price A)	(0.014)	(0.016)	(0.062)	(0.062)	(0.075)	(0.076)
Quality Differential	-0.016	0.001	-0.070	0.016	-0.115	0.069
(=Rating A – Rating B)	(0.010)	(0.015)	(0.051)	(0.065)	(0.090)	(0.112)
Comparison ×		0.031		0.109		0.073
Price Differential		(0.025)		(0.113)		(0.170)
Comparison ×		-0.036*		-0.205**		-0.455**
Quality Differential		(0.020)		(0.101)		(0.190)
All Covariates	YES	YES	YES	YES	YES	YES
# of Observations	1,200	1,200	1,200	1,200	1,200	1,200

Notes: Robust standard errors in parentheses. *** <0.01, ** p<0.05, * p<0.1

Taken in sum, above evidence does not support H1a (price informedness matters in customer churn), but rather supports H1b (product informedness does). The findings further suggest that product transparency exerts a larger and more significant effect on customer churn than price transparency does. That may explain why we observe a negative overall effect of information transparency on customer churn.

While the effects of price and product transparency are compelling, they are examined independently instead of interdependently. However, both effects could be intertwined in practice. Auto insurance is a highly personalized product such that different customers are offered different premiums and may perceive different product or service quality by the same insurance provider. In fact, a firm's insurance offering can stand in the following four market positions, i.e., {price advantage, quality advantage}, {price advantage, quality disadvantage}, {price disadvantage, quality advantage}, {price disadvantage, quality disadvantage}, relative to its competitors' offerings. Does the focal insurance firm need to, and if so, how should it align its transparency strategy with its relative market positions of price and quality for better churn management?

To answer this question, we test the distinct roles of channel transparency in each of these four positions. Specifically, we interact the acquisition channel as a comparison website with each of the four positions that the focal firm's insurance is offered. Table 4.12 shows the results. Columns 2, 4, and 6 show that, on average, a transparent channel is most beneficial when a firm's offering holds a quality (relative to a price) advantage. This finding corroborates with previous evidence that product transparency helps to reduce customer churn (Tables 4.10 and 4.11). This also offers an important insight for pro-active churn management, that is, firm should personalize (or at least segmented) its transparency strategies for different customers based on the relative positions of price and quality in the market where the firm's insurance is offered. Particularly, nudging customers to purchase from a transparent channel (e.g., comparison websites) significantly helps to retain them if the firms' offerings have a product quality advantage in the market; such a nudge makes no difference if the firms' offering has a price disadvantage. We elaborate this in our implications for managerial practice.

Table 4.12.
The Moderating Role of Transparent Channels in the Effects of Focal Firm's Price and Quality Status on Customer Churn

	Dependent Variable: Churn					
	OLS		Probit		Cox Proportional	
	(1)	(2)	(3)	(4)	(5)	(6)
Comparison	-0.043**	0.012	-0.210**	0.054	-0.363**	0.119
	(0.020)	(0.033)	(0.096)	(0.138)	(0.162)	(0.218)
Comparison ×(price advantage, quality advantage)		-0.111*		-0.693		-1.548
		(0.064)		(0.511)		(1.048)
Comparison × (price advantage, quality disadvantage)		-0.050		-0.271		-0.497
		(0.050)		(0.266)		(0.430)
Comparison × (price disadvantage, quality advantage)		-0.078**		-0.398**		-0.727***
		(0.033)		(0.156)		(0.258)
Comparison × (price disadvantage, quality disadvantage)		Baseline		Baseline		Baseline
All Covariates	YES	YES	YES	YES	YES	YES
# of Observations	1,200	1,200	1,200	1,200	1,200	1,200

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.6 Robustness, Heterogeneity, and Economic Significance

Having identified the churn-reducing effect of information transparency and explored the underlying mechanisms, next we extend our empirical analysis to the robustness, heterogeneity, and economic significance of the identified effect. First, we check the robustness of our findings for first-time and repeat customers. We vary the measures of transparent and control channels. We account for other potential confounders related to channel selection, and replicate the analysis using a subjective measure of information transparency by exploiting survey data. Next, we discuss alternative explanations for the churn-reducing effect of transparent channels and explore the heterogeneous effects across customers, their insured vehicles, and their contract choices. Finally, we conduct a conservative calculation of the economic significance.

4.6.1 Robustness Checks

First-time versus Repeat Customers

In the DID estimation, we use the sample of customers who made purchases multiple times from the focal insurance company. It is possible that these repeat customers are generally more loyal, thus less likely to churn, than those who only purchased once. To check if the estimated effect is sensitive to different customer groups, we analyze subsamples of first-time customers (65,791 contract observations) and repeat customers (16,421 contracts for 7,809 customers) separately. We cluster the standard errors for each repeat customer to account for series autocorrelations within their observations. Table I-1 in Appendix I reports the results using LPM for ease of comparison. We find that the churn-reducing effects of using a comparison website for both customer groups are consistent in terms of sign and significance; however, the effect size is larger (0.188, $p<0.01$) for repeat customers (0.038, $p<0.01$). This meets our intuition that loyalty does bring in some heterogeneity; however, irrespective of loyalty

(Columns 1 and 2), using a transparent channel statistically significantly lowers customers' churn likelihood.

Alternative Operationalization for Transparent Channels

We next check if our main results are robust to alternative measures for our independent variable, $Comparison_i$. Specifically, we vary the operationalization of the treatment groups by running a sub-sample analysis on different comparison websites. 82.9% of the 37,735 customers acquired from third-party comparison websites are from a well-known one (referred to as "A") that dominates the market in the study country. We replicate the estimates using customers from comparison website "A" and those from other comparison websites, separately. Table I-2 reports the results. The negative coefficient on $Comparison_i$ still holds, regardless of whichever comparison websites customers used for purchase. This rules out the possibility that differences in comparison websites other than information transparency actually drive the observed effect.

Different Control Groups

We further test if our main results are robust to alternative baseline channels (associated with lower information transparency). In the main analyses, the baseline channel (when $Comparison_i$=0) is an aggregate of all other channels, except for the third-party comparison websites. However, the heterogeneity in information transparency may vary depending on different pairwise comparisons between channels. Using an aggregated baseline that proxies less transparent channels does not consider such heterogeneities in information provision.[xxviii] To mitigate this concern, we check the robustness of the observed effect of information transparency by varying the baseline channels. In addition, we replicate this robustness check by adjusting regression analyses using matching techniques. Table I-3 and I-4 shows the results, which indicate that, the comparison website has a consistent advantage in reducing churn, regardless of whether a less transparent channel is chosen as the baseline channel.

Survey Data Analysis on Channel Selection Bias

While the estimated effect remains robust using various identification strategies that account for or identify observed and unobserved confounders, it is still possible that several factors that are associated with the channel selection before, during or after the initial insurance purchase may actually drive the customers' churn decision. For example, before acquisition, customers may gather product and price information from multiple channels. Our main estimate may be biased if such a multi-channel interference exists. Moreover, customers may be predisposed to be more (or less) satisfied with certain acquisition channels. This predisposition may influence their churn decision later. Furthermore, during customer acquisition, the time duration of getting a quote, ease of use, and likelihood of stopping the quote without actual purchase may be heterogeneous across acquisition channels. These factors represent search and acquisition cost of shopping through different channels. Finally, after acquisition, customers may search or

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[xxviii] For instance, the firm's own quote website functions similar to a third-party comparison website by providing product and price information of an insurance, while only shows that of the focal firm's products. However, online advertising is quite different, compared to the firm's website or a comparison website, in displaying such information.

obtain information of alternative offerings. The probability of this post-search activities may vary if customers are previously acquired from different channels. In summary, all these unobservables before, during, and after customer acquisition may lead to potential selection biases. Hence, to account for these heterogeneities, we design and conduct a survey to directly measure and incorporate them into our main analysis. We restrict survey participants to drivers who reside in the focal country and have insurance shopping experience, and we ask them to rate the likelihood of multi-channel information gathering, satisfaction, search cost, and acquisition costs of all channels (e.g., comparison website) for insurance purchase (See Table J-1 in Appendix J). We also ask information about themselves, their vehicles and insurance.[xxix] Next, and more importantly, we incorporate these newly-measured variables into our main dataset and replicate the analysis. Specifically, we predict and generate values for these new variables using multinomial regressions of them on a set of covariates on customer, vehicle, and insurance (See Table J-3). Then, we use them as covariates in the main analysis. Results are shown in Table J-4, which indicate the robustness of the observed effect, even after accounting for potential confounding variables.

Survey Data Analysis on the Measure of Information Transparency

In the main analysis, we use a comparison website to proxy a channel with high information transparency (as in our hypotheses). While we control for other differences

[xxix]While survey participants may not be customers of the focal company, we do not find that they statistically significant differ from those in the main date set (See Table J-2). This suggests that findings from both survey and our main archival dataset can be generalized to a broader population of insurance customers.

(e.g., acquisition costs) across channels besides information transparency, we do not directly measure information transparency. Next, we exploit a subjective measure of information transparency, and we examine if our main estimate holds consistent when using this alternative measure as independent variable. Specifically, we ask survey participants to rate the level of information transparency for each channel. Then, we predict the value of the perceived transparency for each customer in our main data set, generate a new variable, Transparency, replace our dummy variable, Comparison, and replicate the main analysis. In Table J-5, we find that the churn-reducing effect remains significant (-0.400, $p<0.01$) when we alternate the measure of information transparency.

4.6.2 Treatment Effect Heterogeneity

Next, we investigate alternative explanations for our identified main effect. First, we check if the brand effect actually explains the reason why a transparent comparison website helps to retain customers. Second, we examine the heterogeneous effect of after-sales factors, including service usage and customer satisfaction. Third, we analyze on subsamples to see if our identified effect varies across customers, cars, and contracts.

Brand Image

One plausible explanation for the churn-reducing effect would be that brands are easily compared in a more transparent channel; thus, the brand effect (or firm's reputation in the market) could plausibly be a more dominant driver of customer churn than price/product transparency. This explanation echoes early work on consumer behaviors on online Shopbots (Smith and Brynjolfsson 2001), which suggested that brand is an important predictor of customer choice, and that heavily-branded retailers hold a major advantage over more generic retailers in head-to-head price comparison on highly transparent channel. In our setting, insurance providers with greater popularity exhibit a larger brand effect over other providers. Hence, we need to differentiate the effect of brand image versus product informedness as they both function similarly to signal product quality. We use # Ratings Advantage (=1 if the number of ratings for focal firm (A) > the number of ratings for the best competitor (B), 0 otherwise), indicating a comparative advantage of brand image. Table I-5 in Appendix I presents the results of the brand effect. We observe a significant negative effect of brand image on customer churn (-0.098, $p<0.05$, Column 1), supporting the literature on the brand effect (e.g., Chen and Sudhir 2004, Tang et al. 2010). However, when a comparison website was used, the branding effect is not statistically significant (-0.126, $p>0.1$, Column 2). This suggests that a transparent channel does not necessarily enhance the brand effect, thereby ruling out the alternative explanation that it is due to the easier comparison between brands that drives the customer churn-reducing effect in a more transparent channel.

Service Usage

We examine if the effects of a transparent channel on customer churn vary depending on the level of service usage. Service usage has been discussed extensively in the customer retention literature (e.g., Ahn et al. 2006). For example, in the telecommunications industry, service usage can be measured as the number of phone calls made. However, in the auto insurance industry, service occurs only when the insured cars are damaged or stolen. After a claim and compensation, a customer typically expects a surge in premiums in the next contract term. Often times, she will be sensitive to potential premium increases, and more likely to search for and even switch to other insurance providers (e.g., Roos et al. 2004). Let's consider the churn probability of customers who claim damage across different channels. Recall Hypothesis H1b that if customers are better informed about the product and price, the insurance they purchased would be the best they can choose. Table I-6 shows supportive evidence for this intuition. Column 1 shows that a damage claim significantly induces customer churn (0.015, $p<0.01$). Column 2 shows a negative and significant interaction effect between damage claimed and using a comparison website (-0.022, $p>0.1$). This implies that the churn-inducing effect of damage claims is attenuated in a more transparent channel, supporting the hypothesis that product informedness exerts a long-term effect to retain customers.

Customer Service Satisfaction

The consumer retention literature (e.g., Gustafsson et al. 2003) has documented that customer satisfaction is a major after-acquisition factor that predicts customer churn. Thus, we examine if the effect of customer satisfaction on retention would be different for customers from channels with distinct levels of information transparency. The better a customer is informed of price and product at purchase, the more likely the service experience will meet her expectation. In other words, even if a customer is not satisfied with the service experience, if she comes from a transparent channel, she might be aware of the customer experience ahead of time, thus less likely to churn than those customers from other channels whose prior expectation of the service experience may largely differ from the actual experience later on. Columns 1 and 2 in Table I-7 report the results on customer satisfaction using the focal firm's own customer survey data. We adopt a satisfaction measure using the response to the question: “How satisfied are you with our insurance?”, on a 1-5 scale (1=Very Dissatisfied, 5=Very Satisfied). Column 1 shows that higher satisfaction leads to a lower churn rate (-0.011, $p<0.1$), consistent with extant customer retention literature (e.g., Bolton 1998). Column 2 shows that a negative effect of customer satisfaction on churn is greater for customers from a comparison website versus those from less transparent channels (-0.026, $p<0.1$), supporting that a transparent channel may retain customers in the long term by narrowing the difference between the expected and actual customer experiences in advance at the time of purchase.

Heterogeneity in Customers, Cars, and Contracts

An overall negative effect of a transparent channel on customer churn may not be informative for developing an effective churn management strategy as the heterogeneity in customers’ characteristics, their cars and contracts should be further considered, given that insurance is a highly personalized product. We empirically explore a variety of treatment effect heterogeneity. Table I-8 presents the results. We find the churn-reducing effect of using a comparison website is still very robust, even in the subsample analyses. For example, there exists no difference in terms of gender, original car price, insurance types (i.e., liability, limited comprehensive, comprehensive) for our observed effect. Some insignificant effects (e.g., customers aged below 35 or above 65) may be merely due to relatively small subsample size. In sum, the findings suggest that the churn-reducing effect is very robust across different customer segments. This not only mitigates the concern of sample selection, but importantly, it also indicates that attracting customers from more transparent channels could be effective in retaining customers.

4.6.3 Economic Significance of the Main Effects

The literature has discussed consumer surplus by using transparent/opaque channels (Granados 2010), but firm surplus from a transparency strategy perspective is not clear, despite its long-term economic value. We integrate the estimate of the churn-reducing effect and tenure of churners for back-of-the-envelope calculations of the economic value of allocating customers to transparent acquisition channels. We focus on three managerially-relevant factors, *overall churn rate*, *number of churners (who could have been retained)*, and *revenue gain/loss* if churners from low transparent channels had purchased from a comparison website. We use coefficient (ρ_1) of the LPM estimator for the ease of interpretation. We set the lower bound of relative churn rate as 4.6% (Column 1 in Table 4.4), the *conditional* effect of using a comparison website, and the higher bound of the relative churn rate at 6.1%, the *unconditional* effect simply using the difference in the mean of the customer churn between comparison website customers and non-comparison website customers. Thus, the relative churn rate $\rho_1 \in [0.046, 0.061]$.

First, we calculate the overall churn rate if churners were previously acquired from other channels, had they purchased from comparison website, using the following formula: (the number of churners from a comparison website + (1- ρ1) × the number of churners from other channels) / (total number of customers) Hence, we obtain the overall churn rate in the interval between [45.99%, 46.54%], which is lower than the overall actual churn rate (47.85%) in our dataset, reduced by 2.74% ~ 3.89%.

Second, we calculate the number of churners that could have been retained, had churners who were previously acquired from other channels purchased via a comparison website using the following formula: total number of customers × overall churn rate. We obtain the number of churners in the interval of [37,817, 38,261], which would be smaller than the 39,338 actual churners in our sample. This indicates that a comparison website could have retained about 1,077 to 1,521 additional customers.

Third, we calculate the revenue gain or loss if non-comparison churners could have not churned using the formula: number of saved churners × average premium per month × number of months until March 2015.[xxx] We obtain the revenue gain in the interval between [€382,960, €540,839] for the focal firm. Note that it is a conservative estimate since it is calculated based on the extended customer lifetime value until March 2015 for customers acquired between October 2008 and March 2015. We expect the retained customers would stay longer with the firm and bring in additional revenues.

4.7. Discussion

4.7.1 Summary of Findings

In this study, we examine the role of information transparency in customer churn. Specifically, we focus on comparison websites that provide a high level of information transparency. Utilizing a unique large-scale dataset from a European insurance company, we conducted a series of econometrics analyses, such as LPM, Probit model, and survival analysis. Findings are further cross-validated using a matching technique, as well as a difference-in-differences approach on a quasi-experimental setting where customers

[xxx] = (# months between contract signed month and March 2015 for non-churners) – (contract duration for churners).

could not get access to comparison websites for a period. First, our results demonstrate counter-intuitive, but consistent, evidence that customers acquired from a third-party quote comparison website (the most transparent channel) are at least 4.60% less likely to churn than those from other channels, implying that information transparency helps to reduce customer churn. Second, we investigate the underlying mechanism on what drives the customer churn-reducing effect of information transparency. Suggestive evidence shows that produce informedness prevails price informedness in explaining the overall negative effect of information transparency on customer churn. Finally, we show that the identified effect of information transparency is also economically attractive.

4.7.2 Contributions to Research on Information Transparency and Customer Churn

This research has several theoretical contributions. First, to our knowledge, this is the first study to theorize and quantify the effect of information transparency on customer churn, thereby extending literature on customer retention (e.g., Schweidel et al. 2008). While extant customer retention research has discussed a number of churn drivers (see Ascarza et al. (2017) for a review), such as customer satisfaction, usage behavior, social connection, we extend the literature by introducing and formally theorizing information transparency (more precisely, how much information the customers were exposed to when they were acquired) as a key predictor of customer churn. More specifically, we show evidence that providing transparent information of product quality at the initial acquisition phase has a long-term effect on customer churn.

Second, to study the effect of information transparency on customer churn, we exploit the variation across acquisition channels with different levels of price and product transparency. Specifically, we focus on third-party quote comparison websites which provide the most transparent market information of price and product. Extant literature on acquisition channels (e.g., Verhoef and Donkers 2005) has not discussed the different levels of information transparency. Moreover, we disentangle between product informedness and price informedness, theorize, and empirically examine their effects on customer churn to better understand the underlying mechanisms of produce and price information provision in customer retention.

Third, while existing literature on comparative shopping has extensively focused on price dispersion, price sensitivity, and their immediate or short-term on purchasing choice (e.g., Ellison and Ellison 2009), extending this literature, we focus on the long-term effect of information transparency by capturing the difference in information provision across different acquisition channels.

4.7.3 Implications for Churn Management and Multi-Channel Attribution

Our study also provides insights for managerial practice. First, the churn problem is a core issue for most service industries. Numerous customer retention and churn management programs and strategies have been launched and implemented in firms, but not all of them are successful, and most of them seem futile (Muti 2015, Ascarza 2018). Our findings on the churn-reducing effect of information transparency implies that firms should adjust their customer retention strategy by taking a better advantage of transparent channels in order to proactively manage customer churn. We also shed light on the mechanisms by which a transparent channel works, advising managers to focus more on product transparency to gain a competitive advantage to retain customers in the long run.

Relatedly, but more practically, we advise managers to include information transparency strategy (e.g., investing more in or attributing more to transparent channels) by aligning with their relative positions of price and product quality in the market. For instance, if the firm holds a quality advantage compared to other providers' products or services, the transparency strategy would work the best.

Second, firms do acquire customers from multiple channels, but they do not estimate, or even anticipate, the long-term effect of utilizing multiple channels. Our study looks at the informational role of multiple channels on customer relationship management, differentiates channels based on their level of product and price transparency, and suggests that transparent channels benefit firms in the long-term so that firms consider focusing more on such channels as comparison websites. Moreover, our empirical evidence shows that a comparison website is able to strengthen the positive role of the rating score in reducing customer churn, but it does not significantly affect the effect of price differentials on customer churn. The relative importance of product quality transparency to price transparency is substantial enough so that firms should leverage the potential of transparent channels and prioritizing product transparency for effective customer churn management if they hold a comparative advantage in product quality.

Finally, as firms often confront the question of which channel to invest and how much allocate their budget and resources among multiple channels, our study suggests that firms should invest in high transparent channels, especially when the product quality is high, because of their effectiveness in retaining customers. This also relates to attribution problem in marketing on how to allocate budgets to multiple channels to enhance advertising effectiveness (Kannan et al. 2016). Consistent with this line of work, we suggest that information transparency, especially product transparency, should be taken into consideration as a key metric to evaluate the effectiveness of long-term resource allocation among multiple channels. In practice, for each customer, a firm should differentiate transparency strategies by analyzing the relative market positions of its product offerings in terms of price and quality. Operationally, directing customers to purchase via transparent channels (e.g., comparison websites) significantly helps a firm to retain customers if its product has a quality advantage in the market, while it may be less effective if its product offerings have price disadvantage.

4.7.4 Limitations and Future work

We also acknowledge a number of limitations that create interesting avenues for future research. First, due to data availability, we cannot observe how many channels customers actually checked before their decision to purchase insurance, renew, or terminate their contract. The concern arises when customers obtain as much information as possible from multiple different channels before the acquisition, which may cause our identified effect to be overestimated or underestimated. We show that the concern is actually not serious using the following evidence. First, our difference-in-differences analysis on the quasi-experimental setting avoids possible interference among channels. During the disruption, customers could not access to the comparison website, so they could only use their information collected from less transparent channels to make their decision. The estimated effect size from the quasi-experiment is slightly larger than that from the baseline regressions (Table 4.10), which suggests the interference between transparent and less transparent channels leads to the underestimation of the average churn-reducing effect. Second, in the robustness check, we analyze survey data, measure multi-channel information gathering directly, and find that our identified effect remains robust. Having said that, further efforts to quantify the multi-channel information search behaviors more precisely are needed. For example, linking ex-post churn decision to ex-ante browsing and purchasing behaviors using detailed information (e.g., click-stream data, customer call logs) across channels would be promising for future research.

Second, our dataset is collected from one firm in one industry (i.e., insurance industry) so we cannot observe how customers switch insurance providers over time. While we supplement our main analysis with search cost and acquisition cost across acquisition channels in order to account for potential switching costs to some extent, additional efforts could be taken to make data available for better identifying the actual switching behavior in the insurance market and its causes, especially, information transparency. Our findings can be cautiously generalized to other service industries (e.g., telecommunications, financial services) that the service offerings may be similar. Future research can still use our findings as a starting place to generalize the nature and relationship between information transparency and customer churn in other contexts.

Finally, we did not study the effect of information transparency on balancing customer churn and customer profitability from the firm's perspective. This is practically attractive as likely churners from transparent channels could be different in terms of profitability compared to churners from other channels. Also, some customers may not be profitable to retain. The companies would be better off by letting such customers go. This again calls for a synthetic analysis of customer churn likelihood and their life time value. While we did a conservative estimate on the extended customer lifetime value if customers acquired from low-transparent channels have not had churned, we encourage richer granular data and more rigorous tests for a comprehensive understanding of the business value of utilizing transparent channels in the long term, which merits more attention to bridge consumer relationship management and revenue management.

4.8 Concluding Remarks

Our work represents initial efforts to theorize and quantify the impact of information transparency on customer churn. Moreover, the study unravels the mechanisms by examining the role of price and product transparency in (inducing or reducing) customer churn across channels with distinct levels of information transparency. The study thus extends the information systems, marketing, and economics literatures on the under-researched relationship between customer churn and information transparency, and it provides practical implications for the design of transparency strategy through digital channels, such as allocating more resources to transparent channels to retain customers. Further research could discuss how information transparency helps to retain *different types of customers* with *different information preferences* for *different types of product/services*, and how information transparency helps to balance customer acquisition and retention, gain more profits, and reduce churn.

CHAPTER 5

CONCLUSION

Digital transformation has profoundly changed businesses, segments of society, and individuals' life. In the digital era, we have seen the changing perspective of digitization from the technology-deterministic to human-centric; however, extant research has not paid much attention to such a transition. In this dissertation, I propose a notion, "digital citizenship", to stress and reexamine the nature and impact of digitization from a human-centric view and embed digitization in a broader social context.

To elaborate on the notion of digital citizenship, I study the informative, automate, and transformative roles of digitization in our everyday lives. From the perspective of a driver, this dissertation shows whether, how, and why various digital technologies facilitate human decision making in travel schedule, safety effort, and insurance consumption, and offers implications for all involving parties, including businesses and governments. This dissertation builds on theories from information systems, management, economics, and marketing, and makes solid contributions to the interdisplinary inquiries: (i) how do commuters and governments benefit from digital technology to facilitate mobility? (ii) how can drivers be nudged to make their own safety efforts in a smart city? (iii) how do consumers and businesses develop long-term relationships via digital channels? To wit, this dissertation directs a promising and fruitful avenue for understanding the welfare-inducing role of digital transformation.

BIBLIOGRAPHY

2015 Annual Urban Mobility Scorecard. Retrieved from https://mobility.tamu.edu/ums/

Abhishek, V., Fader, P., & Hosanagar, K. (2012). *Media Exposure through the Funnel: A Model of Multi-Stage Attribution* (SSRN Scholarly Paper No. ID 2158421). Retrieved from Social Science Research Network website: https://papers.ssrn.com/abstract=2158421

Abouk, R., & Adams, S. (2013). Texting bans and fatal accidents on roadways: do they work? Or do drivers just react to announcements of bans? *American Economic Journal: Applied Economics*, *5*(2), 179–99.

Ahn, J.-H., Han, S.-P., & Lee, Y.-S. (2006). Customer churn analysis: Churn determinants and mediation effects of partial defection in the Korean mobile telecommunications service industry. *Telecommunications Policy*, *30*(10), 552–568.

Akerlof, G. A., & Dickens, W. T. (1982). The economic consequences of cognitive dissonance. *American Economic Review*, *72*(3), 307–319.

Allgulin, M., & Ellingsen, T. (2002). Monitoring and pay. *Journal of Labor Economics*, *20*(2), 201–216.

Ameratunga, S., Hijar, M., & Norton, R. (2006). Road-traffic injuries: confronting disparities to address a global-health problem. *The Lancet*, *367*(9521), 1533–1540.

Anderson, M. L. (2014). Subways, strikes, and slowdowns: The impacts of public transit on traffic congestion. *The American Economic Review*, *104*(9), 2763–2796.

Anderson, S. P., & Renault, R. (2006). Advertising content. *The American Economic Review*, *96*(1), 93–113.

Angrist, J. D., & Pischke, J.-S. (2008). *Mostly harmless econometrics: An empiricist's companion*.

Arnott, R. (2001). The economic theory of urban traffic congestion: a microscopic research agenda. *Workshop on Environmental Economics and the Economics of Congestion: Coping with Externalities, Venice International University, Venice Summer Institute, San Servolo, Italy.* Retrieved from http://boots.bc.edu/islandora/object/bcir:103086/datastream/PDF/download/citation.pdf

Arnott, R., & Small, K. (1994). The economics of traffic congestion. *American Scientist*, *82*(5), 446–455.

Arnott, R., De Palma, A., & Lindsey, R. (1991). Does providing information to drivers reduce traffic congestion? *Transportation Research Part A: General*, *25*(5), 309–318.

Arnott, R., Rave, T., Schöb, R., & others. (2005). Alleviating urban traffic congestion. *MIT Press Books*, *1*.

Ascarza, E. (2018). Retention Futility: Targeting High-Risk Customers Might be Ineffective. *Journal of Marketing Research*, *55*(1), 80–98.

Ascarza, E., & Hardie, B. G. (2013). A joint model of usage and churn in contractual settings. *Marketing Science*, *32*(4), 570–590.

Ascarza, E., Fader, P. S., & Hardie, B. G. (2017). Marketing models for the customer-centric firm. In *Handbook of Marketing Decision Models* (pp. 297–329). Springer.

Ascarza, E., Iyengar, R., & Schleicher, M. (2016). The perils of proactive churn prevention using plan recommendations: Evidence from a field experiment. *Journal of Marketing Research*, *53*(1), 46–60.

Ascarza, E., Neslin, S. A., Netzer, O., Anderson, Z., Fader, P. S., Gupta, S., … Neal, D. (2017). In Pursuit of Enhanced Customer Retention Management: Review, Key Issues, and Future Directions. *Customer Needs and Solutions*, 1–17.

Ashenfelter, O., & Greenstone, M. (2004). Using Mandated Speed Limits to Measure the Value of a Statistical Life. *Journal of Political Economy*, *112*(S1), S226–S267.

Athey, S., & Imbens, G. (2016). Recursive partitioning for heterogeneous causal effects. *Proceedings of the National Academy of Sciences*, *113*(27), 7353–7360.

Auer, A., Feese, S., & Lockwood, S. (2016). *History of Intelligent Transportation Systems*. Intelligent Transportation Systems Joint Program Office, U.S. Department of Transportation. Report number: FHWA-JPO-16-329.

Austin, P. C. (2011). An introduction to propensity score methods for reducing the effects of confounding in observational studies. *Multivariate Behavioral Research*, *46*(3), 399–424.

Autor, D. H. (2003). Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing. *Journal of Labor Economics*, *21*(1), 1–42.

Bain Insights. (2012). Calculating The Economics Of Loyalty. Retrieved March 31, 2017, http://www.forbes.com/sites/baininsights/2012/11/15/calculating-the-economics-of-loyalty/

Barth, M., & Boriboonsomsin, K. (2008). Real-world carbon dioxide impacts of traffic congestion. *Transportation Research Record: Journal of the Transportation Research Board*, (2058), 163–171.

Baum-Snow, N. (2007). Did highways cause suburbanization? *The Quarterly Journal of Economics*, *122*(2), 775–805.

Baye, M. R., & Morgan, J. (2002). Information gatekeepers and price discrimination on the internet. *Economics Letters*, *76*(1), 47–51.

Becker, G. S. (1965). A Theory of the Allocation of Time. *The Economic Journal*, 493–517.

Becker, G. S. (1968). Crime and punishment: An economic approach. In *The Economic Dimensions of Crime* (pp. 13–68). Springer.

Ben-Akiva, M., De Palma, A., & Isam, K. (1991). Dynamic network models and driver information systems. *Transportation Research Part A: General*, *25*(5), 251–266.

Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How Much Should We Trust Differences-in-Differences Estimates? *The Quarterly Journal of Economics*, 249–275.

Bharadwaj, A. S., Sambamurthy, V., & Zmud, R. W. (2002). Firmwide IT capability: An empirical examination of the construct and its links to performance. *Emory University*.

Bharadwaj, S., Bharadwaj, A., & Bendoly, E. (2007). The performance effects of complementarities between information systems, marketing, manufacturing, and supply chain processes. *Information Systems Research*, *18*(4), 437–453.

Bhargava, S., & Pathania, V. S. (2013). Driving under the (cellular) influence. *American Economic Journal: Economic Policy*, *5*(3), 92–125.

Blackwell, M., Iacus, S. M., King, G., & Porro, G. (2009). cem: Coarsened exact matching in Stata. *The Stata Journal*, *9*(4), 524–546.

Blomquist, G. (1986). A utility maximization model of driver traffic safety behavior. *Accident Analysis & Prevention*, *18*(5), 371–375.

Bloom, N., Garicano, L., Sadun, R., & Reenen, J. V. (2014). The Distinct Effects of Information Technology and Communication Technology on Firm Organization. *Management Science*.

Bolton, R. N. (1998). A dynamic model of the duration of the customer's relationship with a continuous service provider: The role of satisfaction. *Marketing Science*, *17*(1), 45–65.

Bourgeon, J.-M., & Picard, P. (2007). Point-record driving licence and road safety: an economic approach. *Journal of Public Economics*, *91*(1–2), 235–258.

Boyer, M., & Dionne, G. (1987). The economics of road safety. *Transportation Research Part B: Methodological*, *21*(5), 413–431.

Brockett, P. L., Golden, L. L., Guillen, M., Nielsen, J. P., Parner, J., & Perez-Marin, A. M. (2008). Survival analysis of a household portfolio of insurance policies: how much time do you have to stop total customer defection? *Journal of Risk and Insurance*, *75*(3), 713–737.

Brynjolfsson, E., & Hitt, L. M. (2000). Beyond computation: Information technology, organizational transformation and business performance. *The Journal of Economic Perspectives*, *14*(4), 23–48.

Brynjolfsson, E., & Hitt, L. M. (2003). Computing Productivity: Firm-Level Evidence. *The Review of Economics and Statistics*, *85*(4), 793–808.

Brynjolfsson, E., & Smith, M. D. (2001). The great equalizer? Consumer choice behavior at Internet shopbots. *SSRN*. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=290323

Burchfield, M., Overman, H. G., Puga, D., & Turner, M. A. (2006). Causes of sprawl: A portrait from space. *The Quarterly Journal of Economics*, *121*(2), 587–633.

Burris, S., & Anderson, E. (2013). *Legal regulation of health-related behavior: a half century of public health law research*.

Cawley, J., & Ruhm, C. (2011). *The Economics of Risky Health Behaviors* (Working Paper No. 17081).

Cervero, R. (2002). Induced travel demand: Research design, empirical evidence, and normative policies. *Journal of Planning Literature*, *17*(1), 3–20.

Chalfin, A., Danieli, O., Hillis, A., Jelveh, Z., Luca, M., Ludwig, J., & Mullainathan, S. (2016). Productivity and selection of human capital with machine learning. *American Economic Review*, *106*(5), 124–27.

Chan, J., & Ghose, A. (2013). Internet's dirty secret: Assessing the impact of online intermediaries on HIV transmission. *MIS Quarterly*, *38*(4), 955–976.

Chatterjee, D., Richardson, V. J., & Zmud, R. W. (2001). Examining the shareholder wealth effects of announcements of newly created CIO positions. *MIS Quarterly*, 43–70.

Chen, P.-Y., & Hitt, L. M. (2002). Measuring switching costs and the determinants of customer retention in Internet-enabled businesses: A study of the online brokerage industry. *Information Systems Research*, *13*(3), 255–274.

Chen, P.-Y., & Hitt, L. M. (2006). Information technology and switching costs. *Handbook on Economics and Information Systems*, *1*, 437–470.

Chen, Yihsu, & Whalley, A. (2012). Green infrastructure: The effects of urban rail transit on air quality. *American Economic Journal: Economic Policy*, *4*(1), 58–97.

Chen, Yuxin, & Sudhir, K. (2004). When shopbots meet emails: Implications for price competition on the Internet. *Quantitative Marketing and Economics*, *2*(3), 233–255.

Cheng, Z. A., Dimoka, A., & Pavlou, P. A. (2016). Context may be King, but generalizability is the Emperor! *Journal of Information Technology*, *31*(3), 257–264.

Chevalier, J., & Goolsbee, A. (2003). Measuring prices and price competition online: Amazon. com and BarnesandNoble. com. *Quantitative Marketing and Economics*, *1*(2), 203–222.

Clemons, E. K. (2008). How information changes consumer behavior and how consumer behavior determines corporate strategy. *Journal of Management Information Systems*, *25*(2), 13–40.

Clogg, C. C., Petkova, E., & Haritou, A. (1995). Statistical methods for comparing regression coefficients between models. *American Journal of Sociology*, *100*(5), 1261–1293.

Coben, J. H., & Zhu, M. (2013). Keeping an eye on distracted driving. *JAMA*, *309*(9), 877–878.

Cohen, A., & Einav, L. (2003). The effects of mandatory seat belt laws on driving behavior and traffic fatalities. *Review of Economics and Statistics*, *85*(4), 828–843.

Cole, T. B. (2004). Global road safety crisis remedy sought. *JAMA*, *291*(21), 2531–2532.

Coren, S. (1996). Daylight Savings Time and Traffic Accidents. *New England Journal of Medicine*, *334*(14), 924–925.

Correia, S. (2017). Linear models with high-dimensional fixed effects: An efficient and feasible estimator. *Unpublished, Board of Governors of the Federal Reserve System*.

Couture, V., Duranton, G., & Turner, M. A. (2018). Speed. *Review of Economics and Statistics*, *100*(4), 725–739.

Cowgill, B. (2017). *Automating Judgement and Decision-making: Theory and Evidence from Résumé Screening*.

Cutler, D. M., & Glaeser, E. L. (1997). Are ghettos good or bad? *The Quarterly Journal of Economics*, *112*(3), 827–872.

DeAngelo, G., & Hansen, B. (2014). Life and Death in the Fast Lane: Police Enforcement and Traffic Fatalities. *American Economic Journal: Economic Policy*, *6*(2), 231–257.

Dee, T. S. (2009). Motorcycle helmets and traffic safety. *Journal of Health Economics*, *28*(2), 398–412.

Dee, T. S., & Evans, W. N. (2001). Behavior policies and teen traffic safety. *American Economic Review*, *91*(2), 91–96.

Dewees, D. N. (1979). Estimating the time costs of highway congestion. *Econometrica*, 1499–1512.

Diamond, D. W. (1991). Monitoring and reputation: The choice between bank loans and directly placed debt. *Journal of Political Economy*, *99*(4), 689–721.

Dickens, W. T. (1986). Crime and punishment again: the economic approach with a psychological twist. *Journal of Public Economics*, *30*(1), 97–107.

Dickens, W. T., Katz, L. F., Lang, K., & Summers, L. H. (1989). Employee crime and the monitoring puzzle. *Journal of Labor Economics*, *7*(3), 331–347.

Dionne, G., Pinquet, J., Maurice, M., & Vanasse, C. (2011). Incentive Mechanisms for Safe Driving: A Comparative Analysis with Dynamic Data. *Review of Economics and Statistics*, *93*(1), 218–227.

Downs, A. (1962). The law of peak-hour expressway congestion. *Traffic Quarterly*, *16*(3).

Downs, A. (2001, November 30). Stuck in Traffic. Retrieved April 18, 2019, from Brookings website: https://www.brookings.edu/book/stuck-in-traffic/

Draca, M., Machin, S., & Witt, R. (2011). Panic on the streets of london: Police, crime, and the july 2005 terror attacks. *American Economic Review*, *101*(5), 2157–81.

Dunning, T. (2012). *Natural experiments in the social sciences: a design-based approach*. Cambridge University Press.

Duranton, G., & Turner, M. A. (2011). The fundamental law of road congestion: Evidence from US cities. *The American Economic Review*, *101*(6), 2616–2652.

Duranton, G., & Turner, M. A. (2012). Urban growth and transportation. *Review of Economic Studies*, *79*(4), 1407–1440.

Edlin, A. S., & Karaca-Mandic, P. (2006). The accident externality from driving. *Journal of Political Economy*, *114*(5), 931–955.

Ehrlich, I. (1996). Crime, Punishment, and the Market for Offenses. *Journal of Economic Perspectives*, *10*(1), 43–67.

El Sawy, O. A., Malhotra, A., Park, Y., & Pavlou, P. A. (2010). Research commentary-Seeking the configurations of digital ecodynamics: It takes three to tango. *Information Systems Research*, *21*(4), 835–848.

Ellison, G., & Ellison, S. F. (2009). Search, obfuscation, and price elasticities on the internet. *Econometrica*, *77*(2), 427–452.

Emmerink, R. H., Verhoef, E. T., Nijkamp, P., & Rietveld, P. (1996). Information provision in road transport with elastic demand: A welfare economic approach. *Journal of Transport Economics and Policy*, 117–136.

Faccio, M., & McConnell, J. J. (2018). *Death by Pokémon GO: The Economic and Human Cost of Using Apps While Driving*. National Bureau of Economic Research.

Fader, P. S., & Hardie, B. G. (2007). How to project customer retention. *Journal of Interactive Marketing*, *21*(1), 76–90.

Fagnant, D. J., & Kockelman, K. (2015). Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. *Transportation Research Part A: Policy and Practice*, *77*, 167–181.

Frey, B. S. (1993). Does monitoring increase work effort? The rivalry with trust and loyalty. *Economic Inquiry*, *31*(4), 663–670.

Fridstrøm, L., Ifver, J., Ingebrigtsen, S., Kulmala, R., & Thomsen, L. K. ard. (1995). Measuring the contribution of randomness, exposure, weather, and daylight to the variation in road accident counts. *Accident Analysis & Prevention*, *27*(1), 1–20.

Gandy Jr, O. H. (1989). The surveillance society: information technology and bureaucratic social control. *Journal of Communication*, *39*(3), 61–76.

Ge, Y., Knittel, C. R., MacKenzie, D., & Zoepf, S. (2016). *Racial and gender discrimination in transportation network companies*. National Bureau of Economic Research.

Ghose, A., & Todri, V. (2015). Towards a Digital Attribution Model: Measuring the Impact of Display Advertising on Online Consumer Behavior. *MIS Quarterly*. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2672090

Gissane, W. (1963). The nature and causation of road injuries. *The Lancet*, *282*(7310), 695–698.

Glaeser, E. (2011). *Triumph of the city: How urban spaces make us human*. Pan Macmillan.

Godinho de Matos, M., Pedro, F., & Rodrigo, B. (2018). Target the Ego or Target the Group: Evidence from a Randomized Experiment in Proactive Churn Management. *Marketing Science*, *37*(5), 793–811.

Goldfarb, A., & Tucker, C. (2019). Digital economics. *Journal of Economic Literature*, *57*(1), 3–43.

Goncalves, F., & Mello, S. (2017). *Does the Punishment Fit the Crime? Speeding Fines and Recidivism*.

Gong, J., Greenwood, B. N., & Song, Y. (2018). *Uber Might Buy Me a Mercedes Benz: An Empirical Investigation of the Sharing Economy and Durable Goods Purchase* (SSRN Scholarly Paper No. ID 2971072). Retrieved from Social Science Research Network website: https://papers.ssrn.com/abstract=2971072

Goodwin, P. B. (1996). Empirical evidence on induced traffic. *Transportation*, *23*(1), 35–54.

Gopal, A., & Greenwood, B. N. (2017). Traders, guns, and money: The effects of mass shootings on stock prices of firearm manufacturers in the U.S. *PloS One*, *12*(5), e0177720.

Government Technology. (2010). Driving into the Future. *23*(6), 14-19.

Government Technology. (2011a). Smart highways: Active traffic management technology curbs congestion and improves safety. *24*(1), 14-20.

Government Technology. (2011b). Taming Traffic: Communities Use Technology to Fight Congestion. *24*(7), 16-22.

Granados, N. F., Gupta, A., & Kauffman, R. J. (2006). The Impact of IT on Market Information and Transparency: A Unified Theoretical Framework. *Journal of the Association for Information Systems, 7*(3).

Granados, N., Gupta, A., & Kauffman, R. J. (2010). Research commentary-information transparency in business-to-consumer markets: Concepts, framework, and research agenda. *Information Systems Research, 21*(2), 207–226.

Granados, N., Gupta, A., & Kauffman, R. J. (2012). Online and offline demand and price elasticities: Evidence from the air travel industry. *Information Systems Research, 23*(1), 164–181.

Greenwood, B. N., & Wattal, S. (2017). Show me the way to go home: an empirical investigation of ride sharing and alcohol related motor vehicle homicide. *MIS Quarterly*, (15–054).

Gupta, A., Su, B., & Walter, Z. (2004). Risk profile and consumer shopping behavior in electronic and traditional channels. *Decision Support Systems*, *38*(3), 347–367.

Hadden, J., Tiwari, A., Roy, R., & Ruta, D. (2007). Computer assisted customer churn management: State-of-the-art and future trends. *Computers & Operations Research*, *34*(10), 2902–2917.

Hansen, B. (2015). Punishment and deterrence: Evidence from drunk driving. *American Economic Review*, *105*(4), 1581–1617.

Hansen, J. K. (1997). The economics of traffic safety. *World Bank Report*.

Harrington, W., & Portney, P. R. (1987). Valuing the benefits of health and safety regulation. *Journal of Urban Economics*, *22*(1), 101–112.

Heckman, J. J. (1979). Sample Selection Bias as a Specification Error. *Econometrica*, *47*(1), 153–161.

Heckman, J. J., Ichimura, H., & Todd, P. E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The Review of Economic Studies*, *64*(4), 605–654.

Heckman, J., Ichimura, H., Smith, J., & Todd, P. (1998). Characterizing Selection Bias Using Experimental Data. *Econometrica*, *66*(5), 1017–1098.

Heller, S. B., Shah, A. K., Guryan, J., Ludwig, J., Mullainathan, S., & Pollack, H. A. (2017). Thinking, Fast and Slow? Some Field Experiments to Reduce Crime and Dropout in Chicago. *The Quarterly Journal of Economics*, *132*(1), 1–54.

Hoekstra, T., & Wegman, F. (2011). Improving the effectiveness of road safety campaigns: Current and new practices. *IATSS Research*, *34*(2), 80–86.

Holland, P. W. (1986). Statistics and Causal Inference. *Journal of the American Statistical Association*, *81*(396), 945–960.

Holmes, R. A. (1970). On the economic welfare of victims of automobile accidents. *American Economic Review*, *60*(1), 143–152.

Hsu, W.-T., & Zhang, H. (2014). The fundamental law of highway congestion revisited: Evidence from national expressways in Japan. *Journal of Urban Economics*, *81*, 65–76.

Huang, B., Kechadi, M. T., & Buckley, B. (2012). Customer churn prediction in telecommunications. *Expert Systems with Applications*, *39*(1), 1414–1425.

Hubbard, T. N. (2000). The demand for monitoring technologies: the case of trucking. *The Quarterly Journal of Economics*, *115*(2), 533–560.

Hung, S.-Y., Yen, D. C., & Wang, H.-Y. (2006). Applying data mining to telecom churn management. *Expert Systems with Applications*, *31*(3), 515–524.

Hyder, A. A., & Peden, M. (2003). Inequality and road-traffic injuries: call for action. *The Lancet*, *362*(9401), 2034–2035.

Jacobsen, M. R. (2011). Fuel Economy, Car Class Mix, and Safety. *American Economic Review*, *101*(3), 105–109.

Jacobson, P. D., & Gostin, L. O. (2010). Reducing distracted driving: regulation and education to avert traffic injuries and fatalities. *JAMA*, *303*(14), 1419–1420.

Jamal, Z., & Bucklin, R. E. (2006). Improving the diagnosis and prediction of customer churn: A heterogeneous hazard modeling approach. *Journal of Interactive Marketing*, *20*(3–4), 16–29.

Jenkins, S. P. (1995). Easy estimation methods for discrete-time duration models. *Oxford Bulletin of Economics and Statistics*, *57*(1), 129–136.

Jha, S. K., Pinsonneault, A., & Dube, L. (2016). The Evolution of an Ict Platform-Enabled Ecosystem for Poverty Alleviation: The Case of Ekutir. *MIS Quarterly*, *40*(2), 431–445.

Jin, G. Z., & Leslie, P. (2003). The effect of information on product quality: Evidence from restaurant hygiene grade cards. *The Quarterly Journal of Economics*, *118*(2), 409–451.

Jones, M. A., Reynolds, K. E., Mothersbaugh, D. L., & Beatty, S. E. (2007). The positive and negative effects of switching costs on relational outcomes. *Journal of Service Research*, *9*(4), 335–355.

Kannan, P. K., Reinartz, W., & Verhoef, P. C. (2016). *The path to purchase and attribution modeling: Introduction to special section*. Elsevier.

Kaul, A., & Wittink, D. R. (1995). Empirical generalizations about the impact of advertising on price sensitivity and price. *Marketing Science, 14*(3_supplement), G151–G160.

Kleinberg, J., Lakkaraju, H., Leskovec, J., Ludwig, J., & Mullainathan, S. (2017). Human decisions and machine predictions. *The Quarterly Journal of Economics*, *133*(1), 237–293.

Kocas, C. (2002). Evolution of prices in electronic markets under diffusion of price-comparison shopping. *Journal of Management Information Systems, 19*(3), 99–119.

Lagarde, E. (2007). Road Traffic Injury Is an Escalating Burden in Africa and Deserves Proportionate Research Efforts. *PLOS Medicine*, *4*(6), 170.

Lerner, B. H. (2011). Drunk driving, distracted driving, moralism, and public health. *New England Journal of Medicine*, *365*(10), 879–881.

Levitt, S. D. (2008). Evidence that seat belts are as effective as child safety seats in preventing death for children aged two and up. *Review of Economics and Statistics*, *90*(1), 158–163.

Li, H., & Kannan, P. K. (2014). Attributing conversions in a multichannel online marketing environment: An empirical model and a field experiment. *Journal of Marketing Research, 51*(1), 40–56.

Li, T., Kauffman, R. J., Van Heck, E., Vervest, P., & Dellaert, B. G. (2014). Consumer informedness and firm information strategy. *Information Systems Research, 25*(2), 345–363.

Liang, C., Hong, Y., & Gu, B. (2017). *IT-enabled Monitoring and Labor Contracting in Online Platforms: Evidence from a Natural Experiment*.

Lindgren, B., & Stuart, C. (1980). The Effects of Traffic Safety Regulation in Sweden. *Journal of Political Economy*, *88*(2), 412–427.

Linoff, G. S., & Berry, M. J. (2011). *Data mining techniques: for marketing, sales, and customer relationship management*.

Lochner, L. (2007). Individual perceptions of the criminal justice system. *American Economic Review*, *97*(1), 444–460.

Lynch Jr, J. G., & Ariely, D. (2000). Wine online: Search costs affect competition on price, quality, and distribution. *Marketing Science*, *19*(1), 83–103.

Lyon, D. (2001). *Surveillance society: Monitoring everyday life*. McGraw-Hill Education (UK).

Lyznicki, J. M., Doege, T. C., Davis, R. M., & Williams, M. A. (1998). Sleepiness, driving, and motor vehicle crashes. *JAMA*, *279*(23), 1908–1913.

Makowsky, M. D., & Stratmann, T. (2009). Political economy at any speed: what determines traffic citations? *American Economic Review*, *99*(1), 509–27.

Malhotra, A., Melville, N. P., & Watson, R. T. (2013). Spurring impactful research on information systems for environmental sustainability. *MIS Quarterly*, *37*(4), 1265–1274.

Marthews, A., & Tucker, C. E. (2017). *Government surveillance and internet search behavior*.

McAfee, A., & Brynjolfsson, E. (2017). *Machine, platform, crowd: Harnessing our digital future*. WW Norton & Company.

McCarthy, P. S. (1994). An empirical analysis of the direct and indirect effects of relaxed interstate speed limits on highway safety. *Journal of Urban Economics*, *36*(3), 353–364.

McCartt, A. T., Kidd, D. G., & Teoh, E. R. (2014). Driver cellphone and texting bans in the United States: evidence of effectiveness. *Annals of Advances in Automotive Medicine*, *58*, 99.

Melville, N. P. (2010). Information systems innovation for environmental sustainability. *MIS Quarterly*, *34*(1), 1–21.

Melville, N., Kraemer, K., & Gurbaxani, V. (2004). Information technology and organizational performance: An integrative model of IT business value. *MIS Quarterly*, *28*(2), 283–322.

Michaels, G. (2008). The effect of trade on the demand for skill: Evidence from the interstate highway system. *The Review of Economics and Statistics*, *90*(4), 683–701.

Mitra, A., & Lynch Jr, J. G. (1995). Toward a reconciliation of market power and information theories of advertising effects on price elasticity. *Journal of Consumer Research*, *21*(4), 644–659.

Mogridge, M. J. (1997). The self-defeating nature of urban road capacity policy: A review of theories, disputes and available evidence. *Transport Policy*, *4*(1), 5–23.

Mood, C. (2010). Logistic Regression: Why We Cannot Do What We Think We Can Do, and What We Can Do About It. *European Sociological Review*, *26*(1), 67–82.

MUTI. (2015). The Wrong Way to Reduce Churn. Retrieved May 5, 2016, from: https://hbr.org/2015/10/the-wrong-way-to-reduce-churn

Nagin, D. S., Rebitzer, J. B., Sanders, S., & Taylor, L. J. (2002). Monitoring, motivation, and management: The determinants of opportunistic behavior in a field experiment. *American Economic Review*, *92*(4), 850–873.

Neslin, S. A., Gupta, S., Kamakura, W., Lu, J., & Mason, C. H. (2006). Defection detection: Measuring and understanding the predictive accuracy of customer churn models. *Journal of Marketing Research*, *43*(2), 204–211.

Noland, R. B. (1997). Commuter responses to travel time uncertainty under congested conditions: expected costs and the provision of information. *Journal of Urban Economics*, *41*(3), 377–406.

Norris, C., & Armstrong, G. (1999). *The maximum surveillance society: The rise of CCTV* (Vol. 2). Berg Oxford.

Obermeyer, Z., & Emanuel, E. J. (2016). Predicting the future—big data, machine learning, and clinical medicine. *The New England Journal of Medicine*, *375*(13), 1216.

Organization, W. H. (2015). *Global status report on road safety 2015*. World Health Organization.

Pang, M.-S., & Pavlou, P. A. (2016a). *Armed with Technology: The Impact on Fatal Shootings by the Police*.

Pang, M.-S., & Pavlou, P. A. (2016b). *On Information Technology and the Safety of Police Officers* (SSRN Scholarly Paper No. ID 2746194). Retrieved from Social Science Research Network website: https://papers.ssrn.com/abstract=2746194

Pang, M.-S., Lee, G., & DeLone, W. H. (2014). IT resources, organizational capabilities, and value creation in public-sector organizations: a public-value management perspective. *Journal of Information Technology*, *29*(3), 187–205.

Pang, M.-S., Tafti, A., & Krishnan, M. S. (2014). Information Technology and Administrative Efficiency in U.S. State Governments: A Stochastic Frontier Approach. *MIS Quarterly*, *38*(4), 1079–1101.

Pang, M.-S., Tafti, A., & Krishnan, M. S. (2015). Do CIO IT Budgets Explain Bigger or Smaller Governments? Theory and Evidence from U.S. State Governments. *Management Science*, *62*(4), 1020–1041.

Papageorgiou, M., Diakaki, C., Dinopoulou, V., Kotsialos, A., & Wang, Y. (2003). Review of road traffic control strategies. *Proceedings of the IEEE*, *91*(12), 2043–2067.

Parry, I. W. (2004). Comparing alternative policies to reduce traffic accidents. *Journal of Urban Economics*, *56*(2), 346–368.

Paternoster, R., Brame, R., Mazerolle, P., & Piquero, A. (1998). Using the correct statistical test for the equality of regression coefficients. *Criminology*, *36*(4), 859–866.

Pavlou, P. A., & El Sawy, O. A. (2006). From IT leveraging competence to competitive advantage in turbulent environments: The case of new product development. *Information Systems Research*, *17*(3), 198–227.

Pavlou, P. A., & El Sawy, O. A. (2010). The "third hand": IT-enabled competitive advantage in turbulence through improvisational capabilities. *Information Systems Research*, *21*(3), 443–471.

Peltzman, S. (1975). The effects of automobile safety regulation. *Journal of Political Economy*, *83*(4), 677–725.

Petridou, E., & Moustaki, M. (2000). Human factors in the causation of road traffic crashes. *European Journal of Epidemiology*, *16*(9), 819–826.

Pierce, L., Snow, D. C., & McAfee, A. (2015). Cleaning house: The impact of information technology monitoring on employee theft and productivity. *Management Science*, *61*(10), 2299–2319.

Polinsky, A. M., & Shavell, S. (1979). The optimal tradeoff between the probability and magnitude of fines. *American Economic Review*, *69*(5), 880–891.

Priks, M. (2015). The effects of surveillance cameras on crime: Evidence from the Stockholm subway. *The Economic Journal*, *125*(588).

Rai, A., Pavlou, P. A., Im, G., & Du, S. (2012). Interfirm IT capability profiles and communications for cocreating relational value: evidence from the logistics industry. *MIS Quarterly*, *36*(1), 233–262.

Redelmeier, D. A., & Tibshirani, R. J. (1997). Association between cellular-telephone calls and motor vehicle collisions. *New England Journal of Medicine*, *336*(7), 453–458.

Reinartz, W., Thomas, J. S., & Kumar, V. (2005). Balancing acquisition and retention resources to maximize customer profitability. *Journal of Marketing*, *69*(1), 63–79.

Retting, R. A., Ferguson, S. A., & Hakkert, A. S. (2003). Effects of Red Light Cameras on Violations and Crashes: A Review of the International Literature. *Traffic Injury Prevention*, *4*(1), 17–23.

Rivara, F. P., Grossman, D. C., & Cummings, P. (1997). Injury Prevention. *New England Journal of Medicine*, *337*(8), 543–548.

Rocco, L., & Sampaio, B. (2016). Are handheld cell phone and texting bans really effective in reducing fatalities? *Empirical Economics*, *51*(2), 853–876.

Romem, I., & Shurtz, I. (2016). The accident externality of driving: Evidence from observance of the Jewish Sabbath in Israel. *Journal of Urban Economics*, *96*, 36–54.

Roos, I., Edvardsson, B., & Gustafsson, A. (2004). Customer switching patterns in competitive and noncompetitive service industries. *Journal of Service Research*, *6*(3), 256–271.

Rothenberg, J. (1970). The economics of congestion and pollution: an integrated view. *The American Economic Review*, 114–121.

Rothrock, C. A., & Keefer, L. E. (1957). *Measurement of urban traffic congestion*. Retrieved from https://trid.trb.org/view.aspx?id=120773

Rubin, D. B. (1997). Estimating causal effects from large data sets using propensity scores. *Annals of Internal Medicine*, *127*(8_Part_2), 757–763.

Rust, R. T., & Zahorik, A. J. (1993). Customer satisfaction, customer retention, and market share. *Journal of Retailing*, *69*(2), 193–215.

Saffer, H. (1997). Alcohol advertising and motor vehicle fatalities. *Review of Economics and Statistics*, *79*(3), 431–442.

Sahoo, N., Dellarocas, C., & Srinivasan, S. (2017). *The Impact of Online Product Reviews on Product Returns* (SSRN Scholarly Paper No. ID 2491276). Retrieved from https://papers.ssrn.com/abstract=2491276

Sakhapov, R., & Nikolaeva, R. (2017). Economic Aspects of Traffic Safety Administration. *Transportation Research Procedia*, *20*, 578–583.

Sambamurthy, V., Bharadwaj, A., & Grover, V. (2003). Shaping agility through digital options: Reconceptualizing the role of information technology in contemporary firms. *MIS Quarterly*, 237–263.

Sass, T., & Leigh, J. (1991). The Market for Safety Regulation and the Effect of Regulation on Fatalities - the Case of Motorcycle Helmet Laws. *Review of Economics and Statistics*, *73*(1), 167–172.

Schweidel, D. A., Fader, P. S., & Bradlow, E. T. (2008). Understanding service retention within and across cohorts using limited information. *Journal of Marketing*, *72*(1), 82–94.

Seamans, R., & Zhu, F. (2013). Responses to Entry in Multi-Sided Markets: The Impact of Craigslist on Local Newspapers. *Management Science*, *60*(2), 476–493.

Shapiro, C., & Varian, H. R. (1998). *Information rules: a strategic guide to the network economy*. Harvard Business Press.

Ship, A. N. (2010). The most primary of care—talking about driving and distraction. *New England Journal of Medicine*, *362*(23), 2145–2147.

Small, K. A., & Verhoef, E. T. (2007). *The economics of urban transportation*.

Small, K. A., Verhoef, E. T., & Lindsey, R. (2007). *The economics of urban transportation*. Routledge.

Smeed, R. J. (1949). Some statistical aspects of road safety research. *Journal of the Royal Statistical Society. Series A (General)*, *112*(1), 1–34.

Smith, M. D. (2002). The impact of shopbots on electronic markets. *Journal of the Academy of Marketing Science*, *30*(4), 446–454.

Smith, M. D., & Brynjolfsson, E. (2001). Consumer decision-making at an Internet shopbot: Brand still matters. *The Journal of Industrial Economics*, *49*(4), 541–558.

Soh, C., Markus, M. L., & Goh, K. H. (2006). Electronic marketplaces and price transparency: strategy, information technology, and success. *MIS Quarterly*, 705–723.

Stanton, N. A., & Salmon, P. M. (2009). Human error taxonomies applied to driving: A generic driver error taxonomy and its implications for intelligent transport systems. *Safety Science*, *47*(2), 227–237.

Stock, J. H., & Yogo, M. (2002). *Testing for weak instruments in linear IV regression*. National Bureau of Economic Research Cambridge, Mass., USA.

Strayer, D. L., & Johnston, W. A. (2001). Driven to distraction: Dual-task studies of simulated driving and conversing on a cellular telephone. *Psychological Science*, *12*(6), 462–466.

Strayer, D. L., Drews, F. A., & Crouch, D. J. (2006). A comparison of the cell phone driver and the drunk driver. *Human Factors*, *48*(2), 381–391.

Strayer, D. L., Drews, F. A., & Johnston, W. A. (2003). Cell phone-induced failures of visual attention during simulated driving. *Journal of Experimental Psychology: Applied*, *9*(1), 23.

Tang, Z., Smith, M. D., & Montgomery, A. (2010). The impact of shopbot use on prices and price dispersion: Evidence from online book retailing. *International Journal of Industrial Organization*, *28*(6), 579–590.

Tonry, M. (2008). Learning from the limitations of deterrence research. *Crime and Justice*, *37*(1), 279–311.

Train, K. (1980). A structured logit model of auto ownership and mode choice. *The Review of Economic Studies*, *47*(2), 357–370.

US Department of Transportation Federal Highway Administration. (2005, September). Implementation and Operational Guidelines for 511 Services, Version 3.0. https://ops.fhwa.dot.gov/511/resources/publications/511guide_ver3/511guide3.htm

Valavanis, S. (1958). Traffic safety from an economist's point of view. *The Quarterly Journal of Economics*, *72*(4), 477–484.

Van Dyke, C. W., Walton, J. R., & Ballinger, J. (2016). *Synthesis of Kentucky's Traveler Information Systems* (No. KTC-16-17/SPR16-56-2-1F; p. 54). Kentucky Transportation Center.

Verbeke, W., Dejaeger, K., Martens, D., Hur, J., & Baesens, B. (2012). New insights into churn prediction in the telecommunication sector: A profit driven data mining approach. *European Journal of Operational Research*, *218*(1), 211–229.

Verhoef, P. C. (2003). Understanding the effect of customer relationship management efforts on customer retention and customer share development. *Journal of Marketing*, *67*(4), 30–45.

Verhoef, P. C., & Donkers, B. (2005). The effect of acquisition channels on customer loyalty and cross-buying. *Journal of Interactive Marketing*, *19*(2), 31–43.

Vickrey, W. S. (1969). Congestion theory and transport investment. *The American Economic Review*, 251–260.

Vitaliano, D. F., & Held, J. (1991). Road accident external effects: an empirical assessment. *Applied Economics*, *23*(2), 373–378.

Wachs, M. (2002). Fighting traffic congestion with information technology. *Issues in Science and Technology*, *19*(1), 43–50.

Welsh, B. C., & Farrington, D. P. (2009). Public Area CCTV and Crime Prevention: An Updated Systematic Review and Meta-Analysis. *Justice Quarterly*, *26*(4), 716–745.

Wilde, G. J. (1982). The theory of risk homeostasis: implications for safety and health. *Risk Analysis*, *2*(4), 209–225.

Winston, C. (2013). On the performance of the US transportation system: Caution ahead. *Journal of Economic Literature*, *51*(3), 773–824.

Winston, C., & Langer, A. (2006). The effect of government highway spending on road users' congestion costs. *Journal of Urban Economics*, *60*(3), 463–483.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*.

Xu, L., Duan, J. A., & Whinston, A. (2014). Path to purchase: A mutually exciting point process model for online advertising and conversion. *Management Science*, *60*(6), 1392–1412.

Zhang, J., Wang, F.-Y., Wang, K., Lin, W.-H., Xu, X., & Chen, C. (2011). Data-driven intelligent transportation systems: A survey. *IEEE Transactions on Intelligent Transportation Systems*, *12*(4), 1624–1639.

Zhang, W., Tsimhoni, O., Sivak, M., & Flannagan, M. J. (2010). Road safety in China: analysis of current challenges. *Journal of Safety Research*, *41*(1), 25–30.

Zhang, Y., Zheng, Jinyang, & Tan, Yong. (2018). From Automobile to Autonomous: Does Self-Driving Improve Traffic Conditions? *Workshop on Information Systems and Economics 2017*.

Zhu, K. (2004). Information transparency of business-to-business electronic markets: A game-theoretic analysis. *Management Science*, *50*(5), 670–685.

Zuboff, S. (1985). Automatefin-fonnate: The two faces of intelligent technology. *Organizational Dynamics*, *14*(2), 5–18.

APPENDIX A.

STUDY 1: DETAILS ON DATA

Table A-1.
Sample Metropolitan Statistical Areas

Population Size	Metropolitan Statistical Area (MSA)
Very Large MSA (15) ≥ 3 million population	Atlanta GA; Boston MA-NH-RI; Chicago IL-IN; Dallas-Fort Worth-Arlington TX; Detroit MI; Houston TX; Los Angeles-Long Beach-Anaheim CA; Miami FL; New York-Newark NY-NJ-CT; Philadelphia PA-NJ-DE-MD; Phoenix-Mesa AZ; San Diego CA; San Francisco-Oakland CA; Seattle WA; Washington DC-VA-MD
Large MSA (31) 1 million ~ 3 million population	Austin TX; Baltimore MD; Charlotte NC-SC; Cincinnati OH-KY-IN; Cleveland OH; Columbus OH; Denver-Aurora CO; Indianapolis IN; Jacksonville FL; Kansas City MO-KS; Las Vegas NV; Louisville KY-IN; Memphis TN-MS-AR; Milwaukee WI; Minneapolis-St. Paul MN; Nashville-Davidson TN; Oklahoma City OK; Orlando FL; Pittsburgh PA; Portland OR-WA; Providence RI-MA; Richmond VA; Riverside-San Bernardino CA; Sacramento CA; Salt Lake City UT; San Antonio TX; San Jose CA; San Juan PR; St. Louis MO-IL; Tampa-St. Petersburg FL; Virginia Beach VA
Medium MSA (33) 500,000 ~ 1 million population	Akron OH; Albany NY; Albuquerque NM; Allentown-Bethlehem PA-NJ; Bakersfield CA; Baton Rouge LA; Birmingham AL; Bridgeport-Stamford CT-NY; Buffalo NY; Cape Coral FL; Charleston-North Charleston SC; Colorado Springs CO; Columbia SC; Dayton OH; El Paso TX-NM; Fresno CA; Grand Rapids MI; Hartford CT; Honolulu HI; Knoxville TN; McAllen TX; New Haven CT; New Orleans LA; Omaha NE-IA; Provo-Orem UT; Raleigh-Durham NC; Rochester NY; Sarasota-Bradenton FL; Springfield MA-CT; Toledo OH-MI; Tucson AZ; Tulsa OK; Wichita KS
Small MSA (22) ≤ 500,000 population	Anchorage AK; Beaumont TX; Boise ID; Boulder CO; Brownsville TX; Corpus Christi TX; Eugene OR; Greensboro NC; Indio-Cathedral City-Palm Springs CA; Jackson MS; Lancaster-Palmdale CA; Laredo TX; Little Rock AR; Madison WI; Oxnard CA; Pensacola FL-AL; Poughkeepsie-Newburgh NY; Salem OR; Spokane WA-ID; Stockton CA; Winston-Salem NC

Table A-2.
Correlation Matrix

		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]
[1]	COST	1.000															
[2]	TIME	0.933															
[3]	VMT	0.712	0.715														
[4]	ITS	0.146	0.207	0.066													
[5]	POPULATION	0.249	0.225	0.224	-0.114												
[6]	PERSONINCOME	0.450	0.496	0.335	0.335	0.044											
[7]	ROAD	0.690	0.684	0.971	0.089	0.081	0.328										
[8]	DRIVERRATIO	-0.184	-0.148	-0.242	0.206	-0.340	0.116	-0.225									
[9]	GASOLINE	0.220	0.288	0.114	0.572	-0.063	0.538	0.135	0.412								
[10]	UNEMPLOYMENT	-0.200	-0.187	-0.085	0.200	0.004	-0.035	-0.051	0.267	0.355							
[11]	COMMERCIAL	0.306	0.289	0.528	-0.079	0.100	0.066	0.522	-0.189	-0.136	-0.188						
[12]	PUBLICTRANSIT	0.602	0.555	0.711	0.105	0.410	0.314	0.675	-0.364	0.070	-0.155	0.388					
[13]	MANUFACTURE	-0.147	-0.234	-0.163	-0.290	-0.133	-0.248	-0.150	-0.176	-0.408	-0.198	0.128	-0.135				
[14]	TRANSPORT	-0.151	-0.191	-0.110	-0.030	0.113	-0.142	-0.120	0.114	0.004	0.125	0.275	-0.029	-0.120			
[15]	INFORMATION	0.176	0.193	0.181	-0.012	0.117	0.085	0.164	-0.242	-0.135	-0.202	0.136	0.247	0.081	-0.133		
[16]	EDUCATION	0.129	0.050	0.030	0.126	-0.031	0.108	0.056	-0.053	0.200	0.009	-0.126	0.042	0.068	-0.170	0.142	
[17]	SCIRESEARCH	-0.080	-0.024	-0.116	0.196	0.016	0.199	-0.118	0.009	0.243	0.177	-0.235	0.027	-0.222	-0.020	0.080	0.088

Note: [1]-[17] are the variables in Table 2.4.

APPENDIX B.

STUDY 1: ROBUSTNESS AND SENSITIVITY CHECKS

Table B-1.
Comparison of Traffic and Congestion Prior to 511 Systems Adoption

	Treated MSAs (N=68)	Untreated MSAs (N=31)	Unconditional	Conditional
	(1)	(2)	(3)	(4)
Year=2000				
COST	6.818	6.612	0.206**	0.091
	(0.319)	(0.521)	(0.085)	(0.065)
TIME	3.612	3.405	0.208***	0.097
	(0.281)	(0.479)	(0.077)	(0.059)
TRAFFIC	9.875	9.674	0.201	-0.022
	(1.027)	(0.976)	(0.219)	(0.037)
Year=1999				
COST	6.792	6.581	0.211**	0.056
	(0.333)	(0.546)	(0.089)	(0.059)
TIME	3.585	3.364	0.221***	0.086
	(0.287)	(0.493)	(0.079)	(0.057)
TRAFFIC	9.860	9.635	0.224	-0.052
	(1.028)	(0.970)	(0.219)	(0.042)
Year=1998				
COST	6.744	6.537	0.206**	0.048
	(0.351)	(0.559)	(0.092)	(0.059)
TIME	3.543	3.323	0.219***	0.073
	(0.299)	(0.504)	(0.081)	(0.045)
TRAFFIC	9.836	9.636	0.200	-0.030
	(1.025)	(0.986)	(0.220)	(0.033)

Notes: Table B-1 compares the congestion costs, delay hours, and traffic volume (log transformed) between the treated and the untreated MSAs prior to 511 Systems adoption. The comparison is done unconditionally and conditionally (i.e., conditional on the covariates (e.g., population, road stock, gasoline price, employment status in relevant industries) we incorporated in the main specifications. While the treated MSAs on average have higher congestion level than the untreated ones, this difference is not statistically significant after conditional on the observed heterogeneity we have accounted for in our baseline model.

Table B-2.
Logit Hazard Models Predicting 511 Systems Adoption

DV: ITS	(1)	(2)	(3)	(4)	(5)	(6)	(7)
POPULATION	-1.211**	-1.362**	-1.385**	-1.392**	-1.461**	-1.521**	-1.523**
	(0.574)	(0.639)	(0.646)	(0.651)	(0.662)	(0.669)	(0.676)
PERSONINCOME	-1.016	-1.089	-1.112	-1.127	-1.113	-1.144	-1.150
	(1.005)	(0.989)	(0.988)	(0.991)	(1.005)	(1.008)	(1.008)
ROAD	-0.273	-0.457	-0.484	-0.486	-0.485	-0.538	-0.541
	(0.285)	(0.405)	(0.408)	(0.407)	(0.366)	(0.374)	(0.376)
DRIVERRATIO	-4.977	-4.778	-4.769	-4.802	-4.937	-4.982	-5.063
	(3.460)	(3.374)	(3.387)	(3.399)	(3.421)	(3.440)	(3.465)
GASOLINE	0.656	0.514	0.512	0.530	0.495	0.463	0.474
	(1.248)	(1.244)	(1.235)	(1.230)	(1.239)	(1.232)	(1.224)
UNEMPLOYMENT	-31.979***	-29.315**	-29.300**	-29.553**	-26.966**	-26.131**	-26.334**
	(10.897)	(12.400)	(12.125)	(11.949)	(13.318)	(13.195)	(13.131)
COMMERCIAL	-0.018	-0.001	0.002	0.003	-0.001	0.001	0.001
	(0.216)	(0.212)	(0.213)	(0.213)	(0.201)	(0.198)	(0.199)
PUBLICTRANSIT	0.255*	0.260*	0.260	0.259	0.276*	0.284*	0.285*
	(0.153)	(0.158)	(0.158)	(0.158)	(0.160)	(0.161)	(0.161)
MANUFACTURE	-2.237	-2.639	-2.755	-2.827	-2.330	-2.349	-2.380
	(3.566)	(3.651)	(3.680)	(3.703)	(3.507)	(3.509)	(3.521)
TRANSPORT	1.236	1.873	1.987	2.026	2.958	3.375	3.345
	(5.536)	(5.957)	(6.065)	(6.105)	(6.393)	(6.550)	(6.575)
INFORMATION	-1.935	-1.461	-1.216	-1.012	-2.775	-2.940	-2.842
	(11.455)	(11.413)	(11.465)	(11.524)	(11.159)	(11.128)	(11.169)
EDUCATION	5.637	4.836	4.607	4.416	5.715	5.725	5.621
	(8.295)	(9.047)	(9.245)	(9.263)	(9.020)	(9.234)	(9.205)
SCIRESEARCH	5.065	4.471	4.412	4.476	3.984	3.709	3.695
	(5.487)	(5.503)	(5.470)	(5.427)	(5.502)	(5.472)	(5.460)
$COST_{t-1}$		0.749					
		(1.036)					
$COST_{t-2}$			0.829				
			(1.033)				
$COST_{t-3}$				0.813			
				(1.003)			
$TIME_{t-1}$					0.960		
					(0.984)		
$TIME_{t-2}$						1.163	
						(1.023)	
$TIME_{t-3}$							1.134
							(1.018)
Year FE	YES	YES	YES	YES	YES	YES	YES
# of Observations	794	695	695	695	695	695	695

Notes: Table B-2 reports the results from a hazard model predicting 511 Systems adoption into an MSA. The dependent variable equals to 1 when the MSA experiences 511 Systems implementation (even partially adoption for cross-state MSAs) and 0 otherwise. 511 Systems adoption is an absorbing MSA, so the MSA is dropped from the sample in the years after the dependent variable becomes 1. The independent variables are lagged congestion measures (*COST* and *TIME*). Heteroskedasticity-adjusted standard errors are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B-3.
2SLS Estimation of the Effect of 511 Systems Adoption on Traffic Congestion ǂ

	Instrument: Railroad 1898		Instrument: Expedition 1835~1850		Instruments ǂǂ: Railroad 1898 & Expedition 1835~1850	
	COST	TIME	COST	TIME	COST	TIME
	(1)	(2)	(3)	(4)	(5)	(6)
ITS	-0.127**	-0.166**	-0.105	-0.323	-0.128**	-0.165**
	(0.061)	(0.067)	(0.191)	(0.213)	(0.061)	(0.067)
All Covariates	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
# of Observations	1,953	1,953	1,953	1,953	1,953	1,953
Adj. R-squared	0.669	0.661	0.683	0.591	0.669	0.661
First Stage (DV: ITS)	(7)		(8)		(9)	
Railroad 1898	-0.088***				-0.089***	
	(0.009)				(0.0110)	
Expedition 1835~1850			-0.036***		0.002***	
			(0.008)		(0.010)	
Weak-identification Test (H0: first stage equation is weakly identified)						
KP Wald rk F stat.	89.590		17.969		44.884	
Over-identification test (H0: either of the IVs is exogenous)						
Hansen J *P*-value	-		-		0.4107	

ǂ *Notes:* The 2SLS estimation is based on the pooled data of historical routes, ITS adoption status, traffic congestions for matched 93 MSAs, following Duranton and Turner (2011, 2012). All the time-varying covariates in Table 2.3 are included but omitted here for brevity. We do not incorporate MSA-specific fixed effects in this specification as they will absorb our instrumental variables (IVs) which are cross-sectional and thus only provide between-MSA variations for 511 Systems adoption. As a remedy, we utilize a rich set of MSA-level time-invariant covariate account for the idiosyncrasy of each MSA that might correlate with our IVs. These covariates include geography-related factors, *elevation range within the MSA*, *the ruggedness of terrain in the MSA*, *heating degree days*, *cooling degree days*, *urban sprawl index*, using Burchfield et al. (2006)'s data[xxxi], and socio-economic characteristics, *housing segregation index* (Cutler and Glaeser 1997), *share of college-educated workers*, and *share of poor*, using 2000 decennial census. In addition to the MSA-level time-varying and time-invariant covariates, we incorporate year fixed-effects to account for contemporary changes in the transportation sector across all MSAs, and cluster the standard errors within the same MSAs to account for autocorrelation.

ǂǂ *Notes:* The two IVs are *1898 railroad route kilometers* and *the incidence of major expeditions of exploration between 1835 and 1850*. We test two assumptions, relevance and exogeneity, for validity as an IV. To check the relevance, we use Kleibergen-Paap Wald F statistic and Stock-Yogo weak TD test for the first stage regression of IVs on 511 Systems adoption (Stock and Yogo 2002). The results significantly reject the null hypotheses that the IVs are weak. To investigate the exogeneity, we used Hansen J test. The results do not reject the null hypotheses that either of the IVs is exogenous. Heteroskedasticity-adjusted standard errors, clustered at the MSA level, are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

xxxi http://diegopuga.org/data/sprawl/, retrieved on February 20, 2018.

Figure B-1.
1898 Railroads

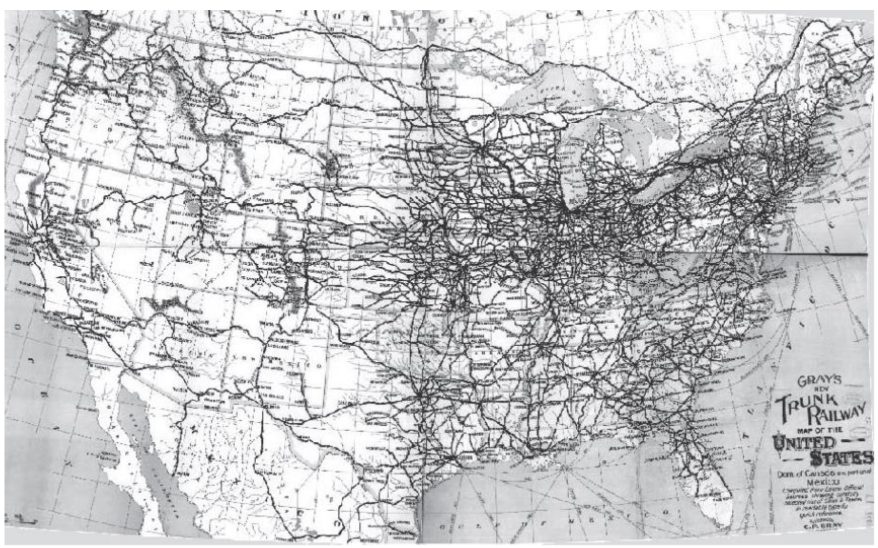


Figure B-2.
Routes of US Major Expeditions of Exploration 1835 to 1850

Source: (Duranton And Turner 2011)

Table B-4.
Replicating Table 2.5 Using Various Subsamples

	Only MSAs that do **not span across states**		Only MSAs that adopted 511 Systems by **state government decisions**		Only MSAs that adopted 511 Systems by **city government decisions**)		Only Observations until 2008 (before the 2009 Financial Crisis)	
	COST (1)	TIME (2)	COST (3)	TIME (4)	COST (5)	TIME (6)	COST (7)	TIME (8)
ITS	-0.027***	-0.025***	-0.012*	-0.010	-0.147***	-0.141***	-0.017*	-0.015*
	(0.008)	(0.008)	(0.007)	(0.007)	(0.034)	(0.031)	(0.010)	(0.009)
POPULATION	0.960***	0.024	0.991***	0.069*	1.571***	0.774***	1.175***	0.167***
	(0.039)	(0.038)	(0.036)	(0.037)	(0.185)	(0.172)	(0.056)	(0.053)
PERSONINCOME	0.207***	0.491***	0.005	0.022	0.085	0.335*	0.084	0.067
	(0.045)	(0.045)	(0.010)	(0.024)	(0.178)	(0.171)	(0.067)	(0.064)
ROAD	0.965***	0.040	1.018***	0.111***	1.718***	0.878***	1.179***	0.175***
	(0.038)	(0.037)	(0.035)	(0.036)	(0.184)	(0.172)	(0.056)	(0.053)
DRIVERRATIO	1.977***	1.354***	2.241***	2.647***	3.315***	2.582***	1.962***	0.538*
	(0.272)	(0.276)	(0.222)	(0.261)	(0.947)	(0.880)	(0.324)	(0.324)
GASOLINE	-0.059***	-0.007	-0.034***	0.056***	0.003	0.033	0.042	0.031
	(0.010)	(0.010)	(0.007)	(0.008)	(0.035)	(0.033)	(0.034)	(0.033)
UNEMPLOYMENT	-0.737***	-0.316	-0.913***	-0.910***	0.327	0.152	-0.949***	-0.854***
	(0.245)	(0.229)	(0.208)	(0.206)	(0.673)	(0.642)	(0.336)	(0.316)
COMMERCIAL	0.018***	0.019***	0.009*	0.003	0.026	0.008	0.011***	0.010***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.025)	(0.024)	(0.003)	(0.003)
PUBLICTRANSIT	0.030***	0.030***	0.026***	0.022***	0.015	0.037	0.025***	0.022***
	(0.006)	(0.006)	(0.005)	(0.005)	(0.046)	(0.041)	(0.006)	(0.006)
MANUFACTURE	-0.170	-0.340***	0.002	-0.126	0.448	0.475	-0.095	-0.090
	(0.131)	(0.123)	(0.092)	(0.092)	(0.612)	(0.601)	(0.090)	(0.087)
TRANSPORT	-0.902*	-0.308	-0.787**	-0.438	-6.274***	-3.389*	0.437	0.470
	(0.468)	(0.444)	(0.368)	(0.368)	(2.103)	(2.011)	(0.372)	(0.355)
INFORMATION	1.195***	1.153***	0.190	-0.020	8.446***	8.193***	0.219	0.194
	(0.393)	(0.379)	(0.290)	(0.297)	(2.111)	(2.032)	(0.262)	(0.255)
EDUCATION	-0.393	-0.098	-0.325	0.122	-9.180***	-6.983***	-0.538*	-0.436
	(0.295)	(0.312)	(0.227)	(0.236)	(2.416)	(2.161)	(0.309)	(0.303)
SCIRESEARCH	-1.021***	-0.985***	-0.859***	-0.727***	-0.778**	-0.614	-0.782***	-0.739***
	(0.107)	(0.098)	(0.098)	(0.093)	(0.387)	(0.393)	(0.094)	(0.083)
MSA FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
# of Observations	1,596	1,596	1,827	1,827	210	210	1,485	1,485
# of MSAs	76	76	87	87	10	10	99	99
Adj. R-squared	0.952	0.952	0.949	0.937	0.982	0.984	0.967	0.964

Notes: Table B-4 reports the difference-in-differences estimates for different subsamples. Heteroskedasticity-adjusted standard errors, clustered at the MSA level, are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B-5.
Comparison Between In-Sample and Out-of-Sample MSAs Prior to 511 Systems Adoption in 1995 and 2001

	In-Sample MSAs	Out-of-Sample MSAs	Unconditional	t-Stat	Conditional	t-Stat
A. Trip-level data based on the NHTS *(Year=1995)*						
Mean trip distance (mile)	7.200	7.184	-0.016		0.269	
	(1.116)	(2.452)	(0.281)	-0.057	(0.374)	0.720
Mean trip duration (min)	14.021	13.356	-0.664*		0.723	
	(1.467)	(2.953)	(0.341)	-1.947	(0.453)	1.590
Mean trip speed (mph)	26.866	27.184	0.318		0.126	
	(2.492)	(4.022)	(0.477)	0.667	(0.617)	0.200
Mean trip number (per driver)	6.113	6.048	-0.066		0.005	
	(0.650)	(1.097)	(0.129)	-0.509	(0.173)	0.030
B. MSA-level data based on HPMS and Census *(Year=1995)*						
Mean daily vehicle miles travelled ('000,000 mile)	36.100	4.012	-32.000***		0.422	
	(50.000)	(2.969)	(3.624)	-8.843	(1.205)	0.350
Mean daily vehicle travel time ('000,000 min)	70.400	7.562	-62.800***		0.566	
	(98.400)	(5.540)	(7.128)	-8.816	(2.200)	0.260
Lane miles ('000 mile)	14.210	1.940	-12.271***		0.537	
	(16.741)	(1.299)	(1.217)	-10.084	(0.504)	1.070
Mean MSA population ('000)	1978.767	220.095	-1758.673***		23.409	
	(2881.403)	(151.258)	(208.655)	-8.429	(39.714)	0.590
C. Trip-level data based on the NHTS *(Year=2001)*						
Mean trip distance (mile)	7.843	7.626	-0.218		-0.032	
	(1.038)	(2.041)	(0.236)	-0.920	(0.305)	-0.100
Mean trip duration (min)	16.649	15.438	-1.212***		0.478	
	(1.553)	(2.564)	(0.303)	-3.996	(0.382)	1.250
Mean trip speed (mph)	24.862	25.439	0.576		-0.097	
	(1.931)	(3.162)	(0.374)	1.540	(0.461)	-0.210
Mean trip number (per driver)	5.726	5.868	0.142		-0.055	
	(0.369)	(0.923)	(0.105)	1.356	(0.140)	-0.390
D. MSA-level data based on HPMS and Census *(Year=2001)*						
Mean daily vehicle miles travelled ('000,000 mile)	42.100	4.562	-37.500***		1.151	
	(56.800)	(3.276)	(4.115)	-9.116	(1.059)	1.090
Mean daily vehicle travel time ('000,000 min)	89.900	9.280	-80.600***		2.399	
	(123.000)	(6.697)	(8.919)	-9.042	(2.279)	1.050
Lane miles ('000 mile)	15.992	2.047	-13.944***		0.775	
	(19.654)	(1.375)	(1.427)	-9.774	(0.509)	1.520
Mean MSA population ('000)	2205.666	235.280	-1970.386***		57.892	
	(3137.074)	(164.976)	(227.172)	-8.674	(41.207)	1.400

Table B-6.
Comparison Between Treated and Untreated MSAs (both In-Sample and Out-of-Sample MSAs) in 1995 and 2001

	In-Sample MSAs				Out-of-Sample MSAs			
	Treated (N=64)	Untreated (N=19)	Difference	t-Stat	Treated (N=131)	Untreated (N=60)	Difference	t-Stat
A. Trip-level data based on the NHTS (Year=2001)								
Mean trip distance (miles)	7.793	8.012	0.218		7.436	8.039	0.603*	
	(0.985)	(1.212)	(0.272)	0.804	(1.704)	(2.602)	(0.316)	1.908
Mean trip duration (min)	16.647	16.657	0.010		15.384	15.555	0.171	
	(1.622)	(1.337)	(0.408)	0.024	(2.247)	(3.166)	(0.401)	0.426
Mean trip speed (mph)	24.746	25.256	0.510		24.973	25.456	0.483	
	(1.817)	(2.284)	(0.504)	1.012	(3.132)	(3.011)	(0.482)	1.002
Mean trip number (per driver)	5.751	5.641	-0.110		5.909	5.779	-0.130	
	(0.374)	(0.346)	(0.096)	-1.143	(0.955)	(0.848)	(0.144)	-0.905
B. MSA-level data based on HPMS and Census (Year=2001)								
Mean daily vehicle miles travelled ('000,000 mile)	46.900	26.000	-20.900		4.512	4.671	0.159	
	(61.900)	(30.500)	(14.700)	-1.415	(3.431)	(2.936)	(0.512)	0.310
Mean daily vehicle travel time ('000,000 min)	101.000	53.500	-47.300		9.360	9.106	-0.255	
	(135.000)	(62.600)	(31.900)	-1.480	(7.209)	(5.467)	(1.047)	-0.244
Lane miles ('000 mile)	17.556	10.723	-6.832		2.043	2.056	0.013	
	(21.23171)	(11.996)	(5.110)	-1.337	(1.454)	(1.196)	(0.215)	0.062
Mean MSA population ('000)	2476.427	1293.631	-1182.796		237.013	231.498	-5.515	
	(3448.866)	(1436.048)	(814.0947)	-1.453	(170.446)	(153.671)	(25.782)	-0.214
C. Trip-level data based on the NHTS (Year=1995)								
Mean trip distance (mile)	7.244	7.050	-0.195		7.101	7.366	0.265	
	(0.994)	(1.478)	(0.292)	-0.666	(2.328)	(2.713)	(0.383)	0.693
Mean trip duration (min)	14.211	13.882	-0.329		13.497	13.049	-0.449	
	(1.344)	(1.709)	(0.374)	-0.880	(2.802)	(3.263)	(0.460)	-0.975
Mean trip speed (mph)	26.684	27.479	0.795		26.515	27.646	1.131*	
	(2.011)	(3.693)	(0.649)	1.225	(3.721)	(4.292)	(0.609)	1.857
Mean trip number (per driver)	6.013	6.253	0.241		6.054	6.033	-0.021	
	(0.514)	(0.917)	(0.164)	1.470	(1.142)	(1.000)	(0.171)	-0.122
D. MSA-level data based on HPMS and Census (Year=1995)								
Mean daily vehicle miles travelled ('000,000 mile)	39.700	23.600	-16.100		4.007	4.023	0.016	
	(54.300)	(29.600)	(13.000)	-1.238	(3.119)	(2.638)	(0.464)	0.034
Mean daily vehicle travel time ('000,000 min)	78.400	43.600	-34.800		7.678	7.308	-0.370	
	(107.000)	(54.500)	(25.600)	-1.359	(5.878)	(4.758)	(0.866)	-0.427
Lane miles ('000 mile)	15.470	9.969	-5.501		1.926	1.970	0.044	
	(17.828)	(11.821)	(4.358)	-1.262	(1.378)	(1.118)	(0.203)	0.216
Mean MSA population ('000)	2216.083	1179.388	-1036.695		221.568	216.877	-4.691	
	(3169.033)	(1340.891)	(748.617)	-1.385	(156.437)	(140.499)	(23.639)	-0.199

Table B-7.
Difference-in-Differences Regressions Adjusted by Coarsened Exact Matching

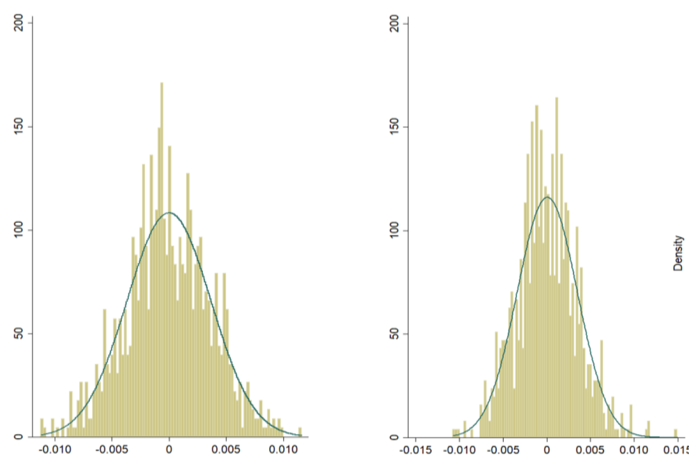
	COST	TIME
	(1)	(2)
ITS	-0.023***	-0.020**
	(0.009)	(0.008)
All Covariates	YES	YES
MSA FE	YES	YES
Year FE	YES	YES
# of Observations	1,706	1,706
# of MSAs	85	85
Adj. R-squared	0.946	0.942

Notes: Table B-7 reports the results from difference-in-differences regressions using weights generated by coarsened exact matching. The matching is based on the population size, unemployment rate, road miles, and traffic volume one year before 511 Systems adoption. These variables are chosen because they are unbalanced for treated and untreated cities. Heteroskedasticity-adjusted standard errors, clustered at the MSA level, are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B-8.
Random (Shuffled) Implementation Test

Estimation	COST	TIME
	(1)	(2)
μ of Random β	-0.00002	0.00006
σ of Random β	0.00370	0.00354
Replications	1000	1000
Estimated β	-0.029	-0.26
Z-Score	-7.84384	-7.3312
P-Value	p<0.01	p<0.01

Notes: Table B-8 reports the results from difference-in-differences regressions using randomly generated placebo variables as independent variables. The placebo generation and regression are replicated 1000 times. μ is the mean of the placebo estimator, while σ is its standard error. This diagnostic test is to determine the probability of the observed effect occurring purely by chance. The comparison between a placebo effect and an estimated effect are statistically significantly different (*p<0.01*), thus eliminating the aforementioned possibility.



(1) Distribution of pseudo effect of random 511 Systems adoption on *congestion costs*

(2) Distribution of pseudo effect of random 511 Systems adoption on *delay hours*

Figure B-3.
Distribution of Coefficients based on Random Treatments

Notes: Figure C3 describes the distributions of the DID estimates of placebo 511 Systems adoption generated from 1,000 replications. As expected, the distributions of the pseudo effects are centered around zero. Together with Table C7, the findings from the random (shuffled) treatment test suggest the observed effect of 511 Systems on congestion costs (-0.029, *p*<0.01), and on delay hours (-0.026, *p*<0.01) are unlikely obtained by random chance.

Table B-9.
Replicating Table 2.5 with Aggregate Congestion Measure

DV: total congestion cost, time, fuel and CO2 aggregated to the city level	COST	TIME	FUEL	CO2
	(1)	(2)	(3)	(4)
ITS	-0.028***	-0.028***	-0.028***	-0.043***
	(0.007)	(0.007)	(0.007)	(0.015)
All Covariates	YES	YES	YES	YES
MSA FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
# of Observations	2,079	2,079	2,079	1,089
# of MSAs	99	99	99	99
Adj. R-squared	0.995	0.995	0.995	0.990

Notes: Table B-9 reports a replication of the main analyses by using aggregate congestion (instead of average congestion per commuter) measures on COST, TIME, FUEL, CO2 (only available for 2001-2014) as dependent variables. Heteroskedasticity-adjusted standard errors, clustered at the MSA level, are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B-10.
Replicating Table 2.5 with Alternative ITS Measures

	ITS variables for MSAs adopted 511 Systems in the 4th quarter of a year are labeled as adopted in the following year.		ITS variables for MSAs that span across states are weighted by the share of areas size in each state.	
	COST	TIME	COST	TIME
	(1)	(2)	(3)	(4)
ITS	-0.030***	-0.027***	-0.020***	-0.018***
	(0.007)	(0.006)	(0.007)	(0.006)
All Covariates	YES	YES	YES	YES
MSA FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
# of Observations	2,079	2,079	2,079	2,079
# of MSAs	99	99	99	99
Adj. R-squared	0.956	0.954	0.956	0.954

Notes: Table B-10 reports a replication of the baseline analysis with alternative ITS measures as the independent variables. Heteroskedasticity-adjusted standard errors, clustered at the MSA level, are included in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table B-11.
Effect of Search Popularity of "Google Maps" on Traffic Congestion

	COST	COST	TIME	TIME
	(1)	(2)	(3)	(4)
GOOGLEMAPS	-0.00027	0.00008	-0.00033*	0.00000
	(0.00018)	(0.00023)	(0.00018)	(0.00022)
ITS	-0.02756***	-0.02393***	-0.02518***	-0.02070**
	(0.00699)	(0.00863)	(0.00671)	(0.00832)
GOOGLEMAPS × ITS		-0.00052***		-0.00049***
		(0.00018)		(0.00017)
All Covariates	YES	YES	YES	YES
MSA FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
# of Observations	2,079	2,079	2,079	2,079
# of MSAs	99	99	99	99
Adj. R-squared	0.955	0.956	0.954	0.954

Notes: Table B-11 reports the effects of Google Maps, as well as its joint effects with 511 Systems adoption, on traffic congestion costs and delay hours. We measure Google Maps by the search popularity of "Google Maps" from Google Trends across 86 MSAs from 2004 to 2014. Such an approach has been used in the IS literature (Gong et al. 2018, Gopal and Greenwood 2017). For the years before 2004, we code *GOOGLEMAPS* as zero. The estimates in Table C10 retains 5 digits after the decimal point as the effect size is quite small. Heteroskedasticity-adjusted standard errors, clustered at the MSA level, are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

APPENDIX C.

STUDY 1: UNDERLYING MECHANISMS

Table C-1.
Effect of 511 Systems Adoption on *Travel Time to Work* for Drivers

DV: *ln* (Travel Time to Work (minutes))	All drivers	Drivers who commute to work within 60 mins	Drivers who commute to work within 60 mins in *heavy-traffic* hours	Drivers who commute to work within 60 mins in *light-traffic* hours
	(1)	(2)	(3)	(4)
ITS	0.0002 (0.0261)	-0.0312* (0.0190)	-0.0467** (0.0231)	0.0002 (0.0329)
Covariates, State & Year FE	YES	YES	YES	YES
# of Observations	8,736,734	8,519,288	5,472,806	3,046,482
Adj. R-squared	0.0210	0.0285	0.0302	0.0295

Notes: Table C-1 reports the results from DID estimations of 511 Systems adoption on travel time to work at the individual commuter-year level. The data are from American Community Survey 1-year estimate on participants in 41 states matched to our sampled states in 2000–2014. California, Texas, and Ohio are dropped because MSAs in these states adopted 511 Systems at different years. In Column 1, we restrict the survey responders to those who commute by driving. In Column 2, we restrict the data to drivers whose commuting time is less than 60 minutes. In Column 3 and 4, we restrict to drivers whose travel time is within 60 minutes and who do or do not travel during peak hours. The covariates are included but omitted for brevity: they are individual-level controls (i.e., age, gender, race, employment status, personal incomes, car ownership) and state-level controls (i.e., population, road miles, employment share in the manufacture, transportation, and information-related sectors). Heteroskedasticity-adjusted standard errors, clustered at the state level, are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C-2.
Effect of 511 Systems Adoption on *Departure Time Choice* for Drivers

DV: Departure to work at heavy-traffic hours (=1 if Yes, =0 if at light-traffic hours)	All drivers	Drivers who commute to work within 60 min
	(1)	(2)
ITS	-0.0013** (0.0007)	-0.0016** (0.0007)
Covariates, State & Year FE	YES	YES
# of Observations	8,289,590	8,084,254
Adj. R-squared	0.0179	0.0180

Notes: Table C-2 reports the results from DID estimations of 511 Systems adoption on departure time to work. All covariates in Table C-1 are included here but are omitted for brevity. Heteroskedasticity-adjusted standard errors, clustered at the state level, are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C-3.
Effect of 511 Systems Adoption on *Transportation Mode to Work*

	Private Transit			Public Transit		
	Private Car	Taxi	Walk & Bike	Bus	Rail	Total
	(1)	(2)	(3)	(4)	(5)	(6)
ITS	-0.0025***	-0.0002***	0.0005**	-0.0009***	0.0031***	0.0021***
	(0.0004)	(0.0000)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Covariates, State & Year FE	YES	YES	YES	YES	YES	YES
# of Observations	9,558,621	9,558,621	9,558,621	9,558,621	9,558,621	9,558,621
Adj. R-squared	0.0915	0.0025	0.0167	0.0270	0.1109	0.1046

Note: Table C-3 reports the results from DID estimations of 511 Systems adoption on a discrete choice of transportation modes to work. All covariates in Table C-1 are included here but are omitted for brevity. Heteroskedasticity-adjusted standard errors, clustered at the state level, are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C-4.
Effect of 511 Systems Adoption on *Frequency and Distance of Daily Trips*

	ln (# of Person Trips)	*ln* (Mile of Person Travel)	*ln* (# of Vehicle Trips)	*ln* (Miles of Vehicle Travel)
	(1)	(2)	(3)	(4)
ITS	-0.007***	-0.035***	-0.016***	-0.049***
	(0.002)	(0.006)	(0.005)	(0.007)
Covariates, Census Tract & Year FE	YES	YES	YES	YES
# of Observations	43,323	43,322	43,323	43,309
# of Census Tracts	28,834	28,834	28,833	28,821
Adj. R-squared	0.969	0.956	0.943	0.950

Notes: Table C-4 reports the effect of 511 Systems adoption on frequency and distance of personal and vehicle trips. The data is retrieved from the National Household Travel Survey (NHTS) in 2001 and 2010. These statistics are aggregated to the census tract level. Per NHTS documentation, *Person Trips* means a trip by one person in any mode of transportation, *Person Miles of Travel* means the number of miles traveled by each person on a trip, *Vehicle trips* means a trip by a single privately-operated vehicle, regardless of the number of persons in the vehicle, and *Vehicle Miles of Travel* means one vehicle mile of travel is the movement of one privately operated vehicle for one mile, regardless of the number of persons in the vehicle. Heteroskedasticity-adjusted standard errors, clustered at the census tract level, are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C-5.
Effect of 511 Systems Adoption on *Travel Time Uncertainty*

	Travel Time Uncertainty Based on TTI	Travel Time Uncertainty Based on TTI
	(1)	(2)
ITS	-1.244***	-1.219***
	(0.052)	(0.053)
Covariates, MSA & Year FE	YES	YES
# of Observations	2,055	2,046
Adj. R-squared	0.659	0.660

Notes: Table C-5 reports the results from the DID regressions on travel time uncertainty. Heteroskedasticity-adjusted standard errors, clustered at the MSA level, are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C-6.
Effect of 511 Systems Adoption on *Route Choice*

	% of Traffic in Highway (% VMT)	% of Traffic in Major Road (%VMT)	% of Traffic in Local Road (%VMT)
	(1)	(2)	(3)
ITS	-0.002	-0.035***	-0.010
	(0.009)	(0.013)	(0.007)
Covariates, MSA & Year FE	YES	YES	YES
# of Observations	2,079	2,079	2,079
# of MSAs	99	99	99
Adj. R-squared	0.496	0.324	0.438

Notes: Table C-6 reports the results from the DID estimation of 511 Systems adoption on traffic allocated to different classes of roads. We control for miles shares of each road types. Heteroskedasticity-adjusted standard errors, clustered at the MSA level, are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C-7.
Effect of 511 Systems and *Road Supply* on Traffic Congestion

	COST		TIME	
	(1)	(2)	(3)	(4)
ITS	-0.028***	-0.019	-0.025***	-0.021
	(0.007)	(0.021)	(0.007)	(0.019)
Road	1.024***	1.033***	0.026	0.034
	(0.036)	(0.037)	(0.034)	(0.035)
Road × ITS		-0.004***		-0.003***
		(0.001)		(0.001)
Covariates, MSA & Year FE	YES	YES	YES	YES
# of Observations	2,079	2,079	2,079	2,079
Adj. R-squared	0.955	0.956	0.954	0.954

Notes: Table C-7 reports the results on the interaction effect of road supply and ITS. Heteroskedasticity-adjusted standard errors, clustered at the MSA level, are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C-8.
Effect of 511 Systems and *Public Transit Services* on Traffic Congestion

	COST		TIME		COST		TIME	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ITS	-0.027***	-0.019	-0.025***	-0.006	-0.029***	0.003	-0.026***	0.018
	(0.007)	(0.022)	(0.007)	(0.021)	(0.007)	(0.016)	(0.007)	(0.015)
Bus	0.016***	0.016***	0.014**	0.014***				
	(0.006)	(0.006)	(0.006)	(0.005)				
Bus × ITS		0.000		-0.004				
		(0.004)		(0.003)				
Rail					-0.004	-0.003	-0.003	-0.002
					(0.006)	(0.006)	(0.005)	(0.005)
Rail × ITS						-0.007**		-0.009***
						(0.003)		(0.003)
All Covariates	YES	YES	YES	YES	YES	YES	YES	YES
MSA & Year FE	YES	YES	YES	YES	YES	YES	YES	YES
# of Observations	2,079	2,079	2,079	2,079	1,813	1,813	1,813	1,813
Adj. R-squared	0.955	0.955	0.954	0.954	0.959	0.959	0.959	0.960

Notes: Table C-8 reports the results on the effect of public transit services on traffic congestion and the joint effect of public transit and ITS. Using the National Transit Data (NTD), we measure public transit service by the number of Vehicles Operated for Maximum Services (VOMS) for both *bus* and *rail*, drawing upon extant transportation economics literature (e.g., Duranton and Turner 2011). All covariates in Table 2.3 are included but omitted. Heteroskedasticity-adjusted standard errors, clustered at the MSA level, are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

APPENDIX D.

STUDY 1: THE USE OF ITS

Table D-1.
Effect of 511 Use on Traffic Congestion (Data: 2010-2014)

	(1) COST	(2) TIME
ln(1+ number of 511 calls)	0.002	0.009
	(0.013)	(0.013)
ln(1+ number of 511 website visits)	-0.019**	-0.016*
	(0.008)	(0.009)
All Covariates	YES	YES
MSA FE	YES	YES
Year FE	YES	YES
Number of MSAs	42	42
Observations	210	210
Adj. R-squared	0.356	0.560

Notes: The data for 511 calls and website visits are only available from Florida, Iowa, Kentucky, and Utah from 2010 to 2014. We use the 11 MSAs (Cape Coral FL, Jacksonville FL, Orlando FL, Pensacola FL-AL, Sarasota-Bradenton FL, Tampa-St. Petersburg FL, Miami FL, Omaha IA-NE, Louisville-Jefferson County KY-IN, Provo-Orem UT, Salt Lake City-West Valley City UT) from these states as a treated group while 31 MSAs in our main dataset that have never adopted 511 Systems as a control group. Heteroskedasticity-adjusted standard errors, clustered at the MSA level, are included in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table D-2.
Effect of Different 511 Functionality on Traffic Congestion (Data: 1994-2005)

	COST	TIME	COST	TIME
	(1)	(2)	(3)	(4)
ITS	-0.017*	-0.014*	-0.025	-0.020
	(0.009)	(0.008)	(0.022)	(0.023)
ITS × Weather Info.			-0.002	-0.006
			(0.051)	(0.051)
ITS × Road Condition Info.			-0.159*	-0.177**
			(0.095)	(0.089)
ITS × Incidents Info.			0.089	0.098
			(0.093)	(0.091)
ITS × Congestion Info.			-0.153**	-0.161**
			(0.069)	(0.067)
ITS × Travel Time Info.			-0.103	-0.168*
			(0.105)	(0.100)
ITS × Variable Message Signs			0.122	0.132
			(0.112)	(0.106)
ITS × 511 Website			-0.093***	-0.093***
			(0.026)	(0.024)
All Covariates	YES	YES	YES	YES
MSA FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
# of Observations	912	912	912	912
# of MSAs	76	76	76	76
Adj. R-squared	0.973	0.969	0.974	0.970

Notes: The data about functionalities of 511 Systems is from a report, entitled "*Implementation and Operational Guidelines for 511 Services"* (September 2005), published by *511 Deployment Coalition*. The data for years after 2005 is not available so that we only use the main dataset until 2005 for this analysis. The functionalities include which information each state 511 Systems made available to the public and through which channels (i.e., variable message signs on the roads, and 511 Websites with interactive traffic maps). Note that all states that adopted 511 systems automatically opened up the 511 call services (the most prominent functionality). Therefore, the estimates on the ITS variable are able to capture the effect of 511 call services. All other functionality variables are cross-sectional and thus we interact them with ITS variable to avoid being absorbed by the MSA fixed effects. Heteroskedasticity-adjusted standard errors, clustered at the MSA level, are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table D-3.
Effects of 511 Systems Adoption and Its Funding on Traffic Congestion

VARIABLES	(1) COST	(2) COST	(3) TIME	(4) TIME
ITS	-0.023***	-0.021	-0.022***	-0.020
	(0.008)	(0.017)	(0.008)	(0.017)
ln(Federal Funding)	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
ITS × ln(Federal Funding)		-0.002**		-0.002***
		(0.001)		(0.001)
All Covariates	YES	YES	YES	YES
MSA FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
# of Observations	1,782	1,782	1,782	1,782
# of MSAs	99	99	99	99
Adj. R-squared	0.960	0.960	0.957	0.957

Notes: The data of federal funding for 511 Systems design, deployment, and modification is retrieved from the Federal Aid archive. The federal funding data is not available after 2011, and thus, we use the time frame of 1994-2011 for this analysis. The Federal Aid dataset records most of the funding (except for a few California counties) allocation for 511 Systems at the state level. For MSAs within the same state, since they access to homogeneous 511 Systems, we constructed a funding measure for these MSAs as the same as their state-level measure. For MSAs spanning across multiple states (e.g., Philadelphia-Camden-Wilmington, PA-NJ-DE-MD, MSA), we constructed a weighted-average measure for 511 Systems funding using a weight measured by road miles-percentages of MSA in each state in the same way we constructed the primary measure for 511 System adoption in the preceding analysis. We matched the funding data to our main dataset of traffic congestion and time-varying covariates, and we used the amount of federal funding for 511 Systems as the independent variable. Heteroskedasticity-adjusted standard errors, clustered at the MSA level, are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table D-4.
Interaction Effects with Population Size

	COST		TIME	
	(1)	(2)	(3)	(4)
ITS	-0.029***	0.002	-0.026***	0.006
	(0.006)	(0.010)	(0.006)	(0.010)
ITS × SMALL MSA	Omitted Baseline		Omitted Baseline	
ITS × MEDIUM MSA		-0.009		-0.012
		(0.011)		(0.011)
ITS × LARGE MSA		-0.027**		-0.031***
		(0.011)		(0.011)
ITS × VERY MSA		-0.045***		-0.050***
		(0.011)		(0.011)
All Covariates	YES	YES	YES	YES
MSA FE	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES
# of Observations	2,079	2,079	2,079	2,079
# of MSAs	99	99	99	99
Adj. R-squared	0.956	0.974	0.954	0.974

Notes: Table D-4 compares the effects of 511 Systems across different MSA sizes. Following the classification by the AUMS dataset, we use dummy variables to indicate MSA sizes - very large MSAs (more than 3 million population), large MSAs (1 million to 3 million population), medium MSAs (500,000 to 1 million population), and small MSAs (less than 500,000 population). We then interacted these variables with the 511 Systems adoption and replicated the estimation. Heteroskedasticity-adjusted standard errors, clustered at the MSA level, are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table D-5.
Quantile Regressions for the Distributional Robust Checks

	Congestion Measure at Different Deciles								
Decile	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
Panel A: *Congestion is measured by COST*									
ITS	0.001	-0.003	-0.016***	-0.017*	-0.031***	-0.031***	-0.045***	-0.050***	-0.051***
	(0.007)	(0.003)	(0.005)	(0.010)	(0.003)	(0.001)	(0.001)	(0.000)	(0.001)
Panel B: *Congestion is measured by TIME*									
ITS	-0.004	-0.007	-0.014**	-0.023***	-0.022***	-0.027***	-0.022***	-0.025***	-0.025***
	(0.005)	(0.004)	(0.006)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
Covariates	YES	YES	YES	YES	YES	YES	YES	YES	YES
MSA FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Table D-5 compares the effects of 511 Systems across MSAs with different levels of traffic congestion using quantile regressions. Decile 0.90 means the congestion severity of an MSA ranks top 10% among all MSAs. The observation is 2,079 with 99 MSAs. MCMC Bootstrap Standard Errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

APPENDIX E

STUDY 2: MORE RESULTS OF MAIN EFFECTS

Table E-1.
Effects of Installation on Percentage Changes in Accident-related Outcomes

	Dependent Variables:			
	ln (1+ No. of Accidents)	*ln* (1+ No. of Persons Injured)	*ln* (1+ No. of Fatalities)	*ln* (1+ Damage to the Vehicles)
	(1)	(2)	(3)	(4)
Installation (0-1)	-0.0027	-0.0053*	-0.0001	-0.0642**
	(0.0033)	(0.0027)	(0.0002)	(0.0255)
Road Segment FE	YES	YES	YES	YES
Week FE	YES	YES	YES	YES
# of Observations	817,596	817,596	817,596	817,596
# of Road Segments	5,241	5,241	5,241	5,241
Adj. R-squared	0.6607	0.4401	0.0545	0.4690

Notes: Robust standard errors (clustered at both road segment and week level) in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table E-2.
Effects of Camera Installation Intensity on Percentage Changes in Accident-related Outcomes

	Dependent Variables:			
	ln (1+ No. of Accidents	*ln* (1+ No. of Persons Injured	*ln* (1+ No. of Fatality	*ln* (1+ Damage to the Vehicles)
	(1)	(2)	(3)	(4)
Installation Intensity (#)	-0.0017	-0.0031*	-0.0000	-0.0353**
	(0.0021)	(0.0017)	(0.0001)	(0.0145)
Road Segment FE	YES	YES	YES	YES
Week FE	YES	YES	YES	YES
# of Observations	817,596	817,596	817,596	817,596
# of Road Segments	5,241	5,241	5,241	5,241
Adj. R-squared	0.6607	0.4401	0.0545	0.4690

Notes: Robust standard errors (clustered at both road segment and week level) in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX F

STUDY 2: TREATMENT EFFECT HETEROGENEITY: TIME AND LOCATION

Table F-1.
Summary Statistics across Location

	Suburban		Urban	
	Freeway	Highway	Urban Express	Urban Road
	(1)	(2)	(3)	(4)
No. of Accidents (#)	5.6067	0.2090	0.0872	0.1882
No. of Persons Injured (#)	0.2326	0.0645	0.0152	0.0915
No. of Fatalities (#)	0.0169	0.0038	0.0011	0.0013
Damage to the Vehicles (¥)	4,752.3822	223.5421	83.6247	251.7614
Treated Road (0-1)	0.0217	0.1090	0.0761	0.1267
Camera Installation (0-1)	0.0028	0.0384	0.0247	0.0505
Installation Intensity (#)	0.0028	0.0344	0.0193	0.0372
# of Observations	7,176	24,336	96,408	763,152

Notes: Table F-1 compares descriptive statistics across accident locations including *Freeway*, *Highway*, *Urban Expressway*, and *Urban Road*. The first two belong to suburban or between-city road system, while the remaining belong to within-city road system. The comparison results in a substantial difference in the accident-related outcomes across locations. Generally, accidents, injuries, fatalities, damages, and penalties per road segment per week seem higher at Freeway and Highway located at suburban compared to those within the urban area. However, the number of accidents associated with distinct road types are different. Therefore, it would be meaningful to check the figure at an aggregate level. Multiplying the mean statistics by the number of observations for accidents at each road type, the total number of accidents are 40,233 (*Freeway*), 5,086 (*Highway*), 8,406 (*Urban Expressway*), and 143,625 (*Urban Road*). The total number of persons injured are 1,669 (*Freeway*), 1,569 (*Highway*), 1,465 (*Urban Expressway*), and 69,828 (*Urban Road*). The total number of fatalities are 121 (*Freeway*), 92 (*Highway*), 106 (*Urban Expressway*), and 992 (*Urban Road*). The total damages are ¥ 34,103,094 (*Freeway*), ¥ 5,440,120 (*Highway*), ¥ 8,062,090 (*Urban Expressway*), and ¥ 192,132,215 (*Urban Road*). These aggregated figures show the *Urban Road* contributed to most of the accidents related outcomes.

Table F-2.
Summary Statistics across Time

	Time of Day		Day of Week	
	Daytime	Night	Weekday	Weekend
	(1)	(2)	(3)	(4)
No. of Accidents (#)	0.2198	0.1382	0.2210	0.1305
No. of Persons Injured (#)	0.0850	0.0522	0.0842	0.0512
No. of Fatalities (#)	0.0012	0.0015	0.0016	0.0010
Damage to the Vehicles (¥)	260.4974	173.5687	267.8334	155.9251
Treated Road (0-1)	0.1205	0.1138	0.1191	0.1181
Camera Installation (0-1)	0.0462	0.0459	0.0474	0.0459
Installation Intensity (#)	0.0347	0.0333	0.0346	0.0346
# of Observations	674,388	482,664	703,404	455,832

Notes: Table F-2 compares descriptive statistics across accident timing including *Daytime* and *Night* for the time of a day, and *Weekday* and *Weekend* for the day of a week. On average, the accidents, injuries, fatalities, damages, and penalties per road segment per week are higher during the *Daytime* than *Night*, and higher during *Weekday* than *Weekend*. This seems coincided with the different traffic volume on the roads at work and leisure times. Similar with what we do for summary statistics across location, we calculate the total number of accidents, injuries, fatalities, damages and penalties across time, which follows a similar finding with that use mean value per road segment per week.

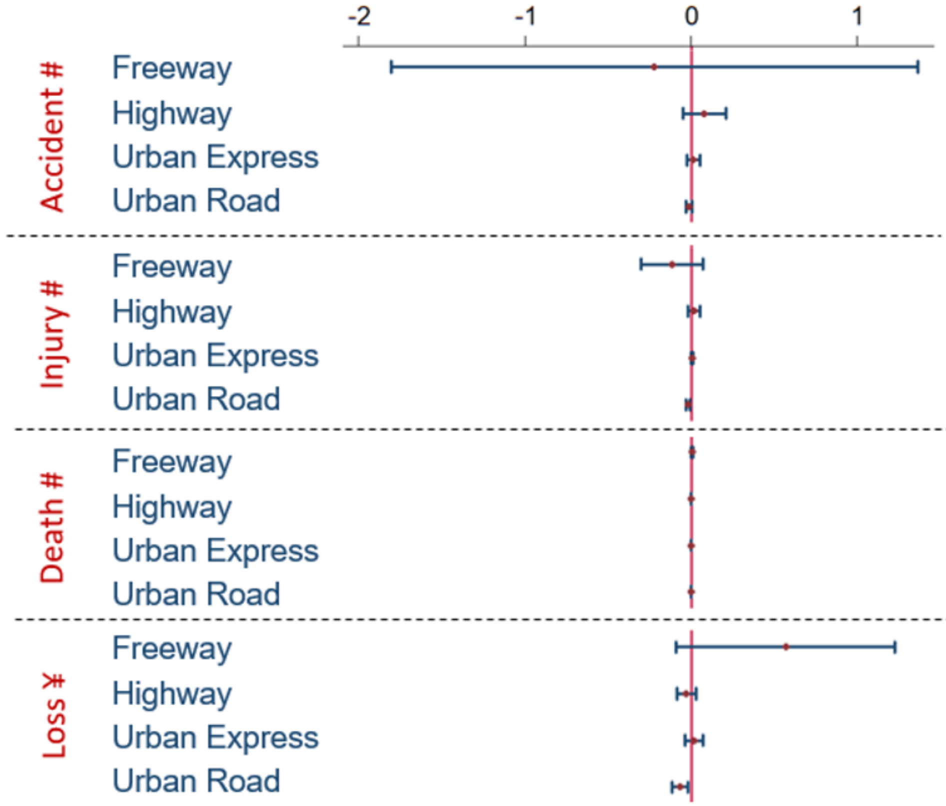


Figure F-1.
Heterogeneity Treatment Effects across Location
(Subsampling by *Types of Roads*)

Notes; Figure F-1 shows the heterogeneous treatment effect across accident location. Interestingly, the effects at Suburban roadways, especially for *Freeway*, are drastically different from those at roads within the Urban area. Evidence shows that camera installation could even induce more damages and at *Freeway*, while it is generally the reverse story for those at *Urban Road*. Recall that more accidents were located at *Urban Road*. Therefore, we believe that, generally, surveillance technology lead positive changes in traffic safety in the urban area.

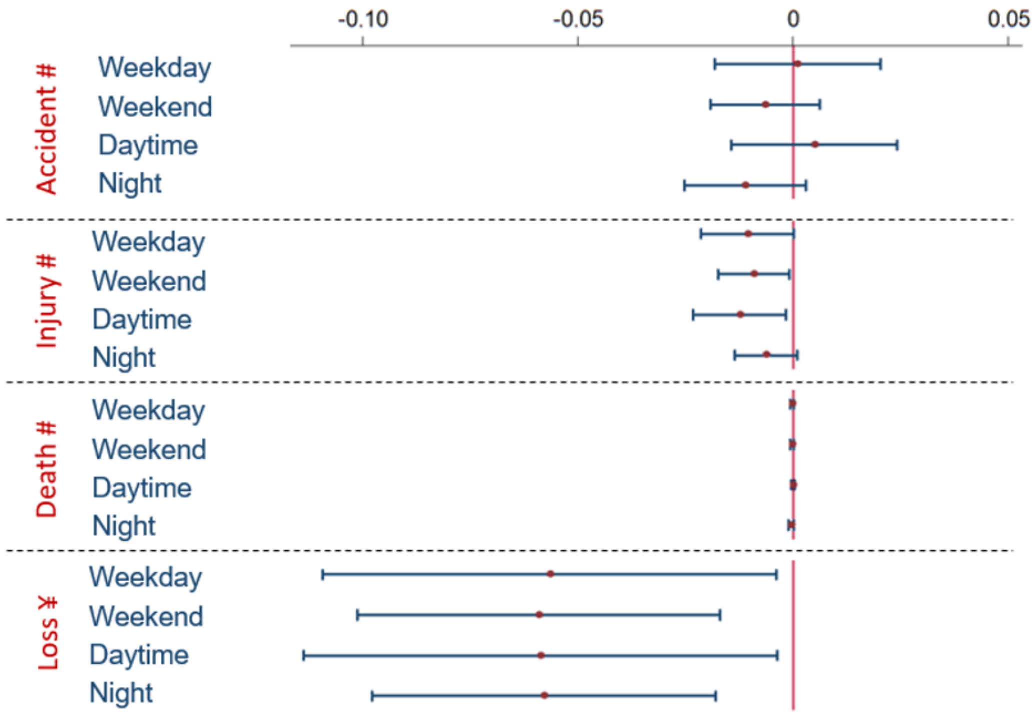


Figure F-2.
Heterogeneity Treatment Effects across Time
(Subsampling by *Time of Day* and *Day of Week*)

Notes: Figure F-2 shows the heterogeneous treatment effect across accident timings. In contrast to the findings on location effects, the analysis by stratifying accident timings does not show much heterogeneity. One plausible reason would be that surveillance technology exerts very similar effects regardless of when an accident is occurred.

APPENDIX G

STUDY 3: MAIN RESULTS FROM DIFFERENT SURVIVAL MODELS

Table G-1.
Results from Survival Models assuming Different Distributions

Dependent Variable: Churn	Cox Hazard	Exponential	Weibull	Gompertz
	(1)	(2)	(3)	(4)
Comparison	-0.199***	-0.170***	-0.186***	-0.204***
	(0.025)	(0.024)	(0.026)	(0.026)
Past purchasing history	0.085***	0.076***	0.085***	0.088***
	(0.003)	(0.003)	(0.003)	(0.003)
Driver gender	-0.042***	-0.039***	-0.042***	-0.042***
	(0.012)	(0.011)	(0.013)	(0.013)
Driver age	-0.004***	-0.003***	-0.004***	-0.004***
	(0.001)	(0.000)	(0.000)	(0.001)
Car age	0.031***	0.032***	0.032***	0.031***
	(0.002)	(0.002)	(0.002)	(0.002)
Engine power	0.076**	0.102***	0.085**	0.073**
	(0.034)	(0.030)	(0.034)	(0.035)
Car value	0.203***	0.140***	0.194***	0.212***
	(0.028)	(0.026)	(0.028)	(0.029)
Total kilometers driven	-0.145***	-0.137***	-0.144***	-0.147***
	(0.003)	(0.002)	(0.003)	(0.003)
Damage free years	-0.047***	-0.041***	-0.047***	-0.047***
	(0.002)	(0.002)	(0.002)	(0.002)
Coverage1 (limited comprehensive)	-0.232***	-0.212***	-0.241***	-0.243***
	(0.015)	(0.013)	(0.015)	(0.015)
Coverage2 (comprehensive)	-0.039*	-0.013	-0.040**	-0.048**
	(0.020)	(0.018)	(0.020)	(0.021)
Total damage	-0.079***	-0.069***	-0.078***	-0.081***
	(0.002)	(0.002)	(0.002)	(0.002)
Average Premium per Month	-0.004***	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Cross-buying other insurance	YES	YES	YES	YES
Contract signed time	YES	YES	YES	YES
# of Observations	80,140	80,140	80,140	80,140

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

APPENDIX H

STUDY 3: MECHANISM TESTING

Table H-1.
Summary Statistics for Variables from Comparison Website Data (N=1200)

	Mean	SD	Min	Max
	(1)	(2)	(3)	(4)
Comparison	0.472	0.499	0	1
Churn	0.132	0.338	0	1
Customer gender	0.343	0.437	0	1
Customer age	44.805	14.251	25	81
Car age	11.998	4.704	0	29
Car value	24713.470	14600.400	7258	96870
Engine power	80.077	38.643	29	210
Total kilometers	15059.583	13957.534	7,000	99,000
Damage free years	6.723	6.493	0	40
Coverage type (liability)	0.380	0.500	0	1
Coverage type (limited comprehensive)	0.320	0.458	0	1
Coverage type (comprehensive)	0.290	0.484	0	1
Monthly premium	32.019	17.853	10.320	239.670
Policy duration months	3.643	1.040	1	5
Travel insurance	0.046	0.209	0	1
Travel accident Insurance	0.007	0.128	0	1
Legal assistance Insurance	0.025	0.156	0	1
Home insurance	0.055	0.228	0	1
Other insurance	0.052	0.302	0	1
Within top 3 recommended	0.171	0.377	0	1
Price advantage	0.868	0.339	0	1
Quality advantage	0.608	0.489	0	1
# Ratings advantage	0.733	0.442	0	1
Price differential	-10.059	11.154	-125. 390	68.860
Quality differential	0.216	0.326	-0.200	1.200
# Ratings differential	304.874	5,027.262	-14,110	3,955

Notes: Price advantage and quality advantage, # ratings advantage, are dummy variables (0-1), measuring whether or not the price, product quality, and brand reputation of the insurance from the focal firm (we collaborated) is higher/lower, or better/worse than that of its best competitors. Price differential, quality differential, # ratings differentials, are continuous variables, measuring to what extent the price, product quality, and brand reputation of the insurance from the focal firm (we collaborated) is higher/lower, or better/worse than that of its best competitors.

APPENDIX I

STUDY 3: ROBUSTNESS CHECKS

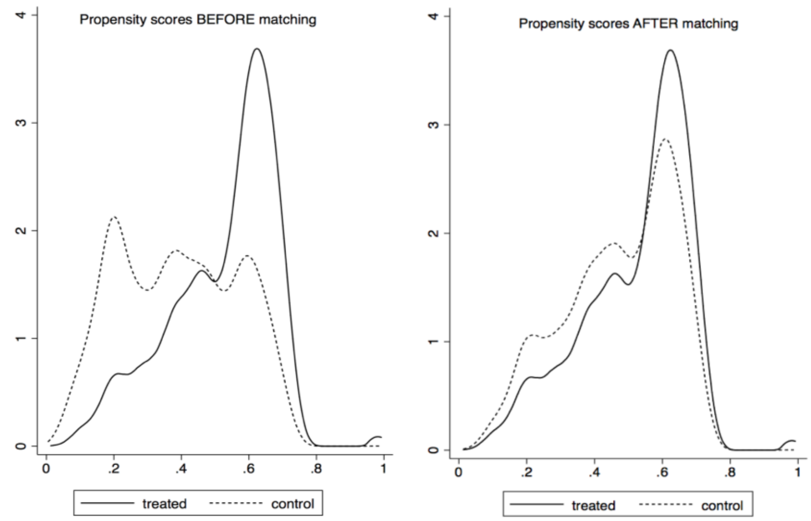


Figure I-1.
Propensity Score Density for Matched Treated and Control Group

Notes: After matching, there exists a substantial overlap (right figure) of the propensity score densities for the two groups (treated: customer from comparison website, control: customers from less transparent channels), indicating matching helps generate reliable estimate to control observed heterogeneity that may drive the channel selection.

Table I-1. Comparison of Churn Probability between Those Who Purchased *Single* Auto insurance and Those Who Purchased *Multiple* Auto insurances respectively

Dependent Variable: Churn	*Customers who purchased*	
	A single car insurance	Multiple car insurances
	(1)	(2)
Comparison	-0.038***	-0.188***
	(0.015)	(0.052)
All Covariates	YES	YES
# of Observations	65,791	16,421
Adj. R-squared	0.384	0.351

Notes: Robust standard errors (are clustered at the customer level in Column (1) since the customers have purchased multiple auto insurances) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table I-2. Comparison of Churn Probability across Different Comparison Website Measures

Dependent Variable: Churn	*Treatment groups: those who purchase insurance from*		
	All comparison websites	Comparison website "A"	Other comparison websites except "A"
	(1)	(2)	(3)
Comparison	-0.046***	-0.075**	-0.0400***
	(0.008)	(0.031)	(0.011)
All Covariates	YES	YES	YES
# of Observations	82,212	75,760	50,929
Adj. R-squared	0.384	0.379	0.410

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table I-3.
Comparison of Churn Probability Using Different Baseline Channels

Dependent Variable: Churn	*Baselines Channels:*			
	All other channels	Firm's own quote website	Inbound telemarking	Online Ads
	(1)	(2)	(3)	(4)
Comparison	-0.046***	-0.011***	-0.035***	-0.071***
	(0.008)	(0.003)	(0.004)	(0.011)
All Covariates	YES	YES	YES	YES
# of Observations	82,212	55,819	54,045	47,828
Adj. R-squared	0.384	0.361	0.362	0.345

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table I-4.
Replication of Table I-3 Using Propensity-Score Matched Customers

Dependent Variable: Churn	*Baselines Channels:*			
	All other channels	Firm's own quote website	Inbound telemarking	Online Ads
	(1)	(2)	(3)	(4)
Comparison	-0.071***	-0.011*	-0.040***	-0.071***
	(0.016)	(0.006)	(0.009)	(0.016)
All Covariates	YES	YES	YES	YES
# of Observations	75,480	54,668	48,600	47,692
Adj. R-squared	0.325	0.324	0.330	0.322

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table I-5.
Brand Image, Comparison Website, and Customer Churn

Dependent Variable: Churn	(1)	(2)
# Ratings Advantage	-0.098**	-0.038
	(0.042)	(0.056)
# Ratings Advantage × Comparison		-0.126
		(0.077)
All Covariates	YES	YES
# of Observations	1,200	1,200

Notes: Brand is measured by advantage in # ratings, indicating the difference in the number of ratings between the focal insurance provider and its best competitor. The higher the advantage in # ratings, the better brand reputation of focal firm compared to the competitor. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table I-6.
Damage Claims, Comparison Website, and Customer Churn

Dependent Variable: Churn	(1)	(2)
Damage Claim	0.015***	0.024***
(=0 if there is at least one damage claimed)	(0.004)	(0.005)
Damage Claim × Comparison		-0.022***
		(0.008)
All Covariates	YES	YES
# of Observations	82,212	82,212

Notes: Damage Claim is a dummy variable indicating whether a customer has claimed a damage (=1 if yes, 0 otherwise). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table I-7.
Service Satisfaction, Comparison Website, and Customer Churn

Dependent Variable: Churn	(1)	(2)
Satisfaction	-0.011*	-0.012*
	(0.006)	(0.007)
Satisfaction × Comparison		-0.026*
		(0.014)
All Covariates	YES	YES
# of Observations	140	140

Notes: Service satisfaction measure is derived from the response to a simple question, “How satisfied are you with our insurance?”, which equals to 1 if very dissatisfied while 5 if very satisfied, in a 1-5 scale. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.

Table I-8.
Heterogeneity in Customers, Cars, and Contracts
(Sub-sample Analyses on the Main Effects)

Dependent Variable: Churn *Independent Variable:* Comparison	Sub-sample	Coefficient	Std. Err.	N
	(1)	(2)	(3)	(4)
Driver Gender	**Male**	**-0.048*** **	**(0.010)**	**56,404**
	Female	**-0.044*** **	**(0.014)**	**25,808**
Driver Age	< 25	-0.024	(0.033)	3,539
	[25, 35]	-0.013	(0.019)	21,128
	[35, 45]	**-0.057*** **	**(0.017)**	**17,924**
	[45, 55]	**-0.065*** **	**(0.016)**	**20,730**
	[55, 65]	**-0.078*** **	**(0.022)**	**10,601**
	[65, 75]	-0.038	(0.030)	6,634
	> 75	0.006	(0.056)	1,656
Pre-purchase history	**No**	**-0.045*** **	**(0.009)**	**70,214**
	Yes	**-0.041* **	**(0.023)**	**11,998**
Original car price	**[0%, 25%]**	**-0.043*** **	**(0.014)**	**20,587**
	[25%, 50%]	**-0.045*** **	**(0.016)**	**20,520**
	[50%, 75%]	**-0.034* **	**(0.018)**	**20,552**
	[75%, 100%]	**-0.061*** **	**(0.019)**	**20,552**
Total kilometers driven	0	0.002	(0.002)	17,772
	[0, 8000]	**-0.105*** **	**(0.024)**	**10,338**
	[8000, 30000]	**-0.049*** **	**(0.011)**	**51,486**
	>30000	-0.027	(0.049)	2,616
Coverage types	**Liability**	**-0.045*** **	**(0.016)**	**30,061**
	Limited Comprehensive	**-0.040*** **	**(0.015)**	**27,195**
	Comprehensive	**-0.064*** **	**(0.014)**	**24,956**
Purchased other types of insurance from the focal insurance firm	**No**	**-0.055*** **	**(0.009)**	**75,026**
	Yes	0.036	0.024)	7,186

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

APPENDIX J

STUDY 3: SURVEY DATA ANALYSIS

Table J-1.
Variables, Definitions, and Values in the Survey Data

Variables	Question Items	Values
(1)	(2)	(3)
Transparency	Please rate the level of information transparency for the following channels for purchasing auto insurance.	0=the LEAST transparent 10=the MOST transparent
Quote Duration	Please estimate how long it takes for you to go through the auto insurance quote process when using the following channels.	1=less than 5 min 2=5-10 min 3=10-20 min 4=more than 20 min
Ease of Use	Please rate the <u>ease of using</u> the following channels.	0=very EASY 10=very DIFFICULT
Channel Satisfaction	Please rate how you are satisfied with the auto insurance quote process when using the following channels.	0=very DISSATISFIED, 10= very SATISFIED
Acquisition Cost	Please rate <u>the likelihood of stopping the process</u> without getting a quote when using the following channels.	0=LEAST likely 10=MOST likely
Multi-Channel Information Gathering	Please rate the likelihood of using the channel *A* to search for information and get an auto insurance quote, while using the channels B to make the actual purchase.	0=the LEAST likely 10=the MOST likely
Post Search	Please rate the likelihood of searching or obtaining information of other insurance providers and offerings after purchasing the current insurance.	0=LEAST likely 10=MOST likely
Driver Age	How old are you?	1=Below 25 2=25-35 3=36-45 4=46-55 5=56-65 6=Above 65
Driver Gender	What’s your gender?	0=Male 1=Female
Car (Year of Production)	What is the year of production of your car?	1=Before 1990 2=1990 … 30=2018
Car Price	What was the list price of your car?	1=less than €5000 2=€5001~€10000 … 16= more than €100,000
Total Kilometer Driven	How many kilometers do you drive your car per year?	1=less than 5000 2=5001~7500 … 9=more than 30,000
Insurance Type	What is the type of your current car insurance?	1=Liability 2=Liability and Collision 3=Comprehensive
Monthly	What is your monthly premium for your car?	0=Less than €25

Premium		1=€25 ~ €50 … 12=More than €300
Other Insurance	Have you purchased any other types of insurance from the current car insurance provider?	0=No 1=Travel accident insurance 2=Home Insurance 3=Life insurance 4=Legal assistance insurance 5=Others insurance

Table J-2.
Comparison of Covariates in the Survey and Main Dataset

	Survey Data (N=226)	Main dataset (N=82,212)	Difference in Mean
	(1)	(2)	(3)
Driver gender	0.301	0.317	-0.016
	(0.460)	(0.465)	(0.031)
Driver age	3.446	3.533	-0.087
	(1.177)	(1.377)	(0.078)
Car year of production	20.258	20.736	-0.478
	(7.004)	(7.367)	(0.467)
Car price	5.407	5.215	0.192
	(4.275)	(2.589)	(0.284)
Total kilometers driven	5.305	5.575	-0.269
	(2.247)	(2.640)	(0.150)
Insurance type	2.301	2.272	0.028
	(0.815)	(0.817)	(0.054)
Monthly premium	3.841	3.601	0.239
	(3.117)	(1.983)	(0.207)
Other insurance	1.243	1.196	0.047
	(1.481)	(0.712)	(0.099)

Table J-3.
Replicating Main Analysis by Using Subjective Transparency Measure

Predicted Variable	Definition	Total (N=82,212)	From a comparison website (N=37,740)	From other channels (N=44,472)	Difference in Mean (4)-(5)
(1)	(2)	(3)	(4)	(5)	(6)
Multi-Channel Information Gathering	Likelihood of getting info. from other channels before purchase	5.219 (0.405)	5.116 (0.381)	5.339 (0.396)	-0.223 (0.549)
Search cost (quotation duration)	Duration of getting a quote via the acquisition channel	2.528 (0.183)	2.405 (0.137)	2.672 (0.115)	-0.266 (0.179)
Ease of use	Ease of use of the acquisition channel	4.741 (0.474)	4.761 (0.553)	4.724 (0.394)	0.037 (0.679)
Satisfaction	Satisfaction of the acquisition channel	6.193 (0.347)	6.378 (0.264)	5.976 (0.298)	0.403 (0.398)
Acquisition cost	Likelihood of stopping quoting without purchase	5.149 (0.474)	5.076 (0.335)	5.212 (0.558)	-0.136 (0.651)
Post search	Likelihood of searching other offerings after acquisition	5.476 (0.507)	5.564 (0.592)	5.401 (0.406)	0.163 (0.718)
Transparency	Subjective transparency of the acquisition channel	6.023 (0.327)	6.474 (0.352)	5.640 (0.304)	0.834* (0.465)

Notes: Table J-3 shows the statistics of above variables in the main data and compare them between treated and untreated channels. The values of these variables are generated through prediction using a multinomial regression of variables in survey (Table J-1) on covariates in Table J-2). These values are heterogeneous across customers, insured vehicles, and contracts. Variables, including *multi-channel information gathering*, *search cost*, *ease of use*, *satisfaction*, *acquisition cost*, and *post search*, are potential confounder that may be correlated both channel selection and churn decision. Table J-4 incorporate these variables to further estimate the effect of comparison website on churn rate. *Transparency* denotes subjective transparency of acquisition channels, which is an alternative measure of transparency instead of our main independent variable, *comparison*. We cross-validate our estimates using both *Transparency* and *comparison* in Table J-5.

Table J-4.
Replicating Main Analysis by Controlling Potential Confounders

	Dependent Variable: Churn							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Comparison	-0.046***	-0.057***	-0.091***	-0.046***	-0.023***	-0.033***	-0.047***	-0.054***
	(0.008)	(0.008)	(0.011)	(0.008)	(0.008)	(0.009)	(0.008)	(0.011)
Multi-Channel Information Gathering		0.068***						0.041***
		(0.006)						(0.008)
Search cost (quote duration)			0.167***					0.073***
			(0.022)					(0.025)
Ease of use				-0.000				0.008
				(0.009)				(0.010)
Satisfaction					-0.054***			-0.060***
					(0.008)			(0.009)
Acquisition Cost						0.058***		0.052***
						(0.006)		(0.007)
Post Search							0.021***	0.028***
							(0.004)	(0.007)
All Covariates	YES	YES	YES	YES	YES	YES	YES	YES
# of Obs.	82,212	82,212	82,212	82,212	82,207	82,212	82,212	82,207
Adj. R-squared	0.384	0.385	0.384	0.384	0.384	0.385	0.384	0.386

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table J-5.
Replicating Main Analysis by Using Subjective Transparency Measure

	Dependent Variable: Churn	
	(1)	(2)
Comparison	-0.046***	
	(0.008)	
Transparency		-0.040***
		(0.008)
All Covariates	YES	YES
# of Observations	82,212	82,212
Adj. R-squared	0.384	0.383

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1