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Privacy Protection, At What Cost?
Exploring the Regulatory Resistance to Data Technology in Auto Insurance

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Abstract

Regulatory and sociological resistance to new market-driven technologies, particularly to those that rely on collection and analysis of personal data, is prevalent even in cases where the technology creates large social value and saves lives. This article is a case study of such tragic technology resistance, focusing on tracking devices in cars which allow auto insurers to monitor how policyholders drive and adjust the premiums accordingly. Growing empirical work reveals that such “usage-based insurance” induces safer driving, reducing fatal accidents by almost one third, and resulting in more affordable and fair premiums. Yet, California prohibits this technology and other states limit its effectiveness, largely in the interest of privacy protection. The article evaluates the justifications fueling the restrictive regulation vis-à-vis the loss of lives resulting from this regulation. It concludes that the social benefits of the tracking technology dramatically outweigh the privacy and related costs.

“Some of you may die, but it’s a sacrifice I am willing to make”
— Lord Farquaad, Shrek (2001)

I. INTRODUCTION

This article is about the puzzling resistance to a life-saving technology.

Here is a novel tracking technology. It is costless to install, and it creates enormous social value to almost everyone involved. It saves thousands of lives, millions of injuries, and billions of dollars. It reduces misallocation, discrimination, and litigation. Yet it faces strong ongoing opposition, both regulatory and sociological, which slows down and curtails its adoption. The opposition is fueled primarily by privacy concerns.

The article presents the technology and shows that without doubt the concrete benefits from it far outweigh even the most pessimistic assessment of any possible, largely speculative, privacy and related costs. The article explores why, in the face of such clear net social value, the resistance lingers. It surveys the justifications for the technology anxiety, grounded in various conceptions of dignified life, power imbalance, and distributive justice. It shows how the tension between the contesting values—between the concrete life-saving benefit and the potential threat to private spheres or to longstanding social practices—shapes the regulation of this technology, and possibly of other pathbreaking innovations in a multitude of areas. This article is part of my broader exploration of that battleground.

The tracking technology at the heart of this article is embedded in devices that—if drivers agree—record how a car is driven and report the data to an auto insurance company. With the knowledge of how, when, and where people drive, and based on data from prior collisions, insurers can directly measure each driver’s accident propensity and charge insurance premiums commensurate with the individualized predictions (Karapiperis et al., 2015). As a result, people drive safer.

To appreciate the value of this technology, let’s take a step back and talk for a minute about auto safety. Road accidents are a major cause of fatalities. Every year, roughly 40,000 people die and close to five million people are injured in the U.S. as result of motor vehicle crashes, with economic costs of half a trillion dollars. The great majority of accidents result from dangerous driving—inattention, speeding, and various forms of cognitive impairment (World Health Organization 2018). Safety technologies, like airbags and seatbelts, have had success in lowering road deaths, but these measures have largely reduced only the severity of injuries and have done little to address risky driving (Rothengatter 2002). Famously, there are some who argue that the perceived safety gains of certain safety improvements make drivers feel more secure and prompt them to drive more recklessly.¹

The law uses various interventions to improve road safety. Traffic fines can affect how people drive and the likelihood of accidents. Speed radars and cameras, for example, deter speeding in the general population and reduce road crashes (Goldenbeld and van Schagen

¹ This is the widely known risk homeostasis theory, or the “Pelzman Effect.” See Pelzman (1975) and Wilde (1986).

2005). But their deterrent effect is local, occurring in the proximity of areas where driving speed is being monitored. Many other dangerous driving patterns, like tailgating or sharp breaking, are either hard to detect or not illegal. Additional regulatory innovations, like graduated drivers' licenses, have also had some effect on crash risks of young drivers, but car accidents continue to be the leading cause of death for teens (NHTSA 2015).

Against this grim background, a major new safety technology has been introduced, not by lawmakers, but rather by insurers, changing the way auto insurance is priced and improving the way policyholders drive. Generally referred to as usage-based insurance (UBI), integrated tracking devices ("telematics") record how a car is driven: how sharply it accelerates or breaks, how often it engages in abrupt lane changes, when and how far it drives, and even the distractions of the driver (texting)—all are factors that don't only correlate with accidents but cause them. They are richly recorded and transmitted to the insurers and communicated to drivers with real time alerts and periodic scores. The abundance of such records, matched with background accident data, gives insurers unprecedented tools to identify risk-increasing driving habits and rate each driver accordingly (Arumugam and Bhargavi 2019). Premiums are no longer determined by indirect non-driving factors correlated with losses, like gender, marital status, or education. Instead, they reflect each policyholder's idiosyncratic driving, and change continuously as these habits evolve.

While there is a lot to celebrate in UBI—not least its replacement of the traditional and sometimes problematic social-demographic rating factors with an accurate new pricing model—by far the most important impact of the technology is the reduction in accidents and road fatalities. When people are tracked, they drive better (Strahilevitz 2006: 1705-06). Why? maybe because they are rewarded with premium discounts. Or maybe because they are more deliberate and less impulsive. Or maybe because the feedback they get from the devices teaches them to drive safer. These mechanisms are strong and quick. Studies measuring the effect show that within a month or so drivers' risk scores improve dramatically. Empirical estimates reviewed in this article put the decline in fatal accidents that results from adoption of UBI in the range of 30 percent. This impact is comparable to, and possibly exceeds, some of the most historically important highway safety technologies.² And it requires no budget, no delay, and no regulation, bestowed equally upon all social-economic groups.

This is where the article should have ended. More safety, more fairness, more savings—lights out. But unfortunately, UBI technology faced, and continues to be weighed down by, regulatory hurdles. From the outset, insurance regulation has only half-heartedly welcomed this innovation. It took time, but by now—almost two decades since the tracking technology was rolled out—UBI powered by tracking devices is available in principle in every state but California. A strong current of resistance to this innovation, based primarily on privacy concerns, accounted for the slow rate of adoption, and continues to foster the outright prohibition in California, as well as new restrictive regulations elsewhere. California law

² Seat belts are widely regarded as one of the most impactful safety technologies. The Department of Transportation estimated a reduction in the risk of death of 45% and of serious injury by 50% (NHTSA 2010). Other empirical studies offer a more modest estimate. See Cohen and Einav (2003), who found that raising the national usage level from 68% to 90% will reduce traffic fatalities by 4% to 8%.

explicitly prohibits the use of driving factors other than mileage, and as a result does not permit insurers to offer policyholders the option of installing recording devices. Some other states, while permitting the use of the tracking technology, limit or burden the entry of insurers into this market and distort their ability to price auto policies in a manner that reflects the UBI data models.

This article examines the regulatory debate. So much of the literature on UBI focuses on its downsides, therefore I chose to begin with the oft-ignored benefits of the technology—the phenomenal reduction in fatal accidents, as well as increased accuracy and fairness in pricing. It is against these upsides that the article then evaluates the restrictions. It identifies the specific reasons for the opposition, which primarily include a concern over policyholders’ privacy, and are further grounded in the potential appropriation and rent-seeking by insurers, in discrimination against weaker social-demographic group, and in the lack of transparency of the UBI algorithms. The article also examines the more fundamental objections to institutions governed by big data analytics—bias, misclassification, and threats to individual autonomy—which might result from the personalization of products and services.

The goal of this article is to highlight the misalignment between these concerns and the social sacrifice required to prioritize them. While the magnitude of the data that tracking devices transmit to insurers are massive and potentially sensitive, and while the personalized premiums raise legitimate questions of distributive equity and transparency, the evaluation of such concerns must be done with an understanding of their true magnitude and how they play out in practice, all in relation to the benefits of the technology. Slowing the implementation of a beneficial innovation has a social cost. At what cost, the article implicitly asks, is it justified to resist a lifesaving technology?

Not to spoil the plot, the gist of what I report is a case of almost startling mismatch: the social value of the tracking technology far, far, outweighs even its most pessimistic downsides. The concerns driving the resistance are dwarfed by the benefits that the regulation inhibits. To put it bluntly, thousands of lives and millions of injuries could be saved on the roads every year without any sacrifice of freedom and autonomy of drivers, and without adverse impact on insurance equity. There is no surrender of control, no diminution of drivers’ personal space, and no loss of transparency. There is, instead greater road safety, better private choices, and more affordable premiums. While the black-box algorithms deployed by insurers are proprietary, policyholders have unprecedented access to the factors that affect their personalized ratings. Shamefully, the so-called protective regulation, which seeks to advance a thin and, in this context, a superfluous notion of privacy, hinders the dissemination of these major benefits and costs endless lives.

This is a pilot study. My focus on UBI and its regulatory torments is a prelude to a more ambitious inquiry which, in ongoing work, I develop. I want to connect the dots, each of which is a new technology or scientific advancement. It has a proven upside, but it could also change longstanding social and economic practices. In the past, these key inventions were mostly automation technologies that displaced humans. Nowadays, many of these are data-driven innovations, like electronic medical records that refashion hospital routines and save numerous lives or biometric data used in law enforcement and international travel.

These innovations are also manifested in other branches of scientific progress, as for example in biotechnological improvements of conventional agriculture, which deliver more and healthier food with less environmental harm. Increasingly, these technological breakthroughs utilize artificial intelligence, adding to their perceived mystery.

The new technologies deliver unparalleled benefits but come with pivotal transformations of existing practices. They retire routines that rely on human expertise, situational knowledge, and intuitions; They introduce synthetic elements not seen before; and they engender new norms of surplus distribution. They rely on models that rely on vast personal data. The fundamental question for society is how to welcome the innovations, and specifically how to prepare for their potential downsides. All too often, the social benefits of these “subversive” breakthroughs are loudly met with an alarmist skepticism—a precautionary instinct—which regrettably dominates the ensuing regulatory approach. These skeptics say: something *could* go terribly wrong with this new method, and although the disaster has not yet happened nor is it likely to happen, and although our present practices are deeply flawed, we should put in place a political and bureaucratic order to safeguard against a potential upheaval, and in the meantime slow down the introduction of the technology, no matter the forgone benefit, until we can make sure that it is fail-proof or harmless.

So prominent and alluring is this precautionary instinct—so often does it seem to be a good approach to the uncertainty brought upon by a new technology—that many of its advocates do not pause to ask, “at what cost”? While some acknowledge, in passing, the social cost of slowing down the adoption of new technologies, they assume—often without analysis—that the sacrifice is worth making. I need a term for regulators and advocates who refuse to consider the appropriate proportion and costs of the regulatory restraints. “Precautionites” seems to describe their motto. It expresses a regulatory position with varying justifications and motivations, for it is a generalization as, say, “conservative” or “progressive” are. But it is a useful abstraction because ‘precaution’—a safeguard against a threat—is the dominant sentiment that the technological innovation evokes in this camp.

I recognize that it is impossible to defeat the precautionite thesis because the ingredients that fuel it are not concrete. What exactly could go wrong, how likely it is, and what might be the consequential harms, are sufficiently nebulous at the infancy of the new technology that, yes, if the perfect storm hits the precautionite instinct would turn out to have been prophetic. It is also not my goal to deny the wisdom of prudence or to resolve longstanding debates regarding the benefits of the “precautionary principle,” which advocates caution and restrictions on new technologies when their effects are unknown. My argument is selective in three ways. First, information: I focus on technologies for which enough experience has accumulated to reduce the outcome uncertainty. Second, the harm: I am interested in cases that do not involve life-life tradeoffs, but rather where the primary harms imagined by precautionites a degradation of some ethical or political ideals, primarily of data privacy. And, third: the benefit: I set up the conversation by assessing the massive upside of the resisted technologies, primarily their life saving potential.³

³ My critique is aimed at a particular embodiment of the precautionary principle and its unintended consequences, in specific contexts where this principle has less traction. It takes no position on the wisdom of

The article begins with a brief description of the UBI tracking technology (Part II) and the law governing it (Part III). Part IV then examines with greater detail the benefits of the technology, highlighting its significant accident reduction effect and pointing to the desirable distributive impact it has in relation to other methods of risk classification. Finally, Part V examines the grounds for the opposition, focusing first on the specific pinpointed reasons provided by the UBI opposition (privacy, appropriation, discrimination, transparency), and then on the more fundamental, and somewhat abstract, precautionite instincts fueling them, surrounding power imbalance, autonomy, and equity.

II. THE TECHNOLOGY

A. Before UBI

Auto insurers, we all know, classify drivers based on the predicted risk of collision. Before usage-based insurance, insurers relied solely on demographics and driving experience to predict policyholders' idiosyncratic risks and set the premiums (Heller and DeLong 2021: 4). They had to settle for fragments of crude risk-correlates. They asked policyholders to declare their car usage habits and mileage, they looped in violations and accidents data, and they learned to rely on socio-economic non-driving proxy factors that were shown, in their data models, to correlate with risk—like gender, age, marital status, school grades, or credit scores. These predictors, most of them devoid of causal relation, allow insurers to rationally sort their policyholders into statistical risk groups and vary the premiums across groups. Some of these demographic factors, however, like homeownership and credit score, are particularly mysterious and regressive, making them politically controversial and subjecting them to restrictive rules in several jurisdictions.⁴

Prior to UBI models, the most important driving factor used by insurers to rate policyholders was annual mileage. “Pay As You Drive” (PAYD) schemes rely on miles as a central accident-predictive factor, for a good reason. As depicted in the Figure below, the more the policyholder drives the greater the likelihood of property or bodily injury claim.⁵

FIGURE 1

Moreover, driving creates insurance externalities. An additional driver increases accidents and insurance costs to other drivers, at a level estimated by Edlin and Karaca-Mandic (2006) in the range of \$1725 - \$3239 (in the 1990's). Thus, paying for insurance in proportion to miles driven makes not only the private insurance contract more efficient; it also harnesses a Pigouvian logic—paying for the negative externality.

cautionary policies in areas where great uncertainty prevails, where the potential downsides can be ruinous, or where the benefit of the technologies is ambiguous.

⁴ Chiglinsky (2021) notes that states such as California, Texas, Colorado, and Washington have various limits on the use of credit score data in car insurance rates. Spears (2019) describes political efforts to limit the use of home ownership and other factors in insurance rate calculations.

⁵ See Bordoff and Noel (2008).

Information about miles driven is low tech—it does not require recording devices (although their presence makes the reports more accurate.) It could be assembled via odometer readings, and even before the dawn of the Big Data tracking era such information was publicly available in states that mandated periodic vehicle inspections, or from platforms like Carfax that sell vehicle history reports to insurers and car buyers. PAYD was a big step to liberate insurers from the accusation leveled against them by Vickrey (1968: 470) that “the manner in which premiums are computed and paid fails miserably to bring home to the automobile user the costs he imposes in a manner that will appropriately influence his decisions.”

Predicting accident risk by miles driven makes insurance premiums more aligned with the expected loss, but its impact on driving is limited. It is an activity level metric, and while the scope of activity is of course important in creating risks, so much of auto accident risk depends on the individual driving habits and precautions, which PAYD does not measure. Two individuals may drive the same number of miles but create dramatically different risks. Moreover, upon further reflection, it is questionable how much PAYD pricing impacts driving levels. Insurance is not like gasoline—where each additional mile driven increases the charge—because policyholders tend to think of it as a fixed cost (Karapiperis et al. 2015: 29-32). Auto insurance premium are set as lump sums and paid annually. The premium comprise 10 to 15% of annual vehicle costs but it adds up incrementally mile-by-mile and is therefore less salient and has a smaller effect on the decision whether to make an additional car trip (Nicols and Kockelman, 2014).

B. The Tracking Technology

Enter usage-based insurance. In 2008, Progressive Insurance Company introduced a revolutionary product in the auto insurance market: the “Snapshot” tracker. A novel technology adopted (and, at the time, patented) by Progressive, it offered policyholders the option to install a free device in their cars, which then tracks and records how the car is driven second-by-second, transmitting the information to the insurer. No longer having to rely on policyholders’ non-verifiable reports regarding their driving habits,⁶ Snapshot measures the exact miles driven, and much more. Based on granular data analyzing causes of past collisions, the new device was programmed to measure factors that reflect these causes. Such factor included hard cornering, rapid acceleration, sharp breaking, nighttime driving, and location in accident-prone roads.

This big data technology offered meaningful improvement in predictive analytics relative to the prior classification methodology. Whereas the old predictors, like gender, accident history, or vehicle type, reflect group characteristics—namely, *average* risks within the pool of drivers with similar traits (like “all men” v. “all women,” or “all youth drivers with GPA of B or above”)—they do not reflect the individual driving habits and the risk posed by any single driver. The tracking system, by contrast, allows for a more personalized classification of risk. Having rich information about each trip and linking it with accident loss data and other external inputs such as maps, road type, and weather, enables the prediction model

⁶ Lemaire, Park, and Wang (2016) explain that “insurers have been reluctant to use annual mileage due to their inability to verify policyholders’ statements and the relative easiness to tamper with odometers”.

to identify the vehicle operation factors that are not only correlated with losses, but are likely to be the causes (Karapiperis et al. 2015: 17). For example, Progressive found that drivers who brake hard more than eight times in 500 miles—a feature that measures unsafe following and speeding—are 73% more likely to be involved in an accident, or that the safest drivers allow an average of 39% more time and 32% more distance to stop (Claims Journal 2015). As a result of this prediction model, the insurer is able to offer more personalized premiums.⁷

Eventually, other insurers managed to overcome barriers to entry imposed by Progressive's bastion of patents and began to catch up, offering their own tracking technology and usage-based schemes in a variety of opt-in programs.⁸ Some insurers offer tracking devices similar to Snapshot. Others rely on smartphone apps, since most smartphones are equipped with sensors (GPS, accelerometers, and gyroscopes) and can readily measure and transmit the vehicle's driving patterns and location as well as a variety of risky distracting usages like texting, web surfing, or handheld phone dialing. In addition, UBI programs increasingly rely on built-in technology in connected cars (Ksycinsky 2022). Tesla, for example, which has access to elaborate usage-data as part of the vehicles' multitude of cameras and auto-pilot capability, now offers drivers in several states a Tesla Insurance plan that rates their driving via continuously evolving "Safety Score" and charges them monthly premiums reflecting that score. With the entry of many competitors, UBI's market share in auto insurance has grown rapidly, reaching a global size of \$28 billion in 2020 (Fortune Business Insights, 2023).

Wireless devices that transmit data to a platform which then uses the data for personalized treatment are of course not unique to insurance. In other sectors, data are used to personalize entertainment, information, and shopping based on what people watch, browse, and buy. In insurance, the driving data are used to improve risk predictions, develop more accurate pricing, and allow for more reliable claims assessment. But it is responsible for more than efficient management of the insurance business. UBI provides drivers with personalized feedback through risk scores, premium adjustments, real time driving alerts, and Manage How You Drive coaching programs. It opens the door to more granular risk management techniques, changing how policyholders drive, and reducing auto accidents. Before reviewing the evidence on the magnitude of this effect, let's briefly review the regulatory landscape in which UBI operates.

III. THE LAW

Most states do not regulate usage-based auto insurance directly. Oops, 'not regulate' is a bit of an exaggeration. States regulate auto insurance rates and policies quite heavily, typically requiring periodic preapproval of the rating plan (Eley 2000). The non-regulating states merely treat UBI models as a type of statistical data which they review when they approve

⁷ In principle, premiums may reflect not only the personalized risk estimate but other factors, including those that are thought to affect each policyholder's willingness to pay and switching costs. To the extent that such third-degree price discrimination is practiced, it is not fueled by the UBI data, and is already occurring under traditional insurance pricing models. Nevertheless, the complexity of UBI algorithms may help insurers price-discriminate on other grounds. This is a concern that auto insurance rate regulation could potentially address.

⁸ See, e.g., GEICO Insurance, *DriveEasy Program*, www.geico.com/driveeasy/; State Farm Insurance, *Drive Safe & Save*, www.statefarm.com/insurance/auto/discounts/drive-safe-save/ .

any new rating plans. Insurers must disclose some metrics of the data and how they are used to determine the rates—no different than any other statistics submitted in support of a rating structure (Heller and DeLong 2021). Many non-regulating states view UBI as potentially raising privacy concerns and require disclosures to policyholders of how the data is used. Increasingly, states are introducing legislation requiring insurers to have data risk management program to avoid unfair discrimination and bias.⁹

Among the states that do regulate UBI *sui generis*, California stands out at the most restrictive, effectively prohibiting the tracking schemes. An outgrowth of Proposition 103—an auto insurance reform initiative that passed in 1988—California law sets strict guidelines and oversight on how auto policies may be priced. Premiums must reflect three “Mandatory Factors”: a driver’s safety record, the number of miles driven annually, and years of driving experience.¹⁰ (The regulation also specifies fifteen “optional” pricing factors, which include some of the familiar risk-correlated features like academic standing and marital status.¹¹) Importantly, under the miles-driven factor, the regulation eventually permitted a “verified actual mileage” input, for which insurers may collect via “technological” devices. But in the same breath it proceeds to prohibit the collection of usage-based data beyond miles:

“An insurer shall only use a technological device to collect information for determining actual miles driven under the Second Mandatory Factor . . . [and] shall not use a technological device to collect or store information about the location of the insured vehicle.”¹²

At some point, as UBI grew in popularity, California insurance regulators signaled their openness to reconsidering, in their words, the “antiquated” system of insurance rating and pricing under Prop. 103, “breathing new life” into it by allowing premiums to be based on how people drive, including reliance on vehicle tracking data (Marinucci and White 2019). But for reasons that I discuss later, these flickering second thoughts quickly perished. Indeed, in response to Elon Musk’s demand that California change its insurance rules to allow Tesla Insurance to use the very same driving information the cars’ operating software already obtains, the California Insurance Commissioner announced (twitted):

“We won't bend on protecting consumer data, privacy, and fair rates. The Department of Insurance continues to uphold and implement the consumer protections set forth in voter-enacted Proposition 103 & since 2009 we have

⁹ See, e.g., COLO. DIV. OF INS., *Draft Proposed Governance and Risk Management Regulation*, SB 21-169 (2023), https://content.naic.org/sites/default/files/national_meeting/H-Cmte-Colorado-Slide-Deck032223.pdf.

¹⁰ Cal. Ins. Code § 1861.02 (a)(1)-(3).

¹¹ The fifteen optional factors are: (1) Type of vehicle; (2) Vehicle performance capabilities; (3) Type of use of vehicle; (4) Percentage use of the vehicle by the rated driver; (5) Multi-vehicle households; (6) Academic standing of the rated driver; (7) Completion of driver training or defensive driving courses by the rated driver; (8) Vehicle characteristics; (9) Marital status of the rated driver; (10) Persistency; (11) Non-smoker; (12) Secondary Driver Characteristics; (13) Multi-policies with the same, or an affiliated, company; (14) Relative claims frequency; (15) Relative claims severity. Cal. Code Regs. tit. 10, § 2632.4 (d).

¹² 10 Cal. Code of Regs., tit. 10, § 2632.5 (c)(2)(F)(i)(5)(a) (specifying the use of a technological device is strictly limited for the purpose of collecting vehicle mileage information).

allowed vehicle data only to determine actual miles driven, and only in a way that protects the driver's privacy."¹³

California stands alone in the U.S. in its outright rejection of UBI, but other states impose restrictions. These include standard non-intrusive safeguards: any opt-in scheme requires policyholders' separate consent, and it must include a right to dispute, regulatory review of the agreement and of the rating algorithm, and liability for data breach. The data may not be used or sold for non-rating purposes, and whenever sold or transferred they must be deidentified.¹⁴ Many states that do permit UBI programs nevertheless establish barriers for approval that delay entry by competitors, sometimes for years. For example, at the time of this draft, only twelve states permitted Tesla Insurance.

More intrusive, and harder to justify, is a class of restrictions that protect policyholders from rate increases. (How much this should be counted as "protection"—considering insurance cross subsidies—and who pays for such protections, will be discussed later.) The New York Guidelines for UBI Programs contains the typical "discount only" rule: insurers are permitted to use the tracking data to reduce premiums, but not to increase them, not to "downtier" the policyholder, nor to deny renewal. It also prohibits insurers who collect the data through a smartphone app-based from using the distracted driving statistics in computing a driver's UBI risk score. New York requires the insurance algorithm to have short memory: a "distracted driving" score has to be "refreshed at each policy renewal."¹⁵

Most states have a more permissive approach to usage-based insurance, some with no specific regulations governing it. For example, Ohio—a "file and use" state—requires insurers to file their rating system but does not apply regulatory oversight and does not condition the plan on its approval. In Maryland, another state with no specific black-letter regulation of UBI, regulators informally apply specific considerations when reviewing a usage-based rating system.

In sum, the regulatory landscape involves growing permissiveness towards UBI schemes that deploy tracking technology, coupled with the standard watery protection of data privacy and security. But significant pockets of resistance remain. At the extreme, there is outright prohibition (only in California). Less extreme are the provisional prohibitions, whereby states slow down the approval of new usage-based insurance providers (as in the case of Tesla Insurance). Finally, there are significant substantive limits on how the data can be used for pricing, with the most significant limitation involving the "discount only" rule (New York and other states).

¹³ California Insurance Commissioner Ricardo Lara, Twitter, Jan. 27, 2022.

¹⁴ See, e.g., NY DEPT. OF FIN. SERV., [Updated Guideline for New York UBI Programs](#) (Plug-in Telematics Devices and Smartphone Apps) (hereinafter, "NY Guidelines") at sec. 14; Wash. RCW 48.18.600, 46.35.020, 46.35.030; Fla. R. 690-128.007.

¹⁵ NY Guidelines, *supra*, at Sec. 10 ("The data collected for the UBI program will not be used to affect policyholders in a negative way (e.g., increasing premiums (including application of surcharges), non-renewing policies, preventing downtiering, etc.)."); Sec. 6a ("A company may collect distracted driving statistics; however, such statistics may not be used in the algorithm to determine the final UBI score/factor."); and Sec. 6ab ("A company may establish a separate distracted driving discount ... provided the score/factor is refreshed at each policy renewal.")

IV. THE BENEFITS

As the regulatory survey shows, usage-based auto insurance that relies on real time tracking is controversial. California prohibits it, other states limit it, and advocacy groups campaign for thinning it down. The reasons why it is resisted—privacy? Discrimination? Redistribution? Market power?—are explored in the next section. But before evaluating these reasons, it is critical to understand the benefits of this technology, because the appropriate limits to an activity cannot be sensibly discussed without an account of the loss of value such limits exert.

Usage-based insurance has generated substantial benefit to insurance companies that led the way in introducing it, but the focus in this section is on the other elements of societal benefits, not on the rents that accrued to insurers. First, there are private benefits to policyholders enrolled in UBI and to other people affected by their driving. Here, far and away the most important component of the social value is the reduction in the incidence of car accidents and road fatalities because of safer driving. Second, there are social benefits that result from changed behavior by policyholders which go beyond reduced collisions, primarily fewer miles driven and the associated reduction in emissions. Surveying these effects uncovers a third and perhaps surprising benefit, one that is associated with the increased actuarial precision of UBI: improved equity and fair redistribution in pricing and access to insurance.

1. Road Safety

It is hardly surprising that UBI causes policyholders to drive more safely and suffer fewer accidents. Multiple channels of causation are responsible for this effect. First, a cognitive channel. The mere knowledge of being tracked prompts drivers to be more aware of their conduct and thus more restrained. The mechanisms are both fear and reward. Fear—due to the sense that a someone is watching and will inflict a monetary sanction on an aggressive driver. (Ellison et al. 1995; Strahilevitz 2006.) And reward—because policyholders experience their improved safety score as an accomplishment, thereby driving in a manner that would secure this satisfaction. (Karapiperis et al., 2015: 24-5). A behavior that is otherwise thoughtless, impulsive, and temperamental becomes more reasoned and judicious.

Second, an information channel. When the tracking software provides specific feedback, by showing policyholders the attributes of their driving that downgrade or elevate their safety score, drivers are coached to drive safe. If the tracking device is set to beep when the driver gets too close to another care, or if it provides an explanation when a change to the safety score is executed, the feedback is informative. We know that people think they are better drivers than they are—Svenson (1981) famously showed that 90% say they are better than average—and the infrequency of accidents offers them little opportunity to reevaluate their immodesty. In fact, Preston and Harris (1965) showed that self-serving assumptions about causality helps drivers deflect such reevaluation even when they are responsible for accidents. There is hope that the instructive tools of UBI, with real time repeated input—a type of drivers-ed for seasoned bad drivers—would defeat people’s reluctance to learn.

Third, and possibly most important, is the price effect. UBI is a scheme of penalties and rewards, reflected in the insurance premium. The financial consequences provide a concrete and ongoing incentive to improve one's driving. Unlike traffic fines, which are incurred only probabilistically, and unlike exposure to hazards which provides motivation only when salient, UBI ratings change continuously with every periodic premium, as often as month-by-month.

Working together, these channels establish a *de facto* privately administered scheme of liability for *risk*. Drivers that violate insurers' safety standards incur a greater cost, proportional to the expected harm. We are often told that insurance creates a moral hazard because it reduces the incentive to take precautions. Well, here is a powerful rebuttal. UBI is a private regulation of safety that disseminates commands for prudent driving and sanctions violators via premium adjustments. (Ben-Shahar and Logue 2012: 236-37; Abraham and Schwarcz 2022). Unlike tort law, which sets vague standards of due care and assigns liability only in the rare occasions when actual harm occurs, UBI's "liability" reflects the ex-ante expected harm, it relies on bright line rules and on frequent premium adjustments, and it offers carrots more often than sticks.

It is therefore hard to dispute that, in theory, UBI would be associated with safer driving. What *is* surprising, even astonishing, is the empirical magnitude of the effect. A recent study by Reimers and Shiller (2020) offered a striking quantitative estimate of the reduction in fatal accidents that results under usage-based insurance. The study found that the introduction of a usage-based program led to early enrollment of 9% of the drivers and to a corresponding reduction of fatal accidents by 4.61%. Assuming these early enrollees are just as likely as others to be in a fatal accident, for 9% of drivers to explain 4.61% aggregate reduction in fatalities they must have experienced a 51% reduction in fatal accidents. Of course, the assumption is false. Early enrollees are not necessarily representative. In fact, Dijksterhuis et al (2016) suggest that they are likely to be among the safest drivers, eager to join a program that rewards them for their caution by premium discounts. If indeed the sample disproportionately includes safe drivers, the reduction of fatal accidents for society at large could be even greater.¹⁶

But this is a crude extrapolation, almost too good to be true. Other studies offer somewhat lower estimates, closer to 30% reduction. Jin and Vasserman (2021) analyzed a dataset of one million drivers enrolled in UBI with a national auto insurer and were able to observe individual safety scores, how they change since enrollment, and the corresponding premium adjustments. While they were unable to observe injuries or fatalities, the data included coverage claims made by policyholders and the costs incurred by the insurer, thus approximating the incidence and gravity of accidents. The authors found that "consumers who opt in to monitoring become 30% safer, on average, while they are being monitored." The incentive effect, which causes these enrollees to drive safer, explains 64% of the risk differences between them and those who are not enrolled and are not unmonitored. The story, then, is incentives: the lower accident rate is primarily due to improved driving, not to

¹⁶ It is also possible that early enrollees are more safety-attuned and are therefore more responsive than the typical driver to the safety-inducing mechanisms of usage-based insurance.

disproportionate adoption by safer drivers. While some self-selection is occurring, Jin and Vasserman found a robust incentive effect among all who opt in.¹⁷

Another study of insurance data by Soleymanian, Weingberg, and Zhu (2019) compared participants in the program to non-participants. It used individual-level day-to-day data from an auto insurer to examine how policyholders changed their driving over time. The study found that in the first couple of months, enrolled policyholders decreased their daily average hard-brake frequency by an average of 21% and improved their risk score. (See Figure 2).

FIGURE 2

There are other notable findings in the Soleymanian, Weingberg, and Zhu (2019) study. The most pronounced safe driving effect was found for young urban drivers, but there were significant improvements also for experienced drivers. Only a tiny fraction of the policyholders in the study—less than 1%—exhibited no improvement in driving and failed to qualify for a premium discount. Here too, as in the Jin and Vasserman (2021) study, the measured effects among the monitored group of drivers were not an artifact of a selection bias, whereby more cautious drivers are disproportionately enrolling into monitored insurance. On the contrary: the policyholders who opted into the UBI program in this study were classified by the insurer, on average, as higher risk. Importantly, this study confirmed two channels by which safe driving is induced. First, the financial reward: in “No Fault” states where auto insurance is more expensive, and where premium reductions are therefore potentially greater, the driving improvements observed were larger. Second, information-on-the-go: receiving a safety alert on a given day was associated with greater reduction in the number of hard brakes in the following day.

The improved risk scores documented in both studies confirms the existence of an accident-reduction effect but does not tell us its magnitude. Several clues, however, provide a rough measure of the magnitude. First, the cost of claims. Jin and Vasserman (2021: 14) find that “a fully monitored period would be 29.5% less costly to insure for the same consumer.” Thus, their 30%-safer estimate is based on this cost-of-claims metric. Second, the correlation between hard brakes and accidents. The incidence of hard brakes reflects various risky driving factors, primarily speeding. The OECD’s Transport Research Centre (2006) report estimates that a 5% reduction of speeding may lead to as much as 10% reduction in injury accidents and a 20% reduction in fatalities. Similarly, a NHTSA (2009) study showed a striking correlation between crashes and hard brakes. Drivers who decelerate 4-5 time more often are also involved in 7-8 more crashes and near-crashes. Thus, if only half of the 21% decrease in hard brakes that Soleymanian, Weingberg, and Zhu (2019) found is due to lower speeds, the decline in injuries and fatalities that results is commensurate with the magnitude found in the above-mentioned studies.

¹⁷ A note of caution: while all layers of enrolled drivers display the incentive effect, it does not tell us whether those who do not opt in are also capable of altering their risk. If self-selection is occurring on the ability to alter risk, the 30% reduction in accidents is an overestimation. This qualification is moderated if drivers do not possess private information on their tendency to respond to monitoring.

Additional confirmation of the magnitude of the accident-reduction effect of UBI comes from a multitude of experimental studies. In study conducted in the Netherlands by Bolderdijk et al. (2011) and in Sweden by Hultkrantz and Lindberg (2011), drivers were incentivized by cash payoffs to reduce their speeding behavior. Speeding incidence was reduced as a result of this intervention, and the effect was particularly strong in high-speed roads. The magnitude of the effect is impressive – a reduction of 14% of volitional speeding by one measure, or a reduction of time proportion of speed violations from 15% percent of total driving time prior to the experiment to 5-8%. Once again, if every 5% reduction of speeding may lead to as much as 10% decrease in injury accidents and a 20% decrease in fatalities (Transport Research Centre, 2006), the accident-reduction magnitude of 30% seems realistic.

Similar effects on speeding and other driving factors were measured in several other experiments.¹⁸ Dijksterhuis et al (2016) showed a drastic reduction in hard braking and acceleration (93% and 69%, respectively). Hultkrantz and Lindberg (2011) designed a study to penalize participants for exceeding speed limit in a manner that simulates insurance premiums. They found that all participants in the tracking scheme reduced speeding violations to some extent, but most pronounced was the effect on the penalized group, who displayed a larger and lasting impact: a reduction of 64% in violations (compared to 15% in the non-penalized group). This suggests that some monetary consequence is essential for having a lasting incentive effect.

These combined estimates of the collision-reduction effect of UBI is further confirmed by the effects of similar, less-techy, tracking program—“How’s My Driving” monitoring of truck fleets. Commercial vehicles often display placards that allow fellow drivers to call and complain about dangerous driving incidents, resulting in sanctions imposed by fleet operators against bad drivers. As reported by Strahilevitz (2006) and Kipling, Hickman, and Gene Bergoffen (2003: 5.3.4), these programs lead to major reductions in crash rates, estimated (perhaps immoderately) between 20%-50%.

Because UBI improves overall safety, it is more often manifested in discounts, rather than increased premiums. Social psychologists showed that people generally rate rewards as more acceptable tools for behavior change than penalties (see, e.g., Wit and Wilke, 1990). This might bolster the effect of UBI, and its potential to be viewed more acceptable than other penalty-based monitoring systems (like speeding and red-light cameras) that typically deploy penalties.

2. Reduced Driving

Standards of safety have two types of effects: on the level of care people take, and on the frequency by which they engage in the regulated activity. The discussion above focused on care, showing that UBI leads drivers to handle their cars more safely. UBI may also affect the level of activity, but here the effect is more nuanced and less well established.

¹⁸ For instance, Dijksterhuis et al (2015) conducted a simulator study that rewarded participants for safer maneuvers recorded a reduction of the number of speeding events by over 90%. It also demonstrated the effectiveness of the implemented UBI system in inducing smooth driving, as time spent on harsh cornering, accelerating, braking, and speeding were all reduced by over 50%.

If verified mileage data is a factor in pricing the premium—if each extra mile of driving results in costlier insurance bill—people would rationally drive less. Several early studies by economists aimed to predict this activity level effect. Edlin (2003) used premium data to calculate average insurance cost of accidents per mile driven. He estimated the equilibrium per-mile premium and, if such pay-as-you-drive premium were to be charged, predicted an approximately 10% decrease in miles driven, nationally. Two follow-up studies, by Parry (2005) and Bordoff and Noel (2008) estimated a 9.1% and 8% reductions in driving, depending on assumptions about fuel prices, with highest reductions in states with more accidents and higher premiums (e.g., 13.5% reduction in New Jersey; only 5.7% reduction in Wisconsin).

In addition, any reduction in driving activity resulting from pay-for-miles could have social benefits beyond the costs of accidents and insurance. Less driving means less emissions, congestion, and time spent on the roads. Parry (2005) estimates that per-mile insurance pricing would reduce gasoline demand by 11.4 billion gallons (9.1 percent) and increase social welfare by \$19.3 billion per year.

These estimates need to be digested with caution. Because UBI measures not only miles driven but also a host of how-you-drive factors, its first order effect is the reduction of accident risk, which lowers the cost of insurance. This reduces the cost of driving. A big enough discount for safety could quickly offset the driving reduction effect of the per-mile charge. People would drive more and buy more cars. What is important, however, is not how much people drive, but whether those who drive are paying for the social cost of their activity. Under UBI, many people would drive more, others may drive less. It is very possible that some, who are currently unable to afford insurance, will be able to drive, while others, who are currently paying too little and driving too much, will drive less and might even be priced out. From a total welfare perspective, this is all very good news, because the negative externalities that presently distort driving choices are reduced. And from a distributive justice perspective, as I will now explain, there is every reason to expect that the affordability effect will eliminate regressive cross-subsidies and barriers to driving.

3. Fair Premiums

Usage-based insurance changes the price people pay for insurance. Who are the winners and losers? If, through better predictive models, premiums are more actuarially accurate, cross-subsidies would be eliminated—but who benefits most from such realignment? This section evaluates the shift to UBI premiums and illustrates three effects. First and most pronounced is the reduction in *total* premiums due to safer driving. If there is a smaller risk to insure, a lower price would be set to insure it. Second, UBI reduce the importance of nondriving demographic factors, which has long been viewed as unfair to low-income drivers. Third, UBI improves the personalized nature of risk prediction, allowing insurers to charge each policyholder a more precise premium, reflecting the risk created by this driver rather than by the larger pool. This greater underwriting accuracy reduces the cross-

subsidies among members of the insurance pool, and it too operates in a manner that favors lower-income drivers.¹⁹ Let's review these effects in turn.

(i) Lower Premiums

Monitored drivers change their driving and become less risky. This reduces the cost of insuring them, and some of the savings trickle down to the policyholders. Tesla's UBI insurance, for example, varies the premium month-by-month, based on the car's safety score in the previous month, calculated based on tracking data. Improving one's score translates into significant discounts.

How much of the reduced accident costs is reflected in premium discounts depends, among other things, on competition among insurers. In the early days of UBI, when only one or a few auto-insurers offered tracking options, profits of these insurers increased in large part due to market power (Reimers and Shiller 2020: 614). Over time, competition grew and discounts expanded. Indeed, Soleymanian, Weingberg, and Zhu (2019: 22) found that:

“Consumers who enroll in the UBI program and allow the automobile insurance company to access their otherwise private driving behavior data become better drivers by the end of the monitoring period and receive discounts (on average of 12%) that apply to all future insurance premiums as long as they remain policy holders with this company.”

Focusing solely on mileage tracking, Bordoff and Noel (2008: 45) predicted that 63.5 percent of households with insured vehicles would save an average of \$496 a year (a 28 percent average reduction in premium) under a fully variable mileage-based insurance program.

Another reason why UBI premiums would potentially be lower is the reduction in the cost of investigating and processing claims. Insurers can verify causes of accidents in a speedy and accurate manner (for example, by digital evidence of the driver's distraction), which reduces administrative costs and, more importantly, reduces exposure to fraudulent claims (EIOPA 2019: 26). According to Palmer (2018), pre-collision velocity data can indicate which vehicle caused a crash and how severe the injuries are, mitigating medical build-up and fraudulent claims.

Finally, while I have not seen data supporting such conjecture, tracking devices are likely provide the additional benefit of locating and recovering stolen cars, which in turn could also deter auto theft. This could reduce the cost of theft coverage in auto policies. Once a sufficient fraction of cars has tracking devices that permit immediate recovery, a deterrent effect that benefits all car owners would be achieved (Ayres and Levitt 1998; Ben-Shahar and Harel 1995).

(ii) Reduced Reliance on controversial rating factors

¹⁹ The progressive effect of driving-factor premiums was already noted for older Pay-As-You-Drive plans. See e.g., Litman (2011) (“PAYD charges premiums by the vehicle-mile, so a lower-risk driver pays 2-4 cents per mile and a higher-risk driver pays 10-20 cents per mile. This [...] tends to benefit lower-income motorists.”).

Usage-based insurance is priced to reflect each policyholder's actual driving activity and the frequency of collision-prone driving maneuvers. It reduces the reliance on other predictors, particularly on group classifications that, based on aggregate historical data, crudely correlate with accident risk. Depending on a state's specific regulations, non-driving rating factors—such as credit score, occupation, marital status, and education—would otherwise be used to price auto insurance policies. These standard classifications are widely regarded as problematic due to their imprecision, poor explainability, and discrimination.

First, the problem of imprecision. While old classification factors are statistically valid predictors of accidents, they are good only *on average*, which means that they are potentially imprecise in any individual case. Men may cause more accidents per mile driven than women, but not all men. Good students may be less prone to reckless driving, but not all good students. Moreover, the classifications apply in an all-or-nothing fashion, not allowing for continuous and incremental measurement. For example, marital status is used by insurer as a risk predictor because married drivers get into fewer accidents—perhaps because they have more to lose (children, financial stability), or because they drive less. But these factors that account for the relation between marital status and accident risk develop over time. A 28-year-old male does not become a better driver the morning after his wedding. The insurance discount, in contrast, applies immediately upon marriage and is removed upon divorce.²⁰

Second, the problem of explainability. Unlike a history of dangerous acceleration and sharp turns—which points to risk a policyholder could review, understand, and intuit—the traditional classification factors are not entirely transparent or sensible, thus making insurance pricing mysterious and puzzling (Austin 1986). Credit score is perhaps the poster case for this enigma. Low credit score is easily understood as a reason for higher interest rates on loans, but why for higher accident probability?

Third, some generalizations used by the standard classification methods could be viewed as discriminatory. The use of credit scores results in people with poor credit paying 122% more than people with best credit (\$1566 extra per year, on average), which led several states (CA, HI, MA) to prohibit it.²¹ The use of sex to price insurance is also controversial, and was prohibited in federally-regulated insurance markets in the landmark Supreme Court case *City of Los Angeles, Dept. of Water and Power v. Manhart*, (435 U.S. 702 [1978]), even when the statistics underlying it were not contested. In that Title VII case, an employer required women employees to make larger pension contributions because they were expected to live, on average, longer than men employees and needed to capitalize a larger pension fund. The Court held that there is no assurance that any individual female policyholder fits the generalization (that is, that she specifically will live longer and reach the age predicted by mortality tables) because not all females are the average female. This practice of putting all females in one bin, separate from all males, was defined as discriminatory against any individual. The European Court of Justice views such practice of gender classifications not only as discriminatory, but also a human rights violation (*Test-Achats ASBL v. Conseil des ministres*, Case C-236/09). Still, many states reject this conception of equal treatment and,

²⁰ See The Zebra, *The State of Auto Insurance* 16 (2021) (“When single people get married, their car insurance rates drop about 6.5%, saving roughly \$96/year.”).

²¹ *Id.*, at 14.

under state insurance law, hold that sex classification is just when based on actuarially sound risk tables (e.g., *Telles v. Comm’r of Ins.*, 574 N.E.2d 359, 361 [Mass. 1991]). This question continues to be one of the more controversial in insurance law (Avraham, Logue, and Schwarcz 2014).

Consumer advocates have long been arguing that the use of some of these classification generalizations disproportionately harms certain disadvantaged classes (Karapiperis 2015: 25). They highlight their potential to penalize young drivers, the poor, senior citizens, urban residents and non-homeowners. This critique was illustrated by Heller and DeLong (2021), which found that a Baltimore driver would pay 46% less in premium for minimum liability coverage if they were a married homeowner in a higher-income ZIP Code. The same report also noted that auto premiums were higher in urban areas, and they exceeded \$500 annually in 24 out of 50 of the nation’s largest cities. Because urban drivers usually drive fewer miles, they would likely pay less if insurance pricing were based on miles driven.

(iii) Distributive Fairness

The discussion of traditional risk classification and the resulting divergence of premiums paid across demographic groups raises questions of insurance equity. Since UBI does not engage in such classification, it removes the cross-subsidies that the current system creates, including those that violate intuitions about distributive justice. Cross-subsidies, it should be stressed, are an intended feature of insurance, and they could flow in desirable directions. For example, when healthier people cross subsidize sicker members within the health insurance pool they offset the impact of unequal health endowments. This rationale does not have much weight in auto insurance, where people are perceived to create the hazards, and therefore a widely accepted maxim in this sector is each policyholder should “carry their own weight.”

Cross-subsidies in insurance could be desirable as a form of progressive redistribution when they operate in favor of low-income policyholders, making insurance more affordable to them. But this rationale, too, flies in the face of classification-based auto insurance, where cross-subsidies are largely regressive, flowing *against* low-income policyholders. Consider, first, the failure of ordinary auto insurance to charge premiums that reflect exact number of miles driven. As a result, low-mileage drivers subsidize high-mileage drivers in each risk class. It is well documented that low-income people tend to drive less and use other forms of transportation (Litman 2011). The Federal Highway Administration (2019) reports that affluent drivers drive more often and farther, with the highest earners driving approximately *twice* the distance compared to those at the low-income echelon. (See Figure 3 below.) Switching to a UBI scheme with premiums reflecting exact miles driven would eliminate this regressive cross-subsidy.

FIGURE 3

Put differently, pricing insurance on usage and actual driving would help lower total transportation costs, which (in 2013) represented one third of income for the lowest income quintile, but only 10% income for the highest (Karapiperis 2015: 47). Simulating this saving, Bardoff and Noel (2008) calculated that under pay-for-miles insurance, households in the

low-income half would have a reduction in insurance cost, with the savings for the lowest bracket reaching over 6% of household income.

FIGURE 4

In addition, full-tailoring that includes pay for actual miles would eliminate the cross-subsidies that result from the partial tailoring of non-driving rating factors, which end up penalizing urban residents, non-homeowners, and senior citizens. These groups are rated as riskier, even though they drive fewer miles. Urban drivers, for example, are more likely to be low income and members of racial minorities, and they drive significantly less (Pucher and Renne 2005). They have also been shown by Soleymanian, Weingberg, and Zhu (2019: 36) to respond more sharply to UBI. The rise in their safety scores in the first months of enrollment is larger than for those living in rural areas. (See Figure 5 below.) A tailoring scheme that identifies how much and how well they drive (and induces them to drive more safely) would allow many of them to escape the high-risk tag.

FIGURE 5

Finally, UBI could favor customers who might otherwise be deemed too risky to insure. Able to price their risk exposure more accurately, insurers can raise their risk tolerance and reach new customers. While some high-risk policyholders would have to pay high premiums, those among them who are currently excluded from the insured activity may be able to purchase insurance (Karapiperis 2015: 43). As a meta-review of the insurance industry by EIOPA (2019) concluded, “there is no evidence as yet that an increasing granularity of risk assessments is causing exclusion issues for high-risk consumers.”

V. THE RESISTANCE

We have a puzzling phenomenon: an innovation that is documented to provide such marvelous benefits to the people who deploy it, from protecting their lives to saving them money, and yet the regulators in charge of protecting people’s lives and money are suspicious towards it. How does such suspicion, and the resulting restrictions it imposes, survive? If the technology is so good, why do lawmakers limit it? Perish the thought, why not mandate it?

In this Section, I explore this tension in two parts. Part V.A presents several concrete objections precautionites raise against UBI: privacy, misappropriation, discrimination, and equity. It evaluates these grounds by challenging the premises underlying each of the objections and the conclusions they entail. Part V.B then attempts to distill from the various opposing accounts the more fundamental worries how the data technology might disrupt existing social order, how it shifts the power dynamics, and how it creates templates of social domination that weaken the dignity and autonomy of individuals. I call these the “theoretical objections” because they require an additional step, typically from political theory, to generate the concern. While I share many of the instincts that elevate both the concrete and the theoretical concerns to the fore, I argue that in the case of UBI the evidence supporting the objections cannot plausibly justify the resistance to the technology.

A. Concrete Objections

Precautionites raise four specific arguments in objection to usage-based insurance, each focusing on an interest of policyholders or of society that would be overlooked or insufficiently protected by the insurance companies that develop and market the plans. These interests are privacy, ownership of data, distributive fairness, and transparency.

1. Privacy

“We won't bend on protecting consumer data, privacy, and fair rates”, said Ricardo Lara, California's Insurance Commissioner, “you shouldn't have to have the insurance companies in the car with you looking over your shoulders every time you brake, every time you steer. That's big brother. That's wrong!” (Chalmers 2018). For regulators and consumer advocates, privacy is the battle hymn for UBI opposition. Indeed, any new digital technology that collects personal data is said to raise privacy concerns, and still more when people's movements are tracked. A prolific literature describes, and often bemoans, how “surveillance” devices infiltrate and establish a permanent foothold in people's personal space—homes, cars, wearables—and allow companies to learn, influence, and control people's lives. UBI tracking technology tells insurers where people drive and at what time, and this information could be private and sensitive. Precautionites warn: you are taking “the spy along for the ride” and this “surveillance monster” will be “the witness against you” (Leefeldt and Danise 2021; Gritzinger 2004).

The opposition to the collection and use of personal data are thought to have heightened relevance in the context of driving. They start with the standard privacy alarms. Perhaps insurers would share insights from the data with commercial parties who want to know where people are. For example, insurers might sell information to geographically specific advertisers (“get 10¢ off every gallon in the nearby Shell station”). Or, perhaps, the data would be breached and misused.

The concerns then build up towards the core of constitutional privacy law. Tracking data could be the smoking gun if subpoenaed and transferred to police and courts for use in criminal and civil proceedings. It is said that “your car can make a very convincing case against you” and “NSA can track people with the Progressive Snapshot” (Leefeldt and Danise 2021). These objections should be taken seriously. While I do not share the anguish that “in some instances, telematics has convicted murderers, hit-and-run drivers and thieves of their crimes”, I recognize the dilemma in permitting law enforcement access into insurers' data. So far, the battle to shield similar databases under the Fourth Amendment has largely failed (*Smith v. Maryland*, 442 U.S. 735 [1979]), reflecting a conviction that the law enforcement benefit outweighs the privacy cost, especially when data are collected in public places like highways. Bypassing the constitutional permission by prohibiting ad hoc the collection of some data and squandering their benefits seems problematic. A better path would be to enact privacy safe harbors for insurance data in concrete contexts like divorce proceedings.

There are also concerns how the presence of the surveillance technology insides the car makes people's day-to-day practices visible and measurable. Converting personal tasks that are traditionally immune from oversight into objective standardized records to which

financial consequences are attached could undermine a sense of freedom autonomy and dehumanize the driver (Levy 2015). Fleet drivers, for example, resist such monitoring schemes as invasive and violating of their privacy. A driver is quoted by Levy (2015) to say: “a computer does not know when we are tired, fatigued, or anything else. . . . I am a grown man and have been on my own for many many years making responsible decisions.” Fleet drivers complain how their ‘scorecards’ are made publicly visible, to create social pressures on underperforming drivers by being shamed or embarrassed in front of co-workers.

Unlike fleet drivers, participation of households in UBI plans is of course optional. But privacy advocates worry how much choice people genuinely have. Like other big data contexts that offer consumers some quid pro quo for allowing their data to be collected, UBI gives people incentives to participate and expose personal information. But this means that those who do not participate are “penalized” by forfeiting the bonuses for joining and the premium discounts associated with safety ratings they might ultimately receive, and might even be screened by insurers, as high-risk. Consumers, it is said, should not have to make “Sophie’s Choice” between their privacy and their ability to obtain affordable services (Bode 2016; Juang 2018).

There is a tendency among privacy advocates to claim that the relatively slow adoption of UBI is due to people’s privacy concerns. Indeed, adoption has been gradual—only 22% of the policyholders have such plan (in 2022), and many who could benefit from it outright, by receiving premium discounts, have not joined. Privacy must be the reason, concluded the Consumer Federation of America. In a 2021 report, the federation explains that “the public reaction has been lukewarm, likely due to privacy concerns and worries about corporate misuse of the collected data.” (Karapiperis et al. 2015:46). While this view would suggest that people are making privacy choices competently and prudently, regulators who restrict UBI say that drivers’ privacy is primary among their reasons. So how significant are the privacy concerns to policyholders? The slow level of adoption may be due to other reasons beyond privacy. Is it status quo bias? Uncertainty how the premium will be affected? Technological anxiety? When the Consumer Federation declared that privacy is the reason people are not joining, the substantiation was rather thin: a 2016 online “news” piece titled *More Americans reject telematics over privacy concerns*, which in turn quoted a single individual driver in San Diego who proclaimed “I know some people say, ‘What do you have to hide,’ but I don’t want big business or Big Brother involved in my personal life. It just creeps me out” (Bronson 2016).

The uproar about privacy in the UBI context makes little sense. First, joining the program is entirely optional and usually requires a deliberate thoughtful choice and quite a bit of effort. It is not a thoughtless or automated click “I Agree” and it is certainly not an auto-enroll opt-out regime. No tracking, unless the policyholder makes the choice to switch from their current program, install the technology, and enroll in a different fee structure. This is a rare instance in the data economy where participation does reflect meaningful consent. While people may be uninformed as what more is done with sensitive bits of data (such as location

and destinations), they typically know that this information is already richly collected and shared by a host of navigation and other apps (Ben-Shahar and Strahilevitz 2016).²²

But more fundamentally, privacy is valuable insofar as it protects and advances other aspects of individual thriving, such as intimate relationships, physical well-being, safety, avoiding intrusions and embarrassment, personal expression, and much more. Absent privacy, these good things might be chilled, diminished, or sabotaged. Privacy is therefore valuable, but not for its own sake, nor is it directly instrumental in promoting autonomy and human agency. It is valuable to the extent that it breeds the activities and capabilities that establish an autonomous life. This is the link missing in the privacy-based opposition to UBI. Driving is distinctly not an intimate act. It is performed in public roads. It is usually guided by a navigation app that already stores location data. It is subject to numerous constraints on freedom—traffic laws, highway patrol, and often-unpleasant interaction with other cars. It directly and dangerously impacts others in a very non-private way. It is costly and polluting. For most drivers, driving is merely a means to mobilize and reach those places that are primary for their pursuit of autonomy. Monitoring this activity through UBI tracking is not akin to public exposure of the private and intimate aspects of one’s life. As succinctly observed by Strahilevitz (2006: 1744), “There are plenty of privacy causes worth defending in contemporary society. [...] motorist obscurity is simply not one of them.”

2. Appropriation

Another category of interests that UBI is said to imperil is the appropriation of value generated by the information (Rubin, Aas and Williams 2023; Van Den Boom 2021). Driving data are aggregated into databases that are property of the insurers and used by them in a one-sided manner. While privacy concerns typically address how the uses of personal data may harm the private spheres of its subjects, data ownership and appropriation expand the lens to the *collective* derogations of consumer value and how the benefits from the databases are unfairly divided.

Policyholders are the ones providing the granular information—it is their behavior that is being measured—and therefore according to the “property” or the “labor” models of personal data they should also reap the benefits (Posner and Weyl 2018). One of the primary implications of the present ownership model, whereby the insurers who collect and build the databases own it, is the inability of policyholders to transfer their personal information profiles to a new insurer to help price a new policy. This cripples people’s ability to shop around and switch carriers, making them hostages to the data-driven pricing advantage of their present insurer. If they switch, they must “start over” and build a new record of safe driving to eventually qualify for discounts.

There are, to be sure, general solutions in the data economy to the lock-in concern, foremost the portability of personal data. For example, portability could be advanced by a ‘data travels with you’ regulation, allowing people to bring their data along when they

²² Indeed, cryptography can be used to mitigate any residual privacy concerns. Specifically, a zero-knowledge proof protocol has already been modeled for insurance claims, whereby insurers receive only the policyholders’ risk scores and predicted claims without access to the granular data used to compute these outputs. See, e.g., Zheng, Lin, and Hu (2022).

switch carriers (similar to cellphone regulation). Or, more comprehensively, portability could be achieved by the creation of a statistical intermediary for insurance similar to credit bureaus that aggregate personal financial data and make them available to any financial institution. A centralized data agent would allow any auto insurer authorized by a consumer to receive their history of driving behavior, at the level of granularity held by the current insurer. But ‘data travels with you’ or intermediation bureaus do not currently exist and would require regulatory mandates. So long as major insurers adhere to their strict data-property practices, UBI puts policyholders at a bargaining disadvantage.

Undoubtedly, the auto insurance contract is a rent seeking contest with a lot at stake: who gets to scoop the surplus from the risk reduction. But auto insurance is also a highly competitive sector, where the cost of insuring a car has barely kept up with the increase in miles driven, and where insurers profits have not increase in past decades (Grace, Leverty, and Powell 2019). Any excess rents captured by early adopters of UBI technology dissipated once their IP-protected market power declined. If UBI reduces accidents by anything resembling the magnitudes documented in Part III above, it is hard to imagine that policyholders are denied a good chunk of this benefit. At the end of the day, if less people crash and die, it is drivers and their passengers who benefit. And more still when they enjoy a reduction in premiums.

Like in any business to consumer relationship, there are one-sided aspects in the UBI insurance contract. Insurers claim trade secrecy over the databases and the proprietary algorithms and design a complex take-it-or-leave-it premium formulae. Below, I discuss how these features trigger what critics regard as an “entrenchment of power” dynamic, which in turn limits consumers’ opportunities. But for the time being we are focusing on rent appropriation in the insurance market, not on the “mass customization” economy at large. Here, while it’s a bit of a mystery how exactly the value of UBI is divided between insurers and policyholders, all the evidence shows that people are benefitting greatly. They are experiencing a meaningful reduction in one of the biggest fatalities risks they and their loved ones face—auto accidents. They are not pegged into crude historical categories based on stale or biased data, afforded instead continuous opportunities to learn and revise their profiles and pay less. And they are fully aware of what they are getting into when they sign up, and how easy it is to quit.

Still, it is fair to ask—are there losers from the UBI rating method? Existing studies make this question hard to answer because many of the UBI schemes they tested had a no-premium-increase constraint (sometimes mandated by law). It may well be that, absent such cap, the precision of UBI’s screening tools could pick out risky policyholders who would end up paying more than they presently do, even counting any ancillary improvement in their driving. Or, in equilibrium, insurers would infer that non-subscribers are higher risk. Any cross-subsidy these subgroups are unintendedly enjoying under existing classifications would vanish. For example, a highly educated wealthy woman who drives recklessly with many near-crashes could see the various classification discounts she currently receives replaced by a low safety score and a corresponding elevated premium. While these redistributive effects are largely desirable, there is a prominent concern that some of UBI’s losers will disproportionately come from weaker social-demographic groups. To this concern I now turn.

3. Discrimination

Insurance is the business of personalized risk classification, and to the extent permitted by law it charges different premiums to different people, depending on their expected risk. That's why life insurance requires health screening to determine individual mortality risk, why home insurance depends on fire and theft mitigation measures installed in each home, and why auto insurers adjust the premiums to each driver's risk signals. But in thus classifying people, insurers are also edging on the border of discrimination, particularly when the factors they use for differentiation are ones on which disadvantaged members of society—low-income people and racial minorities—score less favorably (Karapiperis et al. 2015: 52). There is significant empirical grounding to this general concern with respect to traditional auto insurance risk classification, which relies on non-driving factors like credit history, homeownership, and education. Auto insurance becomes more expensive for protected groups, who, unfortunately, are also those who need it most and can afford it least (Angwin et al. 2017).

The same concern—that risk classification disparately affects weaker groups—is also raised against UBI, based on speculative but not unrealistic assumptions (Brandão 2020). While the traditional non-driving factors are replaced by actual driving metrics, the scores that drivers receive may systematically disfavor some groups relative to others. Indeed, this is a common concern with many machine learning algorithms, which use big data to discover by brute statistical power the factors that are correlated with the predicted outcome (here, accidents). This is why the Federal Insurance Office at the Department of Treasury says that “certain big data methodologies may hide intentional or unintentional discrimination against protected classes” and why it warns, although without any concrete empirical support, that UBI is one area where such concern arises (Heller and DeLong 2021). UBI, in short, is discriminatory.

But wait, UBI is *not* based on group factors and does not count social-demographic factors that might proxy protected-group membership, instead classifying *individual* driving behavior. How, then, could unintended discrimination result? Why would low-income drivers score less favorably when their driving is tracked minute-by-minute? I was able to identify two colorable reasons that are given in support of the biased-classification conjecture: night-time driving and location tracking. It appears that some UBI algorithms rely on the time of the day in which driving occurs, based on statistics showing that night-driving is more hazardous (limited visibility, glare, fatigue, impaired drivers). All else equal, the formula charges night drivers higher premiums. Because low-income workers disproportionately work night shifts and must commute at hours that are rated as more dangerous, UBI premiums would disfavor this group (Heller and DeLong 2021).

The second reason for the alleged disproportionate effect on weaker populations is territorial rating. The parked location of a car and of the trips it takes may be correlated with risks of theft, vandalism, and accidents. Because location is also correlated with characteristics such as race and socio-economic background, location tracking “has a potential for indirect discrimination on such protected characteristics,” so much that using location data for insurance purposes is “similar to redlining practices” (Brandão 2020). Thus,

in recording the timing and location of car trips, UBI is seen “as merely another data mining exercise following on insurer use of credit information—including penalizing consumers not because of driving behavior but because of where and when they drive as a function of work and housing segregation” (Karapiperis et al. 2015: 52).

There is an additional, more speculative, equity concern with UBI. If accident risk is related to *road quality*, and if urban road quality is worse in poor neighborhoods, there will be an incentive for drivers not to travel in these areas (Brandão 2020). This will contribute “to exclusion and the reinforcement of prejudices related to these areas . . . having a deteriorating effect in the local economy and isolating the area in terms of transportation” which, “in turn, could lower investment in infrastructure, lower housing prices, and attract low-income residents thereby creating a spiral of risk and socio-economic reconfigurations.”

This is the point in many an article where the author would acknowledge that total-welfare goals might yet again conflict with distributive concerns and would either urge the reader to prioritize total welfare, especially when the gain is substantial, or, if distributive interests loom large, remind the reader that they could be rationally advanced instead via tax policy tools. If I were to take that path, I would say that the phenomenal saving of lives should be a clear societal priority, and that any unintended effects of traffic safety on weaker populations ought to be addressed through offsetting targeted fiscal measures.

But here I am in an unfamiliar territory. Here, there is no real tradeoff between total welfare and distribution. I admit that I am befuddled by the equity-driven attack on UBI and its attempt to manufacture such tradeoff. In an era of insurance risk classification greatly and bluntly *disfavoring* low-income drivers, where discounts are dispensed to people with big homes, big incomes, and big *résumés*, along comes a technology that helps diminish the weight of these regressive practices and instead measures directly how risky the car trips each person makes. Being poor is no longer a proxy for risk, no longer a reason to charge higher premiums. In fact, poor people would systematically score well on many usage inputs, including the weightiest ones (e.g., miles driven). And with the effect of UBI on accident rate, poor drivers enjoy the additional benefit of fewer accidents. Let’s remind ourselves that advocates for minority neighborhoods vocally “pushed for pay-by-the-mile auto insurance, as a fairer way of pricing insurance” (Karapiperis et al. 2015: 51). If UBI bolsters the Pay-As-You-Drive model with additional non-demographic pay-*how*-you-drive factors, further diminishing the weight of the unfair classification categories, why does it meet the wrath of precautionites? How could a system that is undeniably less discriminatory than any other auto insurance pricing model be condemned?

The precautionite account profoundly confuses the difference between relevant-justified classification and unjust discrimination. When, for example, insurers consider gender as a risk classification factor, they may be violating federal anti-discrimination law. They treat people based on characteristics that society may no longer want to regard as salient indicators of classification and reinforce stereotypes in potentially ruinous ways. They shove all men into a single and more expensive bin of the average man, even though many of them are not dangerous drivers. UBI models, by contrast, examine how you drive, not who are. Yes, critics can still complain that the algorithm will “detect gender” by finding correlations between “neutral driving habits” and gender and spit out premiums that

“although not framed in terms of gender, actually stand for the prohibited variable” and thus have a “tendency to discriminate” (Infantino 2022; see also Prince and Schwarcz 2020). This is a fallacy. Maleness is no longer proxy for risk and men are no longer treated uniformly harsher than women. Only the subset of men observed to engage in the risky habits pay the extra dollar. The sins of some bad male drivers are not visited on all men – only on themselves.

Perhaps I should read between the lines of precautionites’ distributive complaints—not an all-out rejection of UBI, but rather a political strategy to further diminish the incremental (and already shrunk) weight of the specific inputs that are seen as disfavoring low-income drivers. I am worried, however, that they are barking up the wrong tree. Start from the concern that is *prima facie* most sensible – the impact of nighttime driving—which some insurers incorporate into their usage-based formulae. Does night-driving surcharge truly disfavor low-income policyholders? Peak time for car crashes on weekdays is evening rush hour travel (4-8pm), not overnight. Crashes do peak at late night, but only on weekends and for teens—not exactly working-class low-income drivers returning from night shifts (National Safety Council 2021; Shults and Williams 2016).

Even more questionable are the territorial rating conjectures—that owning a car in poor neighborhoods raises UBI rates because cars are more likely to be stolen or vandalized, and this implicit surcharge is akin to “redlining.” It should be noted, first, that the only coverage that is mandated by auto-insurance regulation is the liability coverage (“third party”), which protects victims of accidents, not the policyholder’s car. The likelihood of theft or vandalism affects only the “first party” property coverage, which is optional. But there is a more profound, albeit subtle, manner, in which this conjecture fails. In traditional auto insurance, the place where a policyholder lives and parks their car overnight is the only location that matters, and indeed affluent suburbanites enjoyed chunky discounts. With UBI, it now matters a great deal where the car travels during the day, which means that people no longer get territorially rated based on where they live. The rich and poor may *live* in segregated neighborhoods, but they *drive* the same roads much of the time. UBI offers a lens into this desegregated segment of their lives, attenuating the premium differential.

Finally, there is the mysterious speculation that UBI will have the effect of drivers not entering poor neighborhoods (as if they currently do), all because insurers will charge higher rates to folks who drive in poorly maintained streets, thus worsening the inner city’s isolation and dilapidation. How many implicit and dubious assumptions does this thesis pack! Let’s count: that the asphalt in low-income neighborhoods is in disrepair; that because of it more driving accidents are prone to occur; that insurers have data to monitor how well street blocks are continuously maintained; that the hypothetical incremental charge for driving in poor neighborhoods will be recognized by drivers and cause them to avoid such paths; that the reduced traffic would further depress the neighborhoods’ livelihood and economy; and that this economic slowdown will lead to reduction in local private investments. In fact, none of these assumptions is valid. If anything, the opposite could be true. Roads in poor neighborhoods are less dense; have less cars parked on the streets; and due to lower congestion, drivers take routine paths and become more familiar with their

itineraries. These *are* factors that insurers measure, but they all provide discounts, not overcharges, and they further boost the progressive impact of territorial rating.²³

The house of cards that is the discrimination argument is further weakened by a feature of the statistical models used to estimate drivers' safety scores. One of the mobility data analytics firms I interviewed explained that the algorithm used to build the safety scores are designed to suppress factors that drivers cannot control, which are more likely to also be the ones thought to disfavor lower income people.²⁴

4. Transparency

Who does not believe that transparency is vital, that it is crucial to successful market transactions, that it promotes fairness and accountability? A lot of hopes are hung on transparency as a central tool in American law, making it an unfalsifiable virtue, which for decades has become the most widely adopted and politically resilient regulatory intervention. In every area of the law, and most of all in areas that address imbalance in power, the playing field is sought to be leveled via mandated transparency.

In auto insurance markets, the traditional non-driving rating factors that insurers use are largely transparent. They may sometimes be bad or unfair; they may disparately affect low-income drivers; they may rely on characteristics that society regards as irrelevant; and may even reinforce stereotypes about how different groups behave. But at least they are disclosed and known. For whatever it's worth, insurers must reveal their classification factors when filing the rating plans, and advocacy groups can watch over them.

Usage-based insurance, by contrast, relies on proprietary and often confidential algorithms that could be coded and manipulated by insurers with less oversight. "We shouldn't have to give away our secrets", insurers insist. It is said that "insurance companies and their vendors have generally withheld the full scope of their programs, especially concerning the algorithms that make use of the gathered data and the role of artificial intelligence" (Heller and DeLong 2021: 8). Thus, not only are consumers in the dark on what explains the premiums they are charged, or what data is collected by tracking; the method makes it more difficult for watchdogs to figure out the general patterns of classification. As a result, "certain big data methodologies may hide intentional or unintentional discrimination against protected classes" (Federal Insurance Office 2016).

Prominent observers of the insurance community lament that UBI "has taken a wrong turn. Instead of using telematics to create transparency in auto insurance pricing and create new

²³ The concerns about drivers shying away from poor neighborhood also conflicts with another conjecture—that commercial fleets will prefer poor neighborhood routes because tort liability to injured poor victims is systematically lower. See Porat (2011), Yuracko and Avraham (2018).

²⁴ Insurers distinguish between controllable and noncontrollable variables and use statistical techniques to shrink the weight of the latter. For example, the loss function can be estimated in two steps. The first step involves only the controllable variables. Once their weight is established, the second step adds the noncontrollables. As a result, the latter receive artificially lower weight. Another statistical technique used by insurers is to fit the data into a model that minimizes not the squared errors but rather a loss function that also measures the size of the coefficients of the noncontrollables. Both techniques put lower weight on noncontrollable demographic variables such as nighttime driving, traffic density, and location.

opportunities for loss mitigation, insurers have turned telematics into just another black box rating factor, like credit scoring but without even the limited protections afforded consumers for insurers' use of consumer credit information" (Karapiperis et al. 2015: 51). They are worried that the complexity of the algorithms fails to give policyholder guidance.

Transparency is closely tied to another worthy ambition in the era of artificial intelligence: *explainability*. The decisions or predictions of the system must be *interpretable* to lay persons, so that they can make sense of how their conduct will be evaluated. If UBI reduces reliance on older non-driving surrogates for risk, people need to be told what it is that's being measured. British regulators, for example, emphasize that "insurers should not be allowed to defer to AI as the justification for the selection of data to include and should be required to explain both mathematically and substantively why a relationship to risk exists with each data set included in a telematics program" (Heller and DeLong 2021: 11).

Of course, precautionites want insurance regulators to do more than just require transparency in insurance. They would like to see the enactment of mandatory limits on the underwriting process and on tracking practices, to emphatically ensure that insurance affects redistribution in a desired manner and does not infiltrate personal domains. Well, good luck with that. Recognizing that "many state insurance regulators have only limited authority over the ways that insurers use big data", the lack of transparency becomes a pragmatic area for advocacy, perhaps in the hope that informed consumers will reject UBI. At the bare minimum, since the commanding force of mandatory restrictions is politically unattainable, transparency is the battle hymn. UBI is said to flunk the transparency bar.

This is the point in an article where I would typically launch into a tirade—that the (very European) goal of explaining to people in clear and comprehensible terms the basic logic of an algorithm, the factors it considers, and the reasons it does so, are all a regulatory delusion. People cannot digest such information. But in this case, I tend to think the opposite: UBI achieves almost unparalleled transparency. Every policyholder enrolled in UBI has easy access to an information device that no other auto insurance methodology (and few other algorithms) offer—a "dashboard" that displays the driver's safety score, showing the factors that are being measured, and the specific events during each trip and day that affected the score. Figure 6 below displays screenshots of Geico's and Tesla's dashboards.

FIGURE 6

Even if policyholders try to avoid this information, it would be hard not to know what is being tracked and measured. Furthermore, some UBI devices transmit real time alerts when dangerous maneuvers are recorded (e.g., getting too close to another car). Drivers are reminded periodically of premium changes resulting from adjusted safety scores, with explanations what feature account for the change.

Finally, if transparency were indeed the problem, the right regulatory response would not be to slow down the adoption of UBI, but to mandate additional information tools in it. Such tools are richly available. For example, when a tracking technology is adopted by fleets, truck drivers receive continuous feedback by the programs, they are sometimes allowed to communicate with it if behavior that was counted as risky was unavoidable, and much more

(Levy 2023). Insurance regulation responding to transparency concerns could implement practices that some of the most advanced connected fleets have voluntarily adopted.

B. Theoretical Objections

Part A examined the concrete objection to UBI, involving privacy and its by-products, appropriation, discrimination, and transparency. These are quite common concerns in the data protection sphere. Their gravity may vary across activities, and, as I tried to show, may be less than crushing in the UBI context, but their universality may indicate that some deeper values are thought to be at risk. So, while UBI is a practice where the quartet privacy-appropriation-fairness-transparency may not be particularly alarming, especially compared to the undeniably large social benefits this technology is delivering, it is important to pay attention to what's hovering above (or pulsating below)—to the fundamental values driving the precautionite dissent. With a sense of trepidation—am I going to miss something big?—let me think through what might *really* be driving the anxiety over UBI.

First, power imbalance. Information does not exist in a social vacuum. Sociologically-alert writers are richly portraying how the accumulation of personal data and their computational renditions in the hands of already strong entities—employers, financial institutions, platforms, and, yes, insurers—redefines market interactions, affects social order, and disrupts traditional channels of self-advancement. (See, generally, Kallinikos 2007.) In the context of trucking, Levy (2023) has brilliantly documented the sense of diminution among truck drivers caused by the adoption of tracking devices, very much like the ones employed in UBI. To comply with hours-of-service truck regulation, federal law requires such electronic monitoring, and fleet owners expanded the scope of tracking to tighten control over their drivers. Truckers, to say the least, don't like it. Having an electronic eye observe them in the cabin 24/7 overrides their sense of 'captainship' of the vehicles. Their objection reminds me of the old maritime norm, where a ship's captain and officers were to honor the crew's private space and not enter their living quarters (Raffety 2013). For professional drivers, the micro-decisions that were traditionally "self-contained and immune from immediate oversight" in a manner that retained "a degree of autonomy unmatched in other blue-collar jobs" is now, in the era of "organizational surveillance," visible, measurable, quantifiable, and ultimately subordinated. Electronic monitoring creates new pathways of control over daily practices, and bolsters "the entrenchment of power in modern organizations" (Levy 2023). In short, connected devices "represent another example of consumer capitalism's bulldozing past political questions" (Silverman 2016).

Some of the power disparity objections to UBI echo the appropriation concern. I mentioned the dissatisfaction with insurers' ownership of the databases and the secrecy in managing them. This has, for example, the potential to disfavor policyholders in post-accident claims administration. If there is a dispute between the insurer and the driver during claim settlement about the causes of the accident, the insurer could use tracked information to demonstrate how the car was driven and establish proof for the driver's fault, thereby reducing coverage. But not vice versa: when the driving data vindicates the position of the policyholder, insurers might be less likely to make it available.

More fundamentally, the worry is that UBI data place policyholders “under the domination of insurance company algorithms, whether because they are not sure about the consequences of their travel behavior for future premiums, or they cannot control them. In the paradigm of usage-based policies, any small event (e.g. friend visit, mood change in the case of driving assist, weather change) comes with a possibility of a change of premium” (Brandão 2020: 166). Put differently, UBI creates a constantly shifting payoff structure that limits the opportunity of people to bargain for a known price. When insurers change the algorithm and the resulting premiums, policyholders are powerless.

There is of course another way to tell the UBI story, as one of empowerment of drivers rather than their subjugation and domination. Imagine, hypothetically, that Consumer Reports or The New York Times’ Wirecutter service were to supply drivers with a free tracking app that can be turned on while driving. The app would provide a daily safety score and offer a feature that dings real time alerts to coach drivers on avoiding danger. Like most “free” apps, these services would retain ownership of the data drivers share with them. Would the power domination alarm bells chime? Who would object to these services? Our digital world is loaded with sites that, in exchange for personal data, help people improve far less fateful dimensions of their activity (think: GPS and maps). It is hard to see why the bargain with insurers stands out as a type of domination. The inability to control the formula of a UBI algorithm is a generic artifact of a take-it-or-leave-it commercial world, and it is no different than any existing non-AI insurance scheme. True, in the insurance context there is also a price effect. But, as already established, the vast majority of UBI enrollees receive a discount. UBI is the metaphorical app that, in all but name, people are *paid* to use. The only thing they cannot entirely control is the size of that discount.

There is a second major value that props up the precautionite ethos: autonomy. UBI tracking, like other technologies are installed in private spaces, influence the choices people make in a manner designed and manipulated by commercial entities. People’s freedoms of car handling are subtly but effectively restricted or reshaped. A driver’s seat—a place where one establishes an identity, an avatar, a cultural posture—is no longer private.

Interestingly, there is a dialectic conception of individual autonomy at the center of the fight, as it plays out in the insurance context. At one end, the critics’ discomfort is with the *precision* of the tracking technology. The problem is its ability to record people as they are, know what they do, when, and where. UBI is said to offend people’s autonomy because it is a practice of unwanted “surveillance,” of “intimate invasion,” a “deep body periscope,” allowing insurers to creep into people’s private spaces and observe real, intimate, lives (Jeaningros and McFall 2020). Here, the infringement of autonomy is the diminution of the right to be unknown, to be let alone. This problem of precision does not arise under conventional insurance classification because it is not personalized but based on stereotypes and crude averages, and a customer’s profile does not reflect their true self. Because UBI gives insurers a glimpse into the actual life of the policyholder, they see something that is real and accurate.

At the same time, the critique puts on a different hat, beholden to a contrasting view. Since it is an *algorithm* that receives the personal data and tags it, the profile that insurers ultimately observe is not of a person but merely their algorithmically constructed “data

double”—a reduced form of a person which “flattens and distorts” them. An individual becomes a vector of quantitative parameters, a “context-free numerical representation” (Burk 2021). The person UBI insurance represents is “not so much a whole human individual as a notion,” but rather “an aggregate of data points [that] classify an individual as a body belonging to a risk group” (Jeaningros and McFall 2020).

Subscribers to this view that AI diminishes the individual exhibit an almost romantic longing to the pre-tracking practices of insurance classification that, in Jeaningros and McFall’s (2020) words, “have historically been created and refined through human interaction” and that have relied on “unmediated assessment.” Deployment of data—a type of “broad but indirect knowledge”—is a poor approximation of what is purported to measure, which leads to imprecise inferences, and crowds out reliance on self-knowledge embodied in individual experience (Levy 2023: 67). In the end, rather than personalizing the treatment, UBI’s “mass customization” is a scheme that “depersonalizes” the relationship between the insurer and the policyholder (See also Infantino 2022: 7-8).

As in the context of power imbalance, here too there is another way to tell the story. A driver’s seat is a means to get from here to there. It is not a locus of autonomous validation, but rather a tool to advance other primary choices. It is an activity largely disliked and heavily constrained by hazards, restrictions, stress, oversight, and potential penalties. It is where people impose morally objectionable risks on others, and where in the blink of an eye or of a distracted text message a driver can extinguish the autonomous lives or foreclose the choice-worthy options of others.²⁵ Tracking the driver’s actions and shaping them via incentives may limit some superfluous quantum of freedom, but it certainly doesn’t diminish the value of driving freedom, especially the sum total of freedoms enjoyed by the individuals populating the road. No one thinks that obeying a traffic light limits the ability to pursue meaningful options and that it reduces freedom and autonomy. Some disapprove of, say, red-light cameras, but the argument they marshal is due process, not freedom and autonomy. Like stop signs and traffic lights, UBI might diminish freedom in the sense that drivers who opt in will adjust their behavior; but doing so is a choice. One that increases the value of the freedom to drive insofar as everyone else on the road will be safer.²⁶

It is ironic that ‘autonomy’ and ‘freedom’ arguments are used to justify a prohibition against the *voluntary* enrollment in UBI. Other than in trucks, tracking technology is not mandatory. People who join the scheme are not bartering away any freedoms or options. They are aware of any tradeoff, including the ways they might be restraining themselves. While they might not be aware of what exactly is done with the tracking data, they are choosing to enroll despite their imperfect information. At any time, and they can painlessly reverse their choice. The general autonomy-based argument against surveillance technologies seems misaligned in this context.

A third argument often raised against data-tracking technologies is the problem of systemic errors in the data and the resulting biases in the screening algorithms. Here we face the

²⁵ See, generally Oberdiek (2017: 97) (“If a speeding driver whizzes just past your car, then, while you are lucky not to have been hit, it remains the case that your freedom of (safe) movement was significantly restricted . . . and surely that constitutes a diminution of your autonomy.”)

²⁶ I am grateful to Jared Mayer for suggesting that this analogy be highlighted.

concerns that personal data are collected in imprecise and incomplete ways, representing only a partial and distorted profile of individuals, only to be used in a manner that heightens discrimination or could lead to bad behavior. To take a non-driving example, data from social media often portray thoughtless, sometimes automated, snap actions of people, and do not provide an accurate profile of their real characteristics or of their more deliberate, thoughtful, preferences (Agan et al, 2023). As a result, personalized treatments tailored by algorithms trained by such data would be flawed and could in fact aggravate the gap between preferences and choices. Such errors could have negative societal effects, for example by heightening out-group biases and polarization, and by weakening self-control (Kleinberg, Mullainathan, and Raghavan 2022).

Most disturbingly, an algorithm trained on data that reflect past prejudice or discrimination could thwart social reforms aiming to rectify the underlying inequalities. It could, for example, profile a person as more dangerous because this person had more traffic stops, ignoring racial disparities in stop outcomes, and as a result perpetuate these patterns. This problem is widely noted in relation to personalized risk assessments in law (Starr 2014), but it may also arise in insurance, so much that it is claimed that “AI and big data are game changers when it comes to this risk of unintentional, but “rational,” proxy discrimination” (Prince and Schwarcz 2020: 1257). It is easy to see the relevance of this concern to insurance algorithms that use social-demographic factors in risk classification. But how does it apply to UBI? Wouldn’t a classification that is based on how people drive, rather than on uncontrollable demographic attributes or enforcement outcomes, *eliminate* the concern?

Here, the precautionite argument against big data analytics becomes a bit vague. Some writers allege that UBI schemes *imply* “a discriminatory financialization of personal habits,” that they merely obscure but not eliminate disparate impact, with the result that when discrimination occurs it is invisible to most of those involved, and therefore that they may lead to “perpetuation through algorithms of historical bias” (McFall and Moor 2018). A particularly speculative and surprisingly specific assertion is that “car users will keep being reminded of the socio-economic background of their family and relatives, about aspects of their social circle, about the riskiness of their place of residence, work, leisure, etc. This may also have an important impact in the spread and reinforcement of social prejudice and structural discrimination” (Brandão 2020).

This is not the place to assess the general gravity of such concerns. They are surely valid with respect to many AI technologies, particularly ones introduced without sufficient alertness to the problem. But they are frivolous in targeting UBI. Paradoxically, the precautionite condemnation of this data technology is in tension with their goal of fighting discrimination. When UBI reduces the safety score of a driver who accelerates over 85mph, this does not reflect systemic error, prejudice, or historical bias. And the same hold for most other how-you-drive factors. In fact, the contrary has to be said: rating factors like mileage data favor poorer drivers in a meaningful, progressive way. Of the few driving factors that might disfavor low-income drivers, territorial rating is the most colorable claim. But, as shown earlier, it has significantly lower weight in UBI algorithms relative to traditional insurance rating because what is measured is where people *drive*, not where they *live*. In the end, like the concerns over power disparity and violation of autonomy, the biased error

critique borrows a *template* of an argument that fits first order types of injustice and jams it into a scenario that is only superficially alike but which packs none of the typical pitfalls.

VI. CONCLUSION

In writing this article, I have spoken with many critics of UBI about the benefits of the program. They are often surprised by the evidence regarding the magnitude of the accident reduction effect and the equity of insurance pricing. They worry that UBI may still disfavor low-income drivers, but they candidly acknowledge that it is less objectionable than the social-demographic rating factors. But then I hit a wall. What I see as a win-win (more safety, more fairness) does not seduce the critics. Instead, a plethora of precautionite instincts begin to surface. Maybe there are other ways to improve highway safety without violating “dignitary” interests and without “micromanaging” people. Maybe the personal data would be surreptitiously commercialized by insurers in abusive manners. Or fall into the hands of other entities and used in a less desirable manner. Maybe UBI will catalyze a slippery slope, which, as one critic fears, “may help to domesticate and naturalize surveillance of unwelcome kinds” (Lyon 2018). It’s all just very creepy.

This article is not written to deny the gravity of the issues involved in data tracking and surveillance, and the alarm that in some contexts they might raise. It is written to persuade lawmakers not to use a generic version of this alarm in the present context. What I found striking in many of the hostile reactions to UBI is how indifferent they are to the upside. In article after article, blog post after blog post, UBI precautionites ignore the life-saving value of the technology. Think what you may about the downsides of tracking technologies, my point is that the upside should matter too.

I mentioned earlier that this article is motivated by my interest in the more general phenomenon of ethical resistance to life-saving innovations—an opposition that is based not on the efficacy of the technology but on how it might unfairly unsettle existing social practices and undermine privacy. UBI is where I chose to start because it is a bookend of sorts. It represents the easiest illustration for the gap between the benefit and the possible harm. It is, I tried to show, a case of false alarm. It is a technology with enormous social value accruing to all participants, and with very weak non-consequentialist downsides. It is introduced in a sector—*insurance*—where firms are already in the business of knowing people’s ills and mishaps, where risk, loss, and misfortune are the “product,” and where traditional rating practices give firms information about people’s income, family status, physical condition, and much more. Insurers already know *who we are* in a meaningful, invasive way. Now, with UBI, they are gradually replacing all that with a different set of less intimate information—*how we drive*. And, for good measure, this program removes much of the mystery about the insurance transaction: policyholders can understand their risk ratings and scores, review the factors that explain why their premiums change, and learn to drive better. A regulatory paradigm that impulsively forfeits such advances is bad.

What is left to be said? Early readers of this manuscript urged me to recognize the American spiritual obsession with cars, and the desecration drivers would experience when tracking devices infiltrate their space. “Americans,” wrote Saroyan (1966), “have found the healing of God in a variety of things, the most pleasant of which is probably automobile drives.” This

is certainly a popular literary theme. For many Americans, Seo (2021) writes, driving is “a manifestation of their freedom”, a pleasurable activity where they can be “spontaneous and independent” unchained by “the dictates of social convention”, where they can experience “satisfaction of a deep desire that [is] vital to human flourishing.” Am I so sociologically clueless, so incognizant of the rituals of my adoptive land, that I have failed to recognize the misalignment between technology and folklore?

Or maybe the poetic infatuation with driving the open road is a pie in the sky? In our day-to-day lives, we don't go out for a liberating ride on the open roads. We *commute*. And commuting is a misery. Daniel Kahneman et al. (2004) ranked people's satisfaction with daily activities. Guess who came last. Commuting, respondents say, is the “least enjoyable” activity, worse than housework. Drivers repeatedly explain that what they find most agonizing on the road is the discourteous and dangerous actions of others.

I want to remain agnostic as to this debate. Maybe tracking will suck out the fun of footloose driving. Or, maybe it will instead subdue aggressive drivers and make commuting more tolerable for others. It was at the tip of my tongue to end this article by calling for UBI to be *mandatory*. “Hey, California,” I am itching to say, “How many people should privacy kill? How about saving 1200 lives every year if instead of a banning UBI you mandate it!”

But a mandate, perish that thought, may not be necessary. Over time, drivers would warm up to UBI and enroll voluntarily to enjoy the savings and the safety. Besides, a freedom to not enroll is valuable, especially when its cost is accurately priced. If some drivers find the “healing of God” via open road driving, who am I to repudiate their yearning. Be that as it may, I take comfort in this conversation. Let the last standing critique of UBI be a tender longing for post-urban freedom, rather than hard-core precautionism. I doubt that such critique could justify 30% more fatal collisions.

References

- Abraham, Kenneth S. and Daniel B. Schwarcz. 2022. The Limits of Regulation by Insurance, *Indiana Law Journal* 98: 215-74.
- Agan, Amanda, Diag Davenport, Jens Ludwig, and Sendhil Mullainathan. 2023. *Automating Automaticity: How the Context of Human Choice Affects the Extent of Algorithmic Bias*. Becker-Friedman Institute Working Paper No. 2023-19.
- Angwin, Julia, Jeff Larson, L. Kirchner and Surya Mattu. 2017. Minority Neighborhoods Pay Higher Car Insurance Premiums than White Areas with the Same Risk. *ProPublica*, April 5.
- Arumugam, Subramanian and R. Bhargavi. 2019. A Survey on Driving Behavior Analysis in Usage Based Insurance Using Big Data, *Journal of Big Data* 6: 1-21.
- Austin, Regina. 1986. The Insurance Classification Controversy, *University of Pennsylvania Law Review* 131: 517-84.
- Avraham, Ronen, Kyle D. Logue, and Daniel Schwarcz. 2014. Understanding Insurance Anti-Discrimination Laws, *Southern California Law Review* 87: 195-274.
- Ayres, Ian and Steven D. Levitt. 1998. Measuring Positive Externalities from Unobservable Victim Precaution: An Empirical Analysis of Lojack, *Quarterly Journal of Economics* 111: 43-77.
- Ben-Shahar, Omri and Alon Harel. 1995. Blaming the Victims: Optimal Incentives for Private Precautions Against Crime, *Journal of Law, Economics, and Organization* 11: 434-55.
- Ben-Shahar, Omri and Kyle Logue. 2012. Outsourcing Regulation: How Insurance Reduces Moral Hazard, *Michigan Law Review* 111: 197-248.
- Ben-Shahar, Omri and Lior J. Strahilevitz. 2016 Contracting Over Privacy: Introduction, *Journal of Legal Studies*. 43: S1-S12.
- Bode, Karl. 2016. Consumer Groups slam Comcast's Plan to charge Users for Privacy. *DSL Reports*, August 5.
- Bolderdijk, Jan Willem, J. Knockaert, Linda Steg, and Erik T. Verhoef. 2011. Effects of Pay-As-You-Drive vehicle insurance on young drivers' speed choice: Results of a Dutch field experiment, *Accident Analysis and Prevention* 43: 1181-86.
- Bordoff, Jason E. and Pascal J. Noel. 2008. Pay-As-You-Drive Auto Insurance: A Simple Way to Reduce Driving-Related Harms and Increase Equity. Discussion Paper 2008-09, Brookings Institute, The Hamilton Project.
- Brandão, Martim. 2020. Discrimination issues in usage-based insurance for traditional and autonomous vehicles. Pp. 395-406 in *Culturally Sustainable Social Robotics—Proceedings of Robophilosophy*, edited by M. Nørskov, J. Seibt, and O. Quick. Amsterdam: IOS Press.

Bronson, Caitlin. 2016. More Americans Reject Telematics Over Privacy Concerns, *Insurance Business News*, January 12.

Burk, Daniel. 2021. Algorithmic Legal Metrics, *Notre Dame Law Review* 96: 1147-1204.

Claims Journal. 2015. *Hard Braking Most Likely Predictor of Future Crashes: Progressive*. May 19.

Cohen, Alma and Liran Einav. 2003. The Effects of Mandatory Seat Belt Laws on Driving Behavior and Traffic Fatalities, *Review of Economics and Statistics* 85: 828-43.

Chalmers, Petra. 2019. Ricardo Lara Wants to Give Insurance Companies your Driving Data, *Consumer Watchdog*, August 12.

Chiglinsky, Katherine. 2021. Credit Scores for Car Insurance Become a Target for Regulators, *Bloomberg Businessweek*, December 22.

Dijksterhuis, Chris, Ben Lewis-Evans, Bart Jelijs, Dick de Waard, Karel Brookhuis, and Oliver Tucha. 2015. The Impact of Immediate or Delayed Feedback on Driving Behaviour in a Simulated Pay-as-You-Drive System, *Accident Analysis and Prevention* 75: 93-104.

Dijksterhuis, Chris, Ben Lewis-Evans, Bart Jelijs, Dick de Waard, Karel Brookhuis, and Oliver Tucha. 2016. In-car usage-based insurance feedback strategies. A comparative driving simulator study. *Ergonomics* 59:1158-70.

Edlin, Aaron S. 2003. Per-Mile Premiums for Auto Insurance, in *Economics for an Imperfect World: Essays In Honor of Joseph Stiglitz* 53-82. Cambridge, Mass: MIT Press.

Edlin, Aaron S. and Pinar Karaca-Mandic. 2006. The Accident Externality from Driving. *Journal of Political Economy* 114: 931-55.

EIOPA - European Insurance and Occupational Pensions Authority. 2019. *Big Data Analytics in Motor and Health Insurance: A Thematic Review*. Frankfurt, Germany.

Eley, David. 2000. Rate and Form Regulation in the Twenty-First Century, *Journal of Insurance Regulation* 18: 277.

Ellison, Patricia A, J.M Govern, H.M. Petri, and H.H Figler. 1995. Anonymity and Aggressive Driving Behavior. A Field Study. *Journal of Social Behavior and Personality* 10: 265-72.

Federal Highway Administration. 2019. *Status of the Nation's Highways, Bridges, and Transit*. Washington DC: U.S. Department of Transportation.

Federal Insurance Office. 2016. *Report on Protection of Insurance Consumers and Access to Insurance*. Washington DC: U.S. Department of the Treasury.

- Fortune Business Insights. 2023. *Automotive Usage Based Insurance Market*.
www.fortunebusinessinsights.com/automotive-usage-based-insurance-market-104103.
- Goldenbeld, Charles, and Ingrid van Schagen. 2009. The Effects of Speed Enforcement with Mobile Radar on Speed and Accidents, *Accident Analysis and Prevention* 37: 1135–44.
- Grace, Martin, J. Tyler Leverty, and Lawrence Powell. 2019. Cost Trends and Affordability of Automobile Insurance in the U.S., *Journal of Insurance Regulation* 38(7): 1-23.
- Gritzinger, Bob. 2004. Under the Hood, with Big Brother: Forget Orwell’s 1984—20 Years Later It’s Our Cars That Are Giving Us Up, *Autoweek*, November 7.
- Heller, Douglas and Michael DeLong. 2021. Watch Where You’re Going: What’s Needed to Make Auto Insurance Telematics Work for Consumers, Washington DC: Consumer Federation of America 4.
- Hultkrantz, Lars and Gunnar Lindberg. 2011. Pay-as-you-speed: An Economic Field Experiment, *Journal of Transport Economics and Policy* 45: 415-436.
- Infantino, Marta. 2022. Big Data Analytics, Insurtech and Consumer Contracts: A European Appraisal. *European Review of Private Law* 30: 613-634.
- Jeanningros, Hugo and Liz McFall. 2020. The Value of Sharing: Branding and Behaviour in a Life and Health Insurance Company. *Big Data & Society* 7: 1-14.
- Jin, Yizhou, and Shoshana Vasserman. 2021. Buying Data from Consumers: The Impact of Monitoring Programs in U.S. Auto Insurance, Working Paper No. 29096. National Bureau of Economic Research, Cambridge, Mass.
- Juang, Mike. 2018. A New Kink of Auto Insurance Technology Can Lead to Lower Premiums, But It Tracks Your Every Move. *CNBC*, October 6.
- Kahneman, Daniel, Alan B. Krueger, David A. Schkade, Norbert Schwarz, and Arthur A. Stone. 2004. A Survey Method for Characterizing Daily Life Experience: The Day Reconstruction Method, *Science* 306: 1776-80.
- Kallinikos, Jannis. 2007. *The Consequences of Information: Institutional Implications of Technological Change*. Edward Elgar.
- Karapiperis, Dimitris, Birny Birnbaum, Aaron Brandenburg, Sandra Castagna, Allen Greenberg, Robin Harbage, and Anne Obersteadt. 2015. *Usage-Based Insurance and Vehicle Telematics: Insurance Market and Regulatory Implications*. National Association of Insurance Commissioners and Center for Insurance Policy and Research.
- Kleinberg, Jon, Sendhil Mullainathan, and Manish Raghavan. 2022. The challenge of understanding what users want: Inconsistent preferences and engagement optimization. *EC '22: Proceedings of the 23rd ACM Conference on Economics and Computation*.

Knipling, Ronald R., Jeffrey S. Hickman, and Gene Bergoffen. 2003. *Commercial Truck and Bus Safety*. Washington DC: Transportation Research Board.

Leefeldt, Ed and Amy Danise. 2021. The Witness Against You: Your Car, *Forbes*, March 26.

Lemaire, Jean, Sojung Carol Park and Kili C. Wang. 2016. The Use of Annual Mileage as a Rating Variable, *ASTIN Bulletin* 46: 39-69.

Litman, Todd A. 2011. Pay-as-you-drive Pricing for Insurance Affordability, BC Canada: Victoria Transportation Policy Institute.

Levy, Karen. 2015. The Contexts of Control: Information, Power, and Truck-Driving Work, *The Information Society* 31: 160-74.

Levy, Karen. 2023. *Data Driven: Truckers, Technology, and the New Workplace Surveillance*. Princeton, NJ: Princeton University Press.

Lyon, David. 2018. *The Culture of Surveillance: Watching as a Way of Life*. John Wiley.

Marinucci, Carla, and Jeremy B. White. 2019. Lara Tells Insurers He's 'Receptive' to Their Ideas, Including Vehicle Data Use. *Politico*, July 29.

McFall, Liz and Liz Moor. 2018. Who, or What, is Insurtech Personalizing? Persons, Prices and the Historical Classifications of Risk. *Distinktion: Journal of Social Theory* 19: 193-213.

Michael Ksycinsky. 2022, More Connected Vehicles on the Road Will Impact the Insurance Industry. <https://grapeup.com/blog/connected-vehicles-impact-the-insurance-industry/#>.

National Safety Council. 2021. Injury Facts, Crashes by Time of Day and Day of Week. <https://injuryfacts.nsc.org/motor-vehicle/overview/crashes-by-time-of-day-and-day-of-week/> (last viewed July 13, 2023).

NHTSA. 2009. *Comparing Real-World Behaviors of Drivers with High versus Low Rates of Crashes and Near-Crashes*. U.S. Department of Transportation.

NHTSA. 2012. *Traffic Safety Facts: Children; 2010 Data*. U.S. Department of Transportation.

NHTSA. 2015. *Meta-Analysis of Graduated Driver Licensing Laws*. U.S. Department of Transportation.

Nicols, Brice and Kara Kockelman. 2014. Pay-As-You-Drive Insurance: Its Impacts on Household Driving and Welfare, *Transportation Research Record* 2450: 76-82 (2014).

Oberdiek, John. 2017. *Imposing Risk: A Normative Framework*. Oxford: Oxford University Press.

Palmer, Scott. 2016. Telematics in Auto Claims is Inevitable, *PropertyCasualty360.com*.

Parry, Ian W.H. 2005. Is Pay-as-You-Drive Insurance a Better Way to Reduce Gasoline Than Gasoline Taxes?, *American Economics Association Papers and Proceedings* 95: 288-293.

Peltzman, Sam. 1975. The Effects of Automobile Safety Regulation, *Journal of Political Economy* 83: 677-726.

Porat, Ariel. 2011. Misalignments in Tort Law, *Yale Law Journal* 121: 82-141.

Posner, Eric and Glen Weyl. 2018. *Radical Markets: Uprooting Capitalism and Democracy for a Just Society*. Princeton, NJ: Princeton University Press.

Preston, Caroline E. and Stanley Harris. 1965. Psychology of Drivers in Traffic Accidents, *Journal of Applied Psychology* 49: 284–88.

Prince, Anya and Daniel Schwarcz. 2020. Proxy Discrimination in the Age of Artificial Intelligence and Big Data, *Iowa Law Review* 105: 1257-1318.

Pucher, John and John L. Renne. 2005. Urban-Rural Differences in Mobility and Mode Choice: Evidence from the 2001 NHTS, *Transportation* 32: 165-86.

Raffety, Matthew Taylor. 2013. *The Republic Afloat: Law, Honor, and Citizenship in Maritime America*. Chicago, IL: University of Chicago Press.

Reimers, Imke and Benjamin Shiller. 2020. The Impacts of Telematics on Competition and Consumer Behavior in Insurance, *Journal of Law and Economics* 62: 613-32 (2020).

Rubin, Tzameret H., Tor Helge Aas and Jackie Williams. 2023. Big Data and Data Ownership Rights: The Case of Car Insurance. *Journal of Information Technology Teaching Cases* 13: 82-87.

Rothengatter, Talib. 2002. Drivers' Illusions—No More Risk, *Traffic Psychology and Behaviour* 5: 249-58.

Saroyan, William. 1966. *Short Drive, Sweet Chariot*. Phaedra.

Seo, Sarah. 2021. *Policing the Open Road: How Cars Transformed American Freedom*. Cambridge, Mass: Harvard University Press.

Shults, Ruth A. and Allan F. Williams. 2016. Graduated Driver Licensing Night Driving Restrictions and Drivers Aged 16 or 17 Years Involved in Fatal Night Crashes — United States, 2009–2014. *MMWR Morbidity and Mortality Weekly Report* 65: 725-30.

Silverman, Jacob. 2016. Just How 'Smart' Do You Want Your Blender to Be?. *New York Times*, June 14.

Soleymanian, Miremad, Charles B. Weinberg, and Ting Zhu. 2019. Sensor Data and Behavioral Tracking: Does Usage-Based Auto Insurance Benefit Drivers?, *Marketing Science* 38: 21-43.

Spears, Victoria. 2019. New Bill Aims to Ban Non-driving Factors from Insurance Rate Decisions, *ALM Property Casualty 360*, August 21

Starr, Sonja B. 2014. Evidence-Based Sentencing and the Scientific Rationalization of Discrimination, *Stanford Law Review* 66: 803-72.

Strahilevitz, Lior. 2006., 'How's My Driving?' for Everyone (and Everything?), *New York University Law Review* 81: 1699-1765.

Svenson, Ola. 1981. Are We All Less Risky and More Skillful than Our Fellow Drivers?, *Acta Psychologica* 47: 143-48.

Transport Research Centre. 2006. *Speed Management*. Paris, France: Organization for Economic Co-operation and Development.

Van Den Boom, Freya. 2021. Putting Users Back in Control of Car Data to Fuel Innovations, *Bot Populi*, November 8.

Vickrey, William. 1968. Automobile Accidents, Tort Law, Externalities, and Insurance: An Economist's Critique, *Law and Contemporary Problems* 33: 464-87 (1968).

Wilde, Gerald J.S. 1986. Beyond the Concept of Risk Homeostatis, *18 Accident Analysis and Prevention* 18: 377- 401.

Wit, Arjaan, and Henk Wilke. 1990. The Presentation of Rewards and Punishments in a Simulated Social Dilemma, *Social Behaviour* 5: 231-45.

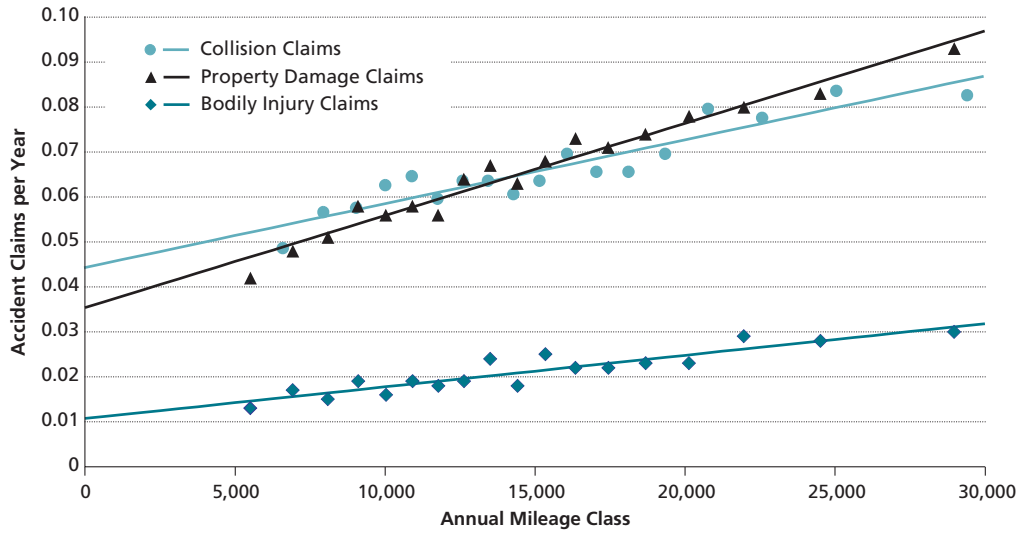
World Health Organization. 2018. *Global Status Report On Road Safety 2018*.

Yuracko, Kimberly and Ronen Avraham. 2018. Valuing Black Lives: A Constitutional Challenge to the Use of Race-Based Table in Calculating Tort Damages, *California Law Review* 106: 325-372.

Zheng, Houyu, You Lin, and Gengran Hu. 2022. A Novel Insurance Claim Blockchains Scheme Based on Zero-Knowledge Proof Technology, *Computer Communications* 195: 207-216.

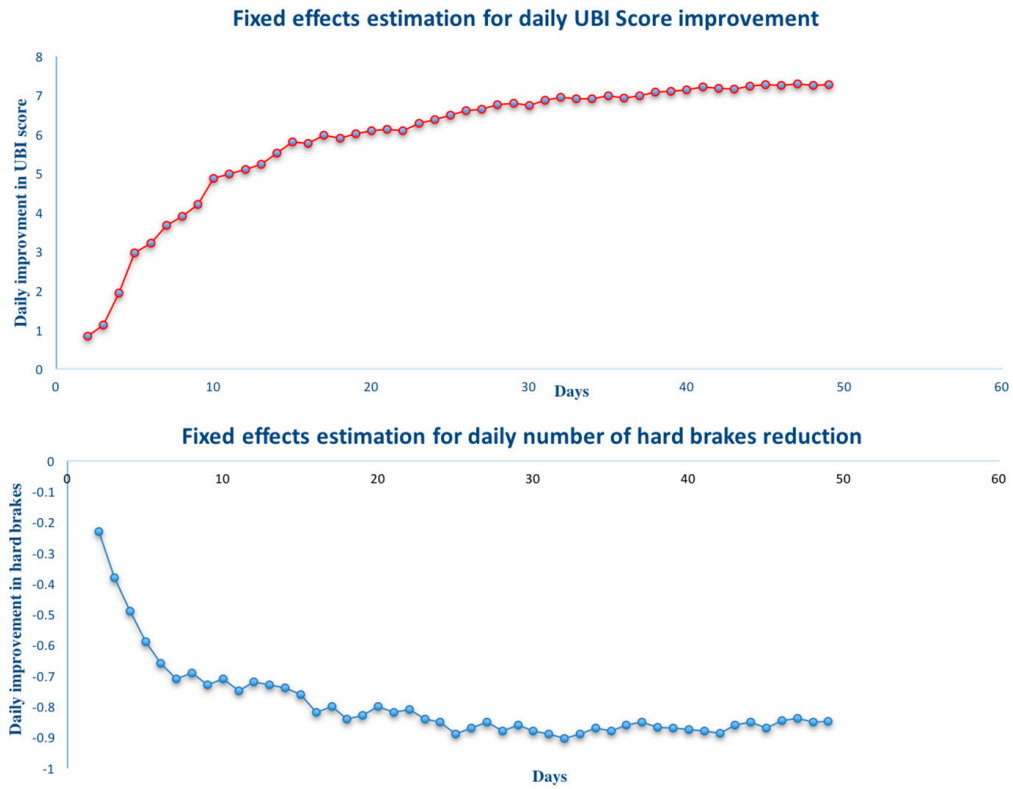
FIGURE 1

Yearly Accident Claims by Annual Mileage



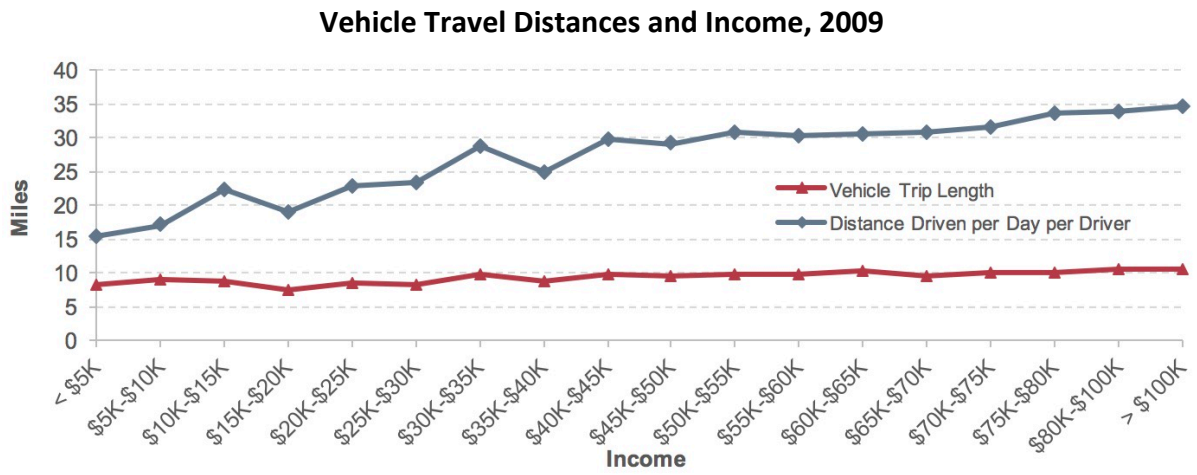
Source: Progressive Insurance 2005.

FIGURE 2



Source: Soleymanian, Weingberg, and Zhu (2019)

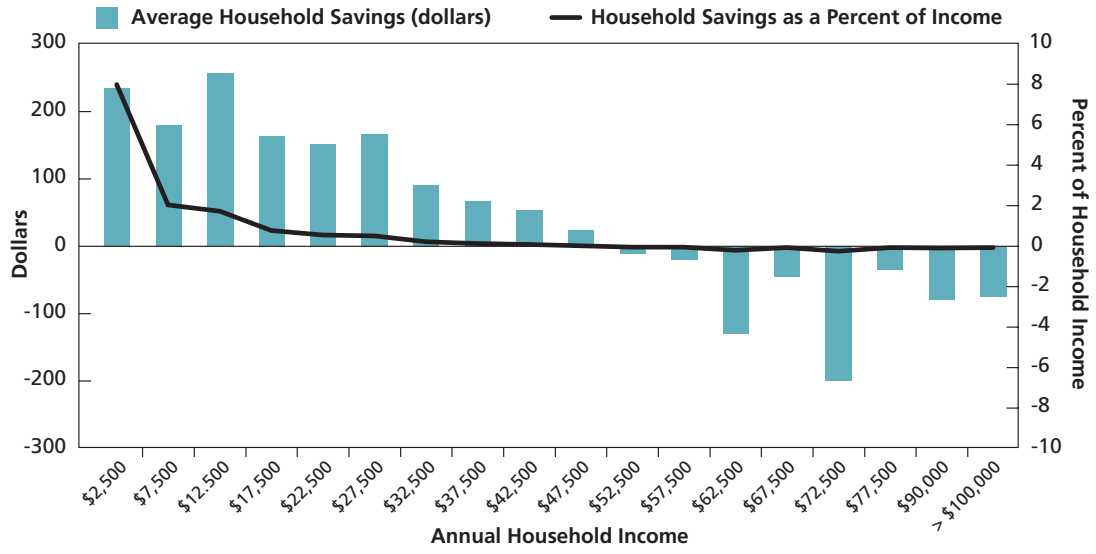
FIGURE 3



Source: National Household Travel Trends, Ch. 3, exhibit 3-27 (Federal Highway Administration 2019)

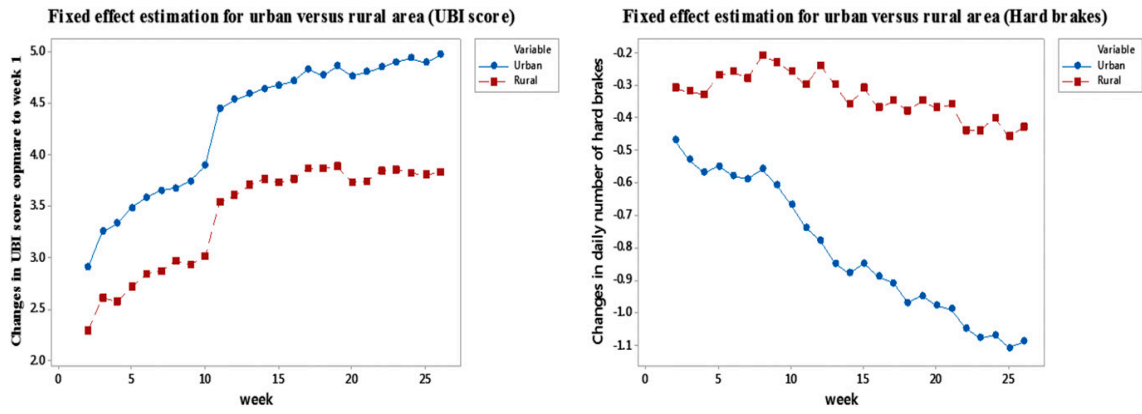
<https://www.fhwa.dot.gov/policy/23cpr/index.cfm>.

FIGURE 4



Source: Bordoff and Noel (2008)

FIGURE 5



Source: Soleymanian, Weingberg, and Zhu (2019)

FIGURE 6

