Transportation Research Part B 182 (2024) 102908

Contents lists available at ScienceDirect

Transportation Research Part B

journal homepage: www.elsevier.com/locate/trb

Autonomous vehicles policy and safety investment: An equilibrium analysis with endogenous demand

Herbert Dawid [a], Xuan Di [b,c,*], Peter M. Kort [d], Gerd Muehlheusser [e,f,g]

[a] Bielefeld University, Department of Business Administration and Economics, and Center for Mathematical Economics, Germany
[b] Columbia University, Department of Civil Engineering and Engineering Mechanics, United States of America
[c] Data Science Institute, Columbia University, United States of America
[d] Tilburg University, Department of Econometrics and Operations Research & CentER, Netherlands
[e] University of Hamburg, Department of Economics, Germany
[f] IZA, Germany
[g] CESifo, Germany

ARTICLE INFO

Keywords:
Mixed traffic
Autonomous vehicles
Endogenous AV demand
Road safety
AV liability
AV market penetration

ABSTRACT

The safety concerns for autonomous vehicles (AV) are shown to be a roadblock to their adoption. This paper addresses these concerns by studying a unified, game-theoretic framework (leader–follower game) of mixed traffic in which AVs and human-driven vehicles (HV) coexist, with endogenous vehicle demand and different types of accidents emerging in mixed traffic as crucial building blocks. We study the interaction between three types of players: (i) a policymaker, who decides on the liability regime and the level of V2I connectivity infrastructure, (ii) an AV producer, who decides on the AV price and safety level, and (iii) consumers, who differ in their preference for each vehicle type and choose the one they like best. Using both analytical and numerical tools, we analyze how the two policy variables, liability and V2I connectivity, affect behavior on the demand and supply side of the vehicle market and, in turn, AV market penetration and overall road safety. We also characterize optimal policies, thereby taking into account the market participants' behavioral responses. Our findings provide guidance for a fast adoption of AVs and a smooth transition from existing traffic conditions to a mixed traffic environment, and assist in decision making for policymakers, legal agencies, traffic operation and transportation planning agencies, as well as car manufacturers.

1. Introduction

1.1. Motivation

In today's transportation sector, vehicles already show a remarkable degree of automation and even fully autonomous vehicles (AVs) are widely believed to become available in the not too distant future (see e.g. European Commission, 2018).[1] AVs are perceived

* Corresponding author at: Columbia University, Department of Civil Engineering and Engineering Mechanics, United States of America.
E-mail address: sharon.di@columbia.edu (X. Di).

[1] Tesla already offers a "Full Self Driving" package since several years; however, drivers must always be ready to immediately take over control. According to the classification system of the Society of Automotive Engineers (SAE), this corresponds to autonomy level 2 (out of 5), see SAE International (2021). In 2021 Mercedes introduced its "Drive Pilot" system, where the human driver is not obliged to monitor the driving at all times, but must only be ready to take over after being prompted by the system (level 3). The system is currently approved for motorways and with a speed of up to 60 km/h. In June 2022, the *United Nations Economic Commission for Europe* (UNCE) has extended the maximum speed to 130 km/h (effective as of 2023) for vehicles which satisfy the respective requirements, see https://unece.org/sustainable-development/press/un-regulation-extends-automated-driving-130-kmh-certain-conditions.

https://doi.org/10.1016/j.trb.2024.102908
Received 25 March 2023; Received in revised form 1 December 2023; Accepted 20 February 2024
Available online 1 March 2024

as potentially being much safer than conventional, human-driven vehicles (HVs) in the long run, in addition to further benefits such as improved traffic flows, better time use en route, and greater mobility of the elderly (see e.g. Fagnant and Kockelman, 2015).

The emergence of AVs gives rise to *mixed traffic*, the coexistence of AVs and HVs on the streets, potentially lasting for decades. This paper addresses several key properties of an automobile sector characterized by mixed traffic: First, mixed traffic gives rise to different types of accidents between AVs and HVs, some caused by the human drivers of HVs, others caused by the autonomous systems of AVs. For the latter, a currently topical question is how to apportion the damage between the AV producer, the AV owner/passenger and the victim(s) by resorting to (product) liability(see e.g Geistfeld, 2017; Shavell, 2020; Di et al., 2020). Moreover, the liability regime will also affect the incentives of AV producers to invest in the safety of their vehicles in the first place (see e.g. Dawid and Muehlheusser, 2022). Together, these two channels render AV liability a crucial task for policymakers.[2]

Second, a further key property of mixed traffic is that consumers have a choice between HVs and AVs. In particular, how quickly AVs will penetrate the market and become ubiquitous on the streets will not only depend on technological feasibility, but also on how much consumers like them. In this respect, a large body of empirical (survey) evidence documents that consumers differ vastly regarding their attitudes towards AV and their willingness to adopt them, and crucial determinants in this respect are liability, vehicle safety and price, and personal attributes (e.g. Kyriakidis et al., 2015; Shabanpour et al., 2018; Cunningham et al., 2019). This suggests that AV demand and market penetration and, consequently, overall road safety will crucially depend on these factors, and how they are addressed by manufacturers and policymakers.

Third, a higher AV market penetration can also be expected to foster road safety trough further channels. For example, AVs can better "communicate" with one another than with HVs thereby reducing the accident risk between AVs (*connectivity*). As individual consumers will tend to not fully take into account such positive spillover effects in their vehicle choice, this suggests a role for public investments in vehicle-to-infrastructure (V2I) connectivity infrastructure. Such investments enhance the attractivity of AVs for consumers, and thus will increase market demand. This in turn makes it more attractive for the AV producer to increase market supply.

In light of these inter-dependencies, it is important to gain a better understanding of how regulatory policies such as the liability regime and the availability of V2I infrastructure affect behavior on the demand and supply side of the vehicle market and, in turn, the mixed traffic structure and overall road safety. In this paper, we study a unified game-theoretic framework of mixed traffic that allows us to take all of these building blocks into account, thereby providing a set of novel results.

1.2. Related work

Our paper contributes to various strands of literature related to AVs that have either studied these building blocks in isolation, or have focused on other aspects of AV behavior in mixed traffic.

First, an extensive empirical literature studying attitudes towards AVs has documented that people differ strongly with respect to their willingness to adopt AVs (see e.g. Schoettle and Sivak, 2014; Kyriakidis et al., 2015; Shabanpour et al., 2018; Cunningham et al., 2019; Wu et al., 2020). Many consumers are concerned about AV safety, vehicle price, liability, and data security, while the perceived benefits from AVs include a higher fuel efficiency, or a more productive use of time during travel. All in all, people have quite diverse perceptions on these factors (see e.g. the surveys by Haboucha et al., 2017; Gkartzonikas and Gkritza, 2019; Jing et al., 2020) that, importantly, are also affected by the choices made by AV producers (e.g. vehicle price and safety) and policymakers (e.g. liability). Dawid and Muehlheusser (2022) explicitly model the demand side in dynamic setting, using a standard framework in industrial economics due to Hotelling (1929) and Salop (1979) where consumers have different preferences regarding horizontally differentiated products (AVs and HVs). As a result, the market shares of AVs and HVs arise endogenously from the players' choices in the game. Their framework focuses on the impact of product liability on the incentives to invest in AV safety as well as the timing of AV market introduction and AV market penetration over time. Feess and Muehlheusser (2024) study a game-theoretic model where the choice between AVs and HVs depends on behavior of AVs in situations of moral dilemma (swerving in unavoidable accidents), but they do not consider a full-fledged market setting.

Second, with respect to the literature on product liability, apart from compensating victims for their harm suffered, one crucial question is whether the threat of liability increases firms' incentives to improve product safety. McGuire (1988) provides supportive (survey) evidence in this respect.[3] (Polinsky and Shavell, 2010) stress that firms have a high incentive to invest in product safety even in the absence of product liability; otherwise, the higher liability costs borne by consumers reduces their willingness to pay for the product, inducing a downward shift of demand. In the context of AVs, legal scholars have since long argued that the emergence of AVs raises important questions regarding liability(see e.g. Geistfeld, 2017; Smith, 2017; Wagner, 2018; Gless et al., 2016).

In recent years the impact of AV liability has also been studied in formal (game-theoretic) models, focusing on the comparison of the two core liability regimes in tort law, strict liability and fault-based liability, and variants thereof. For example, Shavell (2020) considers a case of full AV market penetration (i.e. no mixed traffic) and proposes a liability rule that holds the AV owner strictly liable for all accidents involving the AV, but the damage payments are made to the state, rather than to parties harmed in the accidents. The underlying rationale for this "double liability" rule is the possibility of aligning privately and socially optimal

[2] A further factor might be the imposition of a minimum safety standard (set by the policymaker) which AVs must satisfy in order to be allowed to be launched on the market (see e.g. Dawid and Muehlheusser, 2022).

[3] Rather than improving the safety of existing products, the literature has also analyzed (both theoretically and empirically) how product liability affects firms' incentives to develop new, and potentially safer, products (see e.g. McGuire, 1988; Viscusi and Moore, 1993; Galasso and Luo, 2017, 2022; Schwartzstein and Shleifer, 2013).

behavior with respect to both (driver) precaution and activity levels. Guerra et al. (2022) study the role of manufacturer's residual liability in this respect. Schweizer (2023) generalizes the analysis of Shavell (2020) and Guerra et al. (2022), thereby stressing the potential benefits of AVs in making vehicle behavior observable ex post in court. In settings of mixed traffic, Chatterjee and Davis (2013) and Chatterjee (2016) analyze how varying the loss share with contributory or comparative negligence would distort human's interaction with AVs. Friedman and Talley (2019) employ a multilateral precaution framework to explore how tort law should adapt to the emergence of AVs in mixed traffic. The potentially optimal legal rules include no fault, strict liability, and a family of negligence-based rules. Di et al. (2020) further study how AV manufacturers could strategically select AVs' safety level using a hierarchical game-theoretical model. Chen and Di (2023) model the interaction between AVs and HVs in a specific traffic accident scenario, namely, rear-end crashes, leveraging a matrix game approach. They compare the no-fault, contributory, and comparative liability rules for mixed-traffic platooning. In all of these models, AV demand is either not considered or exogenously given. By contrast, in their framework with endogenous demand, Dawid and Muehlheusser (2022) compare strict and fault-based liability with respect to firms' incentives to invest in product safety and AV market penetration over time, thereby also capturing the channel emphasized by Polinsky and Shavell (2010). De Chiara et al. (2021) consider different liability rules in a static framework in which consumers choose between HVs and AVs, thereby not facing any liability risk when choosing the latter.

A third strand of literature studies the design of autonomous driving strategies in mixed traffic. In particular, using game-theoretic models to design algorithmic decision-making processes for AVs has gained increasing traction in various car encounters, namely, driving (Yoo and Langari, 2012; Huang et al., 2019, 2020a,b, 2021), merging (Yoo and Langari, 2013), lane-changing (Yu et al., 2018; Zhang et al., 2019), and unprotected left-turning behavior (Rahmati and Talebpour, 2017), with the game models categorized as either a two-person non-zero-sum non-cooperative game under (in)complete information (Talebpour et al., 2015), a Stackelberg game (Yoo and Langari, 2012, 2013; Yu et al., 2018; Zhang et al., 2019), or a dynamic mean field game (Huang et al., 2019, 2020a,b, 2021). A detailed survey of mixed traffic modeling using game theory and artificial intelligence methods is provided by Di and Shi (2021). These studies, however, primarily focus on improving traffic efficiency, and they abstract from the possibility of accidents and from economic considerations.

A fourth strand of literature investigates the strategic interaction between relevant parties such as policymakers, vehicle manufacturers, and consumers in contexts like traffic planners' decision in infrastructure deployment, and consumers' choice between AVs and HVs. For example, Chen et al. (2020) studies the subsidy design for purchasing Hybrid Electric Vehicles (HEVs) and Autonomous and Electric Vehicles (AEVs). The key player is the government who aims to find the optimal subsidy to maximize social benefits, including gas emission and charging cost. Luo et al. (2019) propose a Stackelberg game in which the government is the leader who designs AV subsidies and AV manufacturers are followers who aim to maximize revenues by setting pricing strategies. Wang et al. (2022) investigates how the government can utilize AV subsidies and infrastructure investment to improve the AV penetration rate. Li et al. (2020) look into road planners' decision in infrastructure deployment and the routing choice of AVs and HVs in a network equilibrium. Mo et al. (2022) studies a ride-sourcing market where the ride-sourcing platform designs optimal pricing and fleet size for AVs and HVs, and customers choose different travel modes. These studies consider the two-way interaction of government with either firms or consumers. Moreover, none of them considers liability as the domain of governmental decision-making, let alone the interaction with infrastructure investments such as V2I connectivity.

1.3. Framework and results

Against this background, this paper studies the three-way interaction between policymakers, vehicle manufacturers, and consumers in a setting of mixed traffic employing a game-theoretic approach. As for the vehicle demand side, we follow Dawid and Muehlheusser (2022) where consumers can choose between HVs and AVs, and each consumer's preferred vehicle depends on idiosyncratic preferences, price, safety, and potential liability costs in case of accidents. There are four different accident types, AV–AV, AV–HV, HV–AV, and HV–HV (e.g., AV–HV refers to an accident between an AV and an HV that is caused by the AV), and consumers' vehicle choice affects the mixed traffic composition and hence the prevalence of each accident type. As for the supply side, we consider a monopolistic AV producer who decides on the AV's price and safety (a higher safety level is costly, but makes accidents involving AVs less likely), both of which affect consumers' demand for AVs. The HV is provided by a competitive fringe of producers which we do not explicitly model. Finally, we consider a policymaker who decides on (i) the stringency of (product) liability for the AV producer for accidents caused by AVs, and (ii) how much to invest to improve V2I connectivity that reduces the likelihood of accidents in AV-AV interactions.

Consumers and the AV producer aim at maximizing their utility and profit, respectively, while the policymaker aims at minimizing the sum of the social costs from accidents and the costs of providing V2I connectivity infrastructure. From a methodological point of view, we employ a game-theoretic approach by considering a leader–follower game in which the policymaker moves first, followed by the AV producer and the consumers. We use backward induction to determine the subgame perfect equilibrium of the game, thereby applying both analytical and numerical tools.[4]

The equilibrium analysis reveals how the AV market penetration, the mixed traffic structure, and overall road safety depends on the choices of all players, as well as on the model parameters.

The remainder of the paper is organized as follows. Section 2 presents the game-theoretic model that accounts for the policymaker, the AV producer, and consumers. With respect to equilibrium behavior at different stages of decision-making, Sections 3 and 4 contain our findings based on analytical and numerical analysis, respectively. Section 5 concludes and discusses potential future extensions. All proofs are in Appendix A. Appendix B presents the results from various robustness checks, and Appendix C provides additional results on the number of accidents for the different types of vehicle interactions.

[4] The concept of subgame perfection is a standard tool in the analysis of dynamic games with complete information, see e.g. Fudenberg and Tirole (1991).

2. The model

2.1. General setup

We consider a setup with four types of agents: a policymaker, a producer of AVs, producers of HVs, and consumers. HVs are produced by a representative (or competitive) producer and sold at price $p_H \geq 0$, which we take as exogenously given. AVs are produced by a monopolistic firm, the *AV producer*, and sold at price $p_A \geq 0$, which is set by the AV producer. Apart from the price, the AV producer also decides on the level of AV safety, $x \geq 0$, which determines the frequency of accidents. There is a unit-mass of consumers which differ with respect to their preference between the HV and the AV. Each consumer purchases one vehicle, and the choice between the AV and the HV depends, apart from preferences, on the price as well as on the expected liability costs arising from accidents. The quantity of AVs on the street is denoted by Q, and therefore the quantity of HVs is given by $1 - Q$. The policymaker aims at minimizing the sum of the costs generated by accidents and by infrastructure investments. She has two instruments at her disposal. First, the allocation of liability between the AV producer and consumers, where we denote the share of accidental damage covered by the producer by $\beta \in [0,1]$. Second, the level of connectivity infrastructure, denoted by $c \geq 0$, which fosters connectivity between AVs (*V2I connectivity*) and allows them to communicate with each other while en route (see e.g. USDOT, 2019).

2.2. Vehicular encounters in mixed traffic

Before delving into each agent's decision making, we first model accident rates in various vehicular encounters in mixed traffic. Both types of cars can cause accidents, each leading to a damage $D > 0$. Subsequently, we introduce how to formulate accident rates for AV–HV, AV–AV, HV–AV, and HV–HV scenarios.

- **AV–HV and AV–AV accidents**: We denote by $k(x) > 0$ the probability that an AV causes an accident when meeting an HV, which depends on the AV safety level (x), where $k'(x) < 0$ and $k''(x) > 0$. This leads to an expected damage of $k(x)D$ from AV–HV accidents. The probability that an AV causes an accident when meeting another AV is $k(x) - h(c)$, where $h'(c) > 0, h''(c) < 0$ and $k(x) > h(c)$ for all x and c. The function $h(c)$ captures the impact of the degree of (V2I) *connectivity* of AVs, making it less likely that an AV causes an accident when meeting an AV compared to an HV.[5]
- **HV–AV accidents**: The probability that an HV causes an accident with an AV is $g(x)$, where $g'(x) < 0$ and $g''(x) > 0$. Intuitively, $g(x)$ depends on the safety level of the AV (x), because a safer AV can prevent some accident which might have been caused by the HV. A safer AV has a faster reaction time and more sophisticated swerving behavior, which can make up for inattention or careless behavior of the HV's driver.[6] Importantly, this will imply that any investment into AV safety also improves safety of the HV, the AV's rival product. This is a specific feature of AVs, and throughout we refer to it as the *rival externality*.
- **HV–HV accidents**: The probability that an HV causes an accident with another HV is $\bar{g}$, which is independent of the level of AV safety, since there are no AVs involved in these types of accidents.

Throughout we make the following assumption on the two accident functions $k(x)$ and $g(x)$:

Assumption 1. (i) $\bar{g} \leq g(0) < k(0)$, (ii) $\lim_{x\to\infty} \frac{k(x)}{g(x)} < 1$, (iii) $\lim_{x\to\infty} \frac{k(x)}{\bar{g}} < 1$, (iv) $|g'(0)| < |k'(0)|$, (v) $\frac{k'(x)}{g'(x)}$ strictly decreases with x and $\lim_{x\to\infty} \frac{k'(x)}{g'(x)} = 0$.

Fig. 1 depicts the different accident probabilities, with the qualitative characteristics based on Assumption 1. Intuitively, for small AV safety the probability is higher for the AV to cause the accident than an HV in interactions between AVs and HVs (part (i)). Moreover, for large values of x the accident rate of an AV is smaller than that of an HV regardless of whether it interacts with an AV or an HV (parts (ii) and (iii)). Part (iv) formalizes that as long as the safety level of the AV is low, a marginal increase in x more strongly reduces the accident rate of the AV itself than that of an HV. Finally, part (v) captures that for sufficiently large x, AVs are already so far advanced that further increasing x hardly reduces the probability that AVs cause accidents, but rather improves their ability to deal with errors of human drivers.

Below, we present the agents' decisions in the order in which they are taken (see Fig. 2 for an illustration). Since the focus of our paper is on the interplay between the AV producer producing the AV, the consumers, and the policymaker, we treat the (representative) HV producer as a passive party and take the HV price p_H as exogenously given.

2.3. Agents and their decisions

2.3.1. The policymaker

The policymaker has two policy variables at her disposal, the liability regime and the amount of infrastructure investment into V2I connectivity.

[5] Whereas in the main body of the paper we assume that the degree of connectivity affects only the probability of AV–AV accidents, in Appendix B.2 we consider a model extension in which also the probabilities of all other accidents types are reduced as V2I connectivity increases. We show that our qualitative findings remain valid also in this extended framework.

[6] Note that we do not explicitly model the care level of HV drivers. See the frameworks of Di et al. (2020) and De Chiara et al. (2021), where this aspect is explicitly considered.

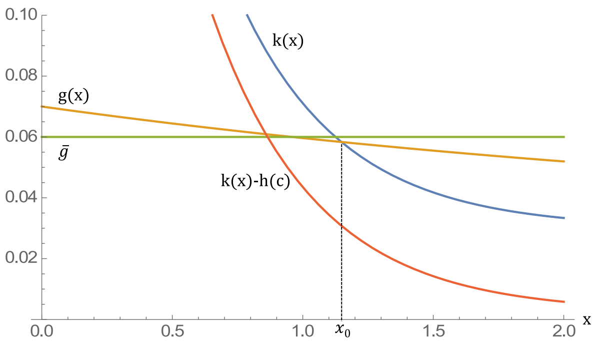

Fig. 1. AV and HV safety depending on safety investment x.

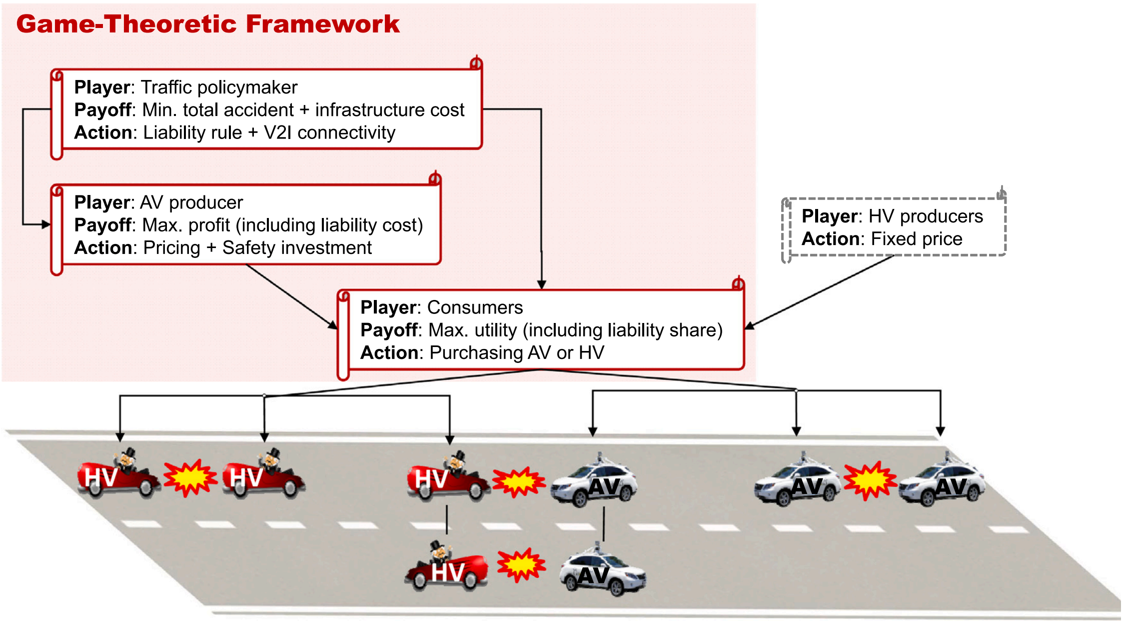

Fig. 2. Illustration of the model structure.

Liability rule. A liability rule determines how the legal system allocates the damage from accidents between the parties involved. Thereby, we assume that the owner of an HV is responsible for the entire damage D caused by her vehicle. This is meant to reflect that, in the current situation with almost only HVs on the street, product liability plays only a minor role for apportioning the damage resulting from accidents.[7]

By contrast, for accidents caused by AVs, producers are expected to face substantially higher liability costs than they currently do with conventional cars. We follow Dawid and Muehlheusser (2022) and assume that a share β of the damage D is borne by the AV producer (*product liability*), where $\beta \in [0, 1]$, while the AV owner/passenger is responsible for the remaining amount $(1-\beta)D$. In light of the current legal discussion summarized in Section 1, the design of liability regimes for AVs is an important policy variable.

Thereby, one has to keep in mind that consumers often do not fully internalize their liability share, for example, due to insurance policies with deductibles, or under-insurance (or even no insurance at all) in combination with wealth constraints. Also in line with Dawid and Muehlheusser (2022), AV owners actually only cover an amount of $\gamma((1-\beta)D) < (1-\beta)D$ with $\gamma' > 0, \gamma'' \leq 0, \gamma(0) = 0, \gamma'(0) \leq 1$.[8] Intuitively, whereas consumers strongly (or even fully) internalize small damage payments,

[7] While car manufacturers do face a (product) liability risk when a car model exhibits systematic technical defects, the vast majority of accidents are the result of erroneous driver behavior (see e.g. the 2008 *National Motor Vehicle Crash Causation Survey*). Hence, the damage from an accident is usually apportioned between the driver/owner of the vehicle causing the accident (and potentially their insurance company) and the parties harmed.

[8] For example, while insurance is mandatory in most U.S. states, uninsured driving is an empirically relevant phenomenon (see e.g. a recent study of the Insurance Research Institute, https://www.insurance-research.org/sites/default/files/downloads/UMNR1005.pdf). Moreover, for insurance contracts with a deductible, the marginal liability effect is equal to one for damages below the amount of the deductible, and zero above it. Finally, a plaintiff might even be

the degree of marginal internalization decreases as the damage becomes larger. Similarly, the owner of an HV covers an amount $\gamma(D) < D$.

V2I connectivity investment. We assume that V2I connectivity reduces the probability of AV–AV accidents compared to AV–HV accidents. The cost of providing a level of AV connectivity c is given by $\zeta(c)$, that is increasing and convex. For simplicity, throughout we consider a quadratic specification $\zeta(c) = \zeta_0 \cdot c^2$, with $\zeta_0 > 0$.

The objective of the policymaker is to minimize the sum of infrastructure and accident costs. Thereby, the policymaker takes into account the effect these decisions will have on the behavior of the AV producer and consumers. In particular, with Q AVs and $1 - Q$ HVs on the street, the expected total number of accidents, denoted by $A(x)$, is given by

$$A(x, Q; \beta, c) = Q \cdot ((k(x) - h(c))Q + k(x)(1 - Q)) + (1 - Q) \cdot (g(x)Q + \bar{g}(1 - Q)). \tag{1}$$

Each term of (1) captures the expected number of accidents for each of the four interaction types (i.e. AV–HV, AV–AV, HV–AV, and HV–HV).[9] The objective of the policymaker is to minimize the sum of accident and infrastructure costs, and is hence given by

$$\Psi(x, Q; \beta, c) = A(x, Q; \beta, c) \cdot D + \zeta(c). \tag{2}$$

2.3.2. The AV producer

The AV producer chooses the AV price, p_A, and safety level, x, in order to maximize expected profit. The associated cost is $\xi(x) = \xi_0 \cdot x^2$, with $\xi_0 \geq 0$. For simplicity we set the (marginal) AV production costs to zero. Denoting by $Q^D(p_A, x; \beta, c)$ the AV demand for a given price p_A, the profit function of the AV producer is given by

$$\Pi(p_A, x; \beta, c) = Q^D(\cdot) \cdot \left[p_A - \beta D \cdot \left(Q^D(\cdot) \cdot (k(x) - h(c)) + (1 - Q^D(\cdot)) \cdot k(x)\right)\right] - \xi(x). \tag{3}$$

The second term in the square bracket captures the AV producer's expected liability cost, taking into account the different probabilities for accidents caused by AVs when interacting with another AV or with an HV.

2.3.3. The consumers

One key contribution of our paper is to explicitly incorporate consumers' (utility-maximizing) choice between the different types of vehicles. In doing so, we consider a setting of *horizontal product differentiation*, i.e. consumers differ in their personal taste with respect to the ideal properties of a vehicle, expressed by their "bliss point". We follow a standard approach in industrial organization due to Salop (1979), in which a unit mass of consumer is uniformly distributed on a circle with circumference 1 with respect to their bliss points.[10] Without loss of generality, the HV and the AV are located at distance one-half on the top and bottom position of the circle, respectively (see Fig. 3).[11] Each consumer has the same gross valuation $v > 0$ for each vehicle type.[12] The optimal purchasing decision will therefore depend on the (individual) relative attractiveness of each type of vehicle, which depends on vehicle prices, the expected costs from accidents, and the *preference* costs, i.e. the reduction in a consumer's utility when the vehicle characteristics do not match her bliss point. Formally, for a consumer with bliss point y, we denote by $d_A(y)$ and $d_H(y)$ the "distance" along the Salop circle between the bliss point and the product position of the AV and HV, respectively. The reduction in utility is proportional to this distance with a sensitivity parameter $t > 0$. The smaller (larger) this distance, the higher (lower) is ceteris paribus the consumer's willingness to purchase the respective vehicle type.

Denoting by $u_A(y, Q)$ and $u_H(y, Q)$ the expected utility of a consumer with bliss point y when purchasing the AV and the HV, respectively, we have[13]

$$\begin{aligned} u_A(y, Q) &= v - t d_A(y) - p_A - [Q \cdot (k(x) - h(c))\gamma((1 - \beta)D) + (1 - Q) \cdot k(x)\gamma((1 - \beta)D)] \\ u_H(y, Q) &= v - t d_H(y) - p_H - [Q \cdot g(x)\gamma(D) + (1 - Q)\bar{g}\gamma(D)]. \end{aligned} \tag{4}$$

Note that, through the expected liability costs, individual utility depends on the overall number of AVs (Q) and HVs ($1 - Q$) on the street.

---

judgement-proof when the damages owed exceed the amount covered by the insurance policy (plus eventual own funds) (see e.g., Gilles, 2006). In all of these cases (or combinations thereof), the actual liability costs is lower than the damage caused in the course of the accident. All we need for our analysis is that a consumer's expected liability cost increases under-proportionally in the damage amount. As will become clear below, when consumers face no restrictions with respect to their ability to make liability payments (i.e. when $\gamma((1 - \beta)D) = (1 - \beta)D$), then under linear demand, any shift of liability between the AV producer and the consumers is offset one-to-one by a respective price change.

[9] The number of accidents for each interaction type is stochastic and follows a binomial distribution characterized by the corresponding accident probability and the number of interactions. For example, the number of AV–AV accidents is binomially distributed according to $B(p, n)$ with $n = Q^2$ as the number of independent AV–AV interactions and $p = k(x) - h(c)$ as the accident probability in each interaction. The expected number of accidents is then given by $np = Q^2(k(x) - h(c))$. Analogous reasoning leads to the expected number of accidents from the other three interaction types.

[10] The concept of horizontal product differentiation goes back at least to Hotelling (1929)'s seminal model with competing ice-vendors on a beach, the famous "Hotelling line". The "Salop circle" is a well-established variant of the Hotelling line which, for our purpose, is slightly more convenient from an analytical point of view. Both models are canonical textbook material in industrial organization, see e.g. Tirole (1988).

[11] That is, we do not model here the location decision of the innovator in the product space.

[12] As is standard in the literature, assuming v to be sufficiently large ensures that each consumer purchases one of the two vehicle types, so that the total vehicle demand is always equal to one.

[13] To ease notation, we only include only certain key variables as explicit arguments in functions representing payoffs, utilities and the like, although they typically also depend on further variables and model parameters.

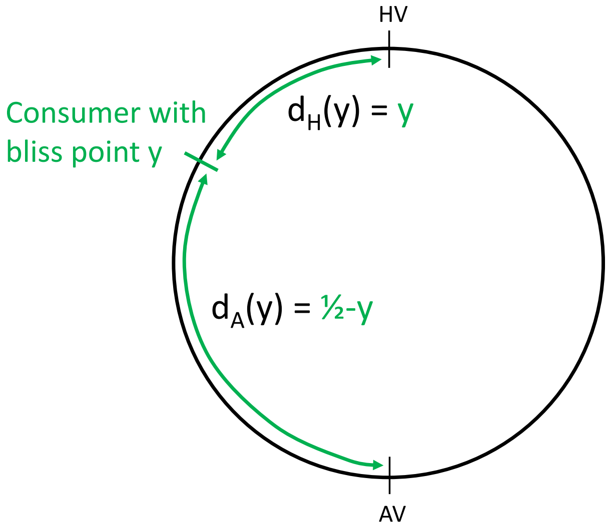

Fig. 3. Consumer choice in the horizontally differentiated market for AVs and HVs.

Each consumer chooses the product which gives her the higher utility. Denoting by $P_A(y)$ the probability that a consumer with bliss point y optimally chooses an AV, we have[14]

$$P_A(y,Q,p_A,x) = \begin{cases} 1 & u_A(y,Q) > u_H(y,Q), \\ 1/2 & u_A(y,Q) = u_H(y,Q), \\ 0 & u_A(y,Q) < u_H(y,Q). \end{cases} \tag{5}$$

Finally, the AV market demand for a given AV price and safety level is then obtained by aggregating the probability of purchasing an AV over all consumers. That is $Q^D(p_A, x; \beta, c)$ solves

$$\int_y P_A(y,Q,p_A,x)dy = Q \tag{6}$$

with respect to Q. Eq. (6) shows that, in contrast to standard models of horizontal product differentiation, in our setup already the determination of AV demand constitutes a fixed point problem. Again this is due to the fact that, through the expected liability costs, each consumer's utility from each vehicle type depends on the total number of AVs and HVs on the street. Since we assume that the AV producer can deliver an arbitrary quantity of AVs at the posted price p_A the actual quantity sold always coincides with the demand Q^D.

2.4. Model summary

Our framework considers essential decisions of key players in the market for AVs. Thereby, the leader–follower structure also captures the timing and time horizon of these decisions: The policymaker's choice of the liability regime and the road safety infrastructure can be considered as long-term decisions which set the institutional framework under which both the supply and the demand side of the market operate.[15] In turn, the AV producer takes the legal and infrastructure environment as given when deciding on crucial AV features such as safety and pricing. Finally, consumers choose their preferred vehicle taking into account the environment set by the policymaker as well as the properties of the AV chosen by the AV producer. Formally, we consider three

[14] If consumers' (perceived) utility from purchasing an AV respectively HV is influenced by some stochastic term reflecting individual idiosyncrasies, this would (under certain distributional assumptions for the stochastic term) give rise to a standard logit model, where the probability of purchasing an AV is given by $P_A = e^{\lambda u_A(y)}/(e^{\lambda u_A(y)} + e^{\lambda u_H(y)})$ for some intensity of choice parameter λ (see McFadden, 1973, 1974). Our modeling of consumer choice can be seen as the limit of such a logit model for $\lambda \to \infty$, which corresponds to the case where the variance of the stochastic term goes to zero.

[15] In our setting the policymaker can commit to not change the legal framework once it has been set. In principle, the liability regime could be adapted over time, for example, in response to improvements in AV safety as a result of investments by the AV producer. However, in practice legal rules are in general quite sluggish, in particular when it comes to (product) liability. For example, the European Union's "Product Liability Directive" has been in place since 1985 and has not been changed since then. Only now, with the advent of the digital age and AI-based autonomous decisions is a revision currently discussed (European Commission, 2022). Legal scholars have also studied the normative question whether the stability of law is socially desirable (see e.g. Shavell, 2008). In particular, and in line with our framework, it has been argued that legal rules should not change unduly, because many parties make their (potentially long-lasting) decisions in reliance on an existing set of legal rules. A setting where the liability regime can be adjusted frequently would create a different incentive structure, as the AV producer might fear that improvements in AV safety today might trigger more stringent liability in the future, and this reduces investment incentives. In their seminal contribution, Freixas, Guesnerie, and Tirole (1985) have coined the term *ratchet effect* for this mechanism.

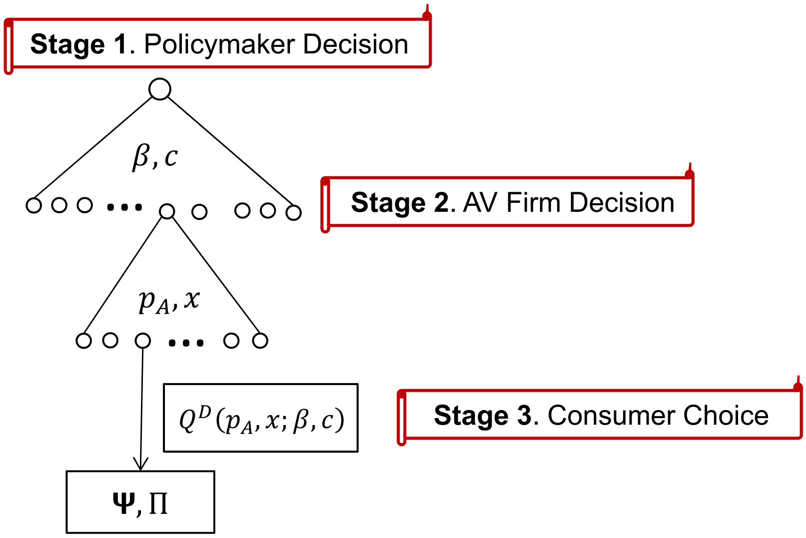

Fig. 4. Extensive-form game tree.

stages. At stage 1, the policymaker decides on the liability regime (β) and on the investment in V2I connectivity (c). At stage 2, the AV producer decides on the AV price (p_A) and safety level (x). At stage 3, each consumer chooses her preferred type of vehicle. Formally, the three stage interaction can be described as an extensive form game with complete information, that is illustrated by Fig. 4. Among the four types of agents in our model only two, the policymaker and the AV producer, are strategic players. The interaction has the form of a leader–follower game with the policymaker as the leader and the AV producer as the follower. The decision of a single consumer has no measurable impact on the objective functions of all other agents, and hence consumers are not strategic players. Since we take the price of the HV as given, also HV producers are no players in the game. Fig. 4 illustrates the extensive-form game tree for these 3 stages.

2.5. Equilibrium

In our analysis, we characterize the subgame perfect equilibrium of the game, thereby following the principle of backward induction (see e.g., Fudenberg and Tirole, 1991). Following this approach, we determine the AV producer's optimal level of AV safety investment and AV price for given policy variables β and c. Furthermore, in setting these variables, the policymaker takes into account how they affect the subsequent optimal behavior of the AV producer. At equilibrium,

1. no consumer can improve her utility by switching the car purchase choice (for given values of β, c, p_A, x);
2. the AV producer cannot improve its net profit by changing the investment in AV safety and the price of the AV (for given values of β, c);
3. the policymaker cannot further reduce the total accident and infrastructure cost by switching the liability regime and the level of connectivity investment.

In Fig. 5 we outline the different steps in our equilibrium analysis. First, we determine the AV quantity $Q^D(p_A, x; \beta, c)$ sold (stage 3). Using this, we formulate the AV producer's problem and determine the optimal price function $p_A^m(x; \beta, c)$ and the optimal level of investment $x^*(\beta, c)$ (stage 2). Finally, using a numerical approach, we calculate the values β^* and c^* minimizing the policymaker objective function (stage 1).[16] This then gives rise to the equilibrium outcomes in terms of actions and payoffs of the players.

Due to the sequential structure of the game, equilibrium existence can be established by showing that the maximization problems at stages 2 and 3 have a (finite) solution. For stage 2, this follows immediately from the continuity of the profit function $\Pi^m(\cdot)$ and the compactness of the relevant range of values of p^A and x.[17] As for stage 1, the set $[0,1] \times [0, \bar{c}]$ of relevant values of (β, c) is compact such that the Weyerstrass extreme value theorem implies the existence of an optimal solution for each (compact) segment of this set. Although, in general $\Psi(\cdot)$ is not necessarily continuous with respect to (β, c) (which is due to potential jumps of $x^*(\beta, c)$),

[16] Before determining β^* and c^*, in Section 4.1, we also use numerical methods to perform a sensitivity analysis of the AV producer's optimal AV safety investment with respect to β and c.

[17] Since the AV producer's revenue is bounded from above and the cost function $\xi(x)$ is quadratic, there is an upper bound $\bar{x}$ such that $\Pi^m < 0$ for all $x > \bar{x}$. Similarly, there is an upper bound $\bar{c}$ such that the optimal value of c is always below $\bar{c}$.

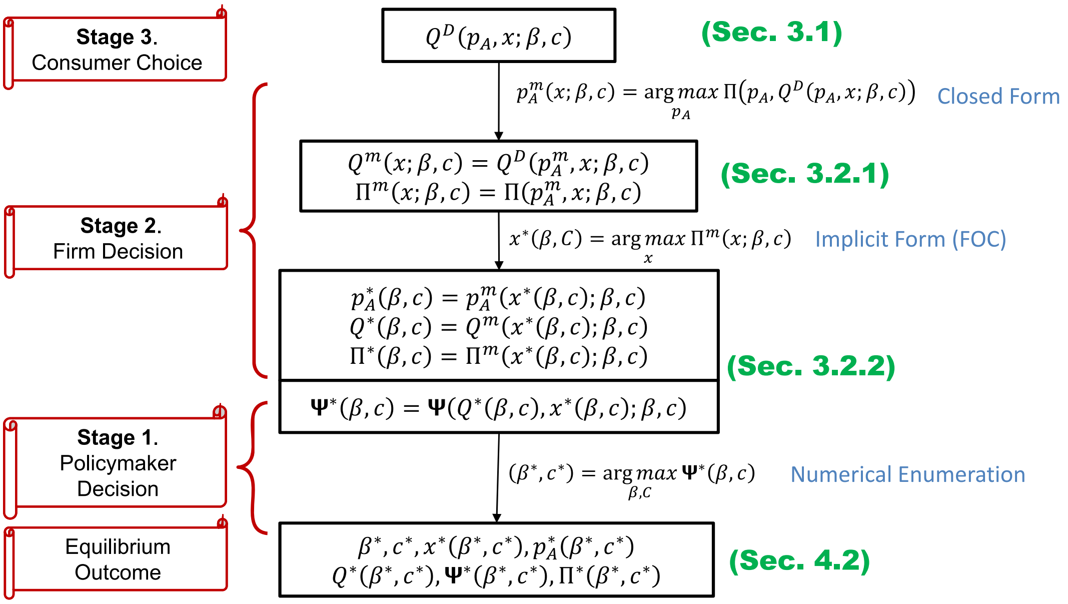

Fig. 5. Equilibrium analysis using backward induction.

abstracting from pathological cases where $x^*(\beta, c)$ jumps infinitely often on $[0,1] \times [0, \bar{c}]$, the existence of a maximizer of $\Psi(\cdot)$ is ensured.[18]

We split the equilibrium analysis into two parts. First, in Section 3 we derive analytical results characterizing the optimal consumer choice and the resulting demand function (stage 3) as well as the optimal behavior of the AV producer (stage 2). In Section 4 we then employ numerical methods to analyze the sensitivity of optimal behavior of the AV producer with respect to the two policy variables β and c, and to determine the policymaker's optimal choice (stage 1).

3. Analytical findings

3.1. The demand for AVs

In a first step, we determine the demand for AVs for given vehicle prices (p_A and p_H), a given AV safety level (x) and a given liability regime (β) and level of connectivity c. To ease notation, throughout this subsection we drop the arguments β and c in all functions. Taking into account (5) and (6) we obtain that the quantity $Q^D(p_A, x)$ has to satisfy

$$\int_y \mathbf{1}_{u_A(y, Q^D(.)) \geq u_H(y, Q^D(.))} dy = Q^D(.). \tag{7}$$

It follows from (4) that if a consumer with bliss point y prefers the AV, this is also the case for all consumers with bliss points y' satisfying $d_A(y') < d_A(y)$. Hence, consumers choosing AVs are located symmetrically around the location of the AV producer (see Fig. 3). If the quantity $Q^D(.)$ is in the interior of its range $[0,1]$, the indifference condition $u_A(\tilde{y}, Q^D(.)) = u_H(\tilde{y}, Q^D(.))$ has to hold for the consumer whose bliss point $\tilde{y}$ has the property $d_A(\tilde{y}) = \frac{Q^D(.)}{2}$. Inserting $d_A(\tilde{y}) = \frac{Q^D}{2}$ and $d_H(\tilde{y}) = \frac{1-Q^D}{2}$ into the utility function and solving $u_A(\tilde{y}, Q^D) = u_H(\tilde{y}, Q^D)$ for Q^D then yields the function $\tilde{Q}^D(p_A, x)$. This denotes the total AV demand in all cases where it is in the interior of $[0,1]$:

$$\tilde{Q}^D(p_A, x) = \frac{1}{t - (r_1(x) - r_2(x))} \cdot \left(\frac{t}{2} + r_2(x) + p_H - p_A \right), \tag{8}$$

which is linear in the AV price p_A and where $r_1(x) = g(x)\gamma(D) - (k(x) - h)\gamma((1-\beta)D)$ and $r_2(x) = \bar{g}\gamma(D) - k(x)\gamma((1-\beta)D)$. Intuitively, $r_1(x)$ captures the change in the incentive to buy an AV if there is one additional AV on the street: in this case, when purchasing an HV, the consumer's expected costs from accidents increases by $g(x)\gamma(D)$. When purchasing an AV instead, the expected accident costs increases by $(k(x) - h)\gamma((1-\beta)D)$. Similarly, $r_2(x)$ captures the change in the incentive to buy an AV if there is one additional HV on the street: in this case, when purchasing an HV, the consumer's expected costs from accidents increases by $\bar{g}\gamma(D)$. When purchasing an AV instead, the expected accident costs increases by $k(x)\gamma((1-\beta)D)$. Hence, for both $r_1(x)$ and $r_2(x)$, when the difference between

[18] Ruling out infinitely many jumps of $x^*(\beta, c)$, the set $[0,1] \times [0, \bar{c}]$ can be partitioned into finitely many subsets, where the function $\Psi(\cdot)$ is continuous in each subset and therefore has a finite maximizer. Comparing the maximal values of $\Psi(\cdot)$ across these subsets then yields the global maximizer.

the two respective types of accident costs is positive (negative), the incentive to buy an AV increases (decreases). Taken together, the difference $r_1(x) - r_2(x)$ in (8) captures the externality induced by one consumer, i say, who switches from the HV to the AV, on all other consumers. In particular, the expected liability costs of an HV owner changes by $(g(x)-\bar{g})\gamma(D)$. If x is sufficiently small then this expression is positive and hence there is a negative AV consumer externality for HV users. Moreover, the switch of consumer i leads to a reduction of the expected liability cost for AV owners of $h\gamma((1-\beta)D)$. This effect is due to V2I connectivity between AVs and the resulting fewer accidents in AV–AV compared to AV–HV interactions. Taking into account that AVs demand cannot exceed the market size, normalized to one, and has to be non-negative, we obtain the demand function $Q^D(p_A, x) = \max[0, \min[1, \tilde{Q}^D(p_A, x)]]$.

Taking into account the findings from the literature on AV adoption as discussed above, our analysis considers a setting in which consumers are willing to buy AVs only if these vehicles exhibit some minimal level of safety. To ensure this, we impose the following assumption throughout:

Assumption 2.

(i) $k(0)\gamma(D) > \frac{t}{2} + p_H + \bar{g}\gamma(D)$,

(ii) for every $\beta \in [0,1]$ there exist an AV safety level x^l such that $k(x^l)(\beta D + \gamma((1-\beta)D)) = t/2 + p_H + \bar{g}\gamma(D)$.

Part (i) of the assumption ensures that if there is no investment in AV safety ($x = 0$), even the consumer with the strongest preference for the AV (i.e. $d_A(y) = 0$ and $d_H(y) = 1/2$) prefers the HV. This holds regardless of the liability regime (β) even when the AV producer offers the AV at a price equal to marginal costs (i.e. $p_A = k(0)\beta D$, which is the lowest price the AV producer could set without incurring a loss). In particular, taking into account (4), with $x = 0$ and all other consumers purchasing the HV, the utility of the consumer with $d_A(y) = 0$ when buying the AV is $u_A(y,0) = v - k(0)(\beta D + \gamma((1-\beta)D))$. Under Assumption 2(i) this expression is for all β lower than the utility from purchasing an HV, which is given by $u_H(y,0) = v - t/2 - p_H - \bar{g}\gamma(D)$. Hence, for $x = 0$, AV demand is zero. Assumption 2(ii) implies that AV demand is positive if AV safety investment x exceeds a critical level x^l. In this case the consumer with the strongest preference for the AV (i.e. $d_A(y) = 0$ and $d_H(y) = 1/2$) prefers the AV even when all other consumers opt for the HV ($Q = 0$), and AVs are sold at marginal cost $p_A = k(x)\beta D$. More precisely, we have $u_A(y,0) = v - k(x)(\beta D + \gamma((1-\beta)D))$ (which increases with x) and $u_H(y,0) = v - t/2 - p_H - \overline{g}\gamma(D)$. Hence, under Assumption 2(ii), $u_A(y,0) > u_H(y,0)$ for $x > x^l$ which guarantees a positive AV demand in this case. As we will show below, this condition also ensures that for $x > x^l$, the AV producer indeed sells a positive AV quantity under optimal pricing. Whereas Assumption 2(ii) ensures that AV demand is positive for sufficiently large x, the following assumption guarantees that, in equilibrium, HVs are not driven out of the market, and we therefore have a scenario with mixed traffic:

Assumption 3. $t/2 > g(x)\gamma(D) + p_H \;\; \forall x \geq 0$.

This assumption guarantees that regardless of the level of AV safety investment, there are always consumers who prefer the HV. More precisely, it ensures that the consumer with highest preference for HV ($d_H(y) = 0$ and $d_A(y) = 1/2$) prefers the HV even if all other consumers opt for the AV ($Q = 1$). This consumer's utility from the AV and HV is $u_A(y,1) = v - t/2 - p_A - (k(x) - h)\gamma((1-\beta)D)$ and $u_H(y,1) = v - p_H - g(x)\gamma(D)$, respectively. Under Assumption 3, $u_H(y,1) > u_A(y,1)$ holds for all x and therefore this consumer chooses the HV. Together, Assumptions 2(ii) and 3 ensure that both vehicle types have a positive market share for $x > x^l$. Moreover, for $x > x^l$ the denominator of the expression for the total AV demand given in (8) is positive.[19]

3.2. The optimal behavior of the AV producer

3.2.1. AV pricing and resulting AV quantity

Given optimal consumer choice, we now determine the profit maximizing AV price p_A for the AV producer for a given AV safety level x. Taking into account that x is fixed, the objective of the firm is to maximize (3) with respect to p_A. This leads to the following result:

Proposition 1. *Assume that $x \geq x^l$. Then the optimal AV price and the resulting AV quantity are*

$$p_A^m(x) = \frac{1}{2(z_1(x) - \beta h D)}\left[z_1(x)z_2(x) + \beta D(z_1(x)k(x) - 2z_2(x)h)\right], \tag{9}$$

$$Q^m(x) = \frac{z_2 - \beta k(x) D}{2(z_1(x) - \beta h D)} < 1, \tag{10}$$

where $z_1(x) = t - (r_1(x) - r_2(x))$ and $z_2(x) = \frac{t}{2} + r_2(x) + p_H$. This yields a maximized profit of

$$\Pi^m(x) = \tilde{\Pi}(p_A^m(x), x) = \frac{1}{2}Q^m(x)^2(z_1(x) - \beta h D) - \xi(x). \tag{11}$$

[19] This follows since $t - (r_1(x) - r_2(x)) = t - g(x)\gamma(D) - h\gamma((1-\beta)D) + \bar{g}\gamma(D) = \left[\frac{t}{2} - p_H - g(x)\gamma(D)\right] + \left[\frac{t}{2} + p_H + \bar{g}\gamma(D) - h\gamma((1-\beta)D)\right] > 0$. It follows directly from Assumption 3 that the first of the two square brackets is positive, while the positivity of the second square bracket is implied by Assumption 2(ii), and $h < k(x)$ for all x.

The following Corollary establishes that under our assumptions the optimal quantity $Q^m(x)$, as given in (10), is strictly positive for $x > x^l$.

Corollary 1. *The monopoly quantity $Q^m(x)$ is strictly positive if and only if $x > x^l$.*

Assumption 2(ii) defines the threshold x^l as the minimal AV safety such that AV demand becomes positive if the AV producer prices the AV at marginal cost. Together, Proposition 1 and Corollary 1 show that also under optimal pricing of the AV producer, there is mixed traffic in equilibrium, i.e. both vehicle types have a strictly positive market share if and only if $x > x^l$.

In a next step, we investigate in more detail how the optimal AV quantity varies in the AV safety level, x. Taking the derivative of $Q^m(x)$ yields

$$\begin{aligned}\frac{\partial Q^m(x)}{\partial x} &= \frac{\left[-k'(x)(\gamma((1-\beta)D)+\beta D)(z_1(x)-\beta hD)+g'(x)\gamma(D)(z_2(x)-\beta Dk(x))\right]}{2(z_1(x)-\beta hD)^2}\\ &= \frac{1}{2(z_1(x)-\beta hD)}\left[-k'(x)\gamma((1-\beta)D)-k'(x)\beta D+g'(x)\gamma(D)2Q^m(x)\right],\end{aligned} \tag{12}$$

where in the second line we use (10).

Since the denominator is positive (see the proof of Proposition 1), the sign of $\frac{\partial Q^m(x)}{\partial x}$ coincides with that of the square bracket in (12). Intuitively, an increase in x affects the optimal AV quantity $Q^m(x)$ through three channels, indicated by the three terms in that square bracket: First, it reduces the expected liability cost for AV drivers in accidents caused by the AV, thereby leading to an upward shift of the AV demand curve.[20] Second, from the perspective of the AV producer, the marginal cost of selling an AV is given by the expected liability payment, which decreases with x. A decrease in marginal cost leads to a downward movement of the monopoly price along the demand curve and, hence, to higher AV demand. Third, it makes the HV safer and hence more attractive for consumers, thereby generating a *rival externality*, the size of which depends on $Q^m(x)$. This effect reduces AV demand.

Whereas the rival externality makes HVs more attractive and therefore has a negative effect on AV demand, the other two effects have a positive effect on AV demand (recall that $k'(x) < 0$ and $g'(x) < 0$). Taking into account that the rival externality becomes more pronounced as $Q^m(x)$ increases, for $Q^m(x)$ close to zero, the negative rival externality is essentially non-existent, so that $Q^m(x)$ is increasing in x in this range. However, as $Q^m(x)$ increases, the rival externality becomes relatively more important. The following proposition shows that the rival externality dominates for sufficiently large x, so that $Q^m(x)$ decreases with x.

Proposition 2. *The optimal AV quantity $Q^m(x)$ increases with x for sufficiently small $x > x^l$. Furthermore, there exists an $\tilde{x} > x^l$ such that $Q^m(x)$ decreases with x if and only if $x \geq \tilde{x}$.*

From an economic point of view, the key insight from the proposition is that a costly investment into AV safety potentially has a detrimental effect on AV demand. For this reason, one might think that it will never be optimal for the AV producer to choose a level of x, which leads to that segment of AV demand. However as we show next, this is not necessarily the case.

3.2.2. AV safety investment

The AV producer maximizes its profit $\Pi(x)$ with respect to x, anticipating how x will affect optimal AV pricing and demand $Q(x)$ as determined above. The maximization problem of the AV producer is hence

$$\max_x \Pi(x) = \frac{1}{2}Q^m(x)^2(z_1(x)-\beta Dh)-\xi(x). \tag{13}$$

Lemma 1. *For sufficiently small ξ_0, the AV producer's maximization problem (13) has an interior solution, x^*, that satisfies the condition*

$$Q^m(x^*)Q^m(x^*)'\cdot(z_1(x^*)-\beta Dh)+\tfrac{1}{2}Q^m(x^*)^2 z_1(x^*)'-2\xi_0 x^*=0. \tag{14}$$

To gain an intuition for the lemma, consider the first order condition (14). The first term represents the marginal revenue generated by the change in quantity induced by a marginal increase of x via $Q^m(x)'$. The second term is the direct effect of an increase of the safety level on the AV producer's profit for a fixed quantity. The third term is the marginal cost of investment. The second term becomes more important relative to the first one the larger $Q^m(x^*)$ is. The third term increases with x^*.

Recall from Proposition 2 above that AV demand increases (decreases) with the AV safety level x for small (large) x. As shown next, for sufficiently small investment costs, the AV producer optimally chooses a large value of x, thereby indeed locating in the decreasing segment of AV demand:

Proposition 3. *For any given values of β and c, the optimal investment level x^* decreases with ξ_0. Furthermore, there exists a threshold $\bar{\xi}$ such that for all $\xi_0 < \bar{\xi}$, the optimal investment level x^* satisfies $Q^m(x^*)' < 0$ for all values of $\beta \in [0,1]$ and $c \geq 0$.*

[20] While an AV is less likely to cause an accident with another AV than with an HV (where the difference in the accident probabilities is just h), the marginal change of accident probability with respect to x is $k'(x)$ in both cases.

Due to the non-linearity of the first order condition (14) determining the optimal investment level x^*, we can neither derive a closed form expression for x^* nor give an analytical characterization of its dependence from key parameters, such as ξ_0, β and c. This prevents us from deriving a closed form expression for the threshold $\bar{\xi}$, but the proposition establishes the existence of such a threshold. Intuitively, if the investment cost parameter ξ_0 is small, it is optimal for the firm to choose a high investment level x^* and, correspondingly, the AV quantity is high.[21] Hence the interplay of the second and the third term in the first order condition are crucial for determining the optimal value x^*. In particular, this implies that for sufficiently small ξ_0, it is optimal for the AV producer to invest a lot, thereby pushing the AV quantity into a region where it is already decreasing in x, i.e. more investment into AV safety increases demand for the HV, the AV's rival product (formally, x^* is above the threshold $\tilde{x}$ defined in Proposition 2). Doing so is nevertheless optimal for the AV producer since the resulting large AV quantity generates a strong incentive to reduce the expected liability costs, even if this comes along with a dampening effect on AV demand. As the optimal investment level x^* cannot be studied analytically, the remaining steps of the equilibrium analysis require a numerical approach.

4. Numerical experiments

In this section, we further analyze the developed modeling framework using numerical experiments, accompanied by various sensitivity analyses. Algorithm 1 contains the pseudo-code summarizing our approach to calculate the equilibrium values in these experiments.

Algorithm 1: Algorithm for equilibrium solution.

Input: A finite set of grid points $(\beta^i, c^i), i = 1, \cdots, I$.
First-order condition for $\max_x \Pi^m(x; \beta, c)$: $FOC(x; \beta, c)$
Set $\Psi_{min} = 10^6$;
for $i \leftarrow 1$ to I **do**
  Determine numerically $X = \{x : FOC(x; \beta^i, c^i) = 0\}$;
  $x_{temp}(\beta^i, c^i) = x \in X, s.t. \quad \Pi^m(x; \beta^i, c^i) \geq \Pi^m(y; \beta^i, c^i), \forall y \in X$;
  if $\Psi(Q^*(x_{temp}(\beta^i, c^i)), x_{temp}(\beta^i, c^i); \beta^i, c^i)) < \Psi_{min}$ **then**
    $\Psi_{min} = \Psi(Q^m(x_{temp}(\beta^i, c^i)), x_{temp}(\beta^i, c^i); \beta^i, c^i)$;
    $\beta^* = \beta^i, c^* = c^i$;
    $x^* = x_{temp}(\beta^i, c^i)$;
  end if
end for
Output: β^*, c^*, x^*

Throughout the numerical analysis we use a parameter setting that satisfies the conditions stated in Assumptions 1–3.[22] With this parameter setting, under the optimal AV safety investment the AV turns out to be always safer than the HV, i.e. $k(x^*(\beta, c)) < g(x^*(\beta, c))$ for all $\beta \in [0, 1]$ and $c \in [0, \bar{c}]$. In Appendix B.1 we show that our results are qualitatively robust for a wide range of parameter variations.

4.1. Impact of policy variables on AV safety investment, market penetration and road safety

We next analyze how the optimal AV safety investment, the AV quantity and the resulting number of accidents vary with the two policy variables, i.e. the liability regime (β) and the level of communication infrastructure (c). While we have suppressed this dependence in the previous analysis for notational convenience, from now on we take it explicitly into account and write $x^* = x^*(\beta, c)$, $Q^m(x^*(\beta, c)) = Q^*(\beta, c)$, and $A^*(\beta, c) = A(x^*(\beta, c), Q^*(\beta, c); \beta, c)$.

1. Impact of the liability regime. Consider first the impact of the liability regime (β), which is illustrated in Fig. 6 for the case of low (left column) and high (right column) marginal costs of AV safety investment (ξ_0), respectively.[23] An increase in β has two effects, namely a *safety effect* and a *quantity effect*:

1. *The safety effect* induces the AV producer to invest more in AV safety (see first row of Fig. 6), which would reduce the number of accidents if there is no change in the quantities of AVs and HVs. Intuitively, the main effect is that a higher β increases the liability costs per unit of AV sold, which in turn leads to a higher safety investment incentive. A similar effect has been identified in the literature on product liability (e.g. McGuire, 1988; Viscusi and Moore, 1993; Galasso and Luo, 2022).

[21] In particular, the AV quantity is sufficiently high such that the negative *rival externality* effect, i.e. the third effect in the numerator of (12), dominates the first two positive effects in that expression. Numerical analysis shows that the threshold $\bar{\xi}$ is given by the value of ξ for which $Q^m(x^*)' = 0$ for $\beta = 1$ and $c = 0$. Intuitively, both high values of β and low values of c induce a small AV quantity $Q^m(x^*)$, and therefore a relatively small rival externality. Hence, if ξ_0 is sufficiently small such that $Q^m(x^*)' < 0$ for $\beta = 1$ and $c = 0$, this also holds for all $\beta \in [0, 1]$ and $c \geq 0$.

[22] In particular, we set $g(x) = \underline{g} + g_0 e^{-\mu x}$, $k(x) = \underline{k} + k_0 e^{-\nu x}$, $h(c) = \underline{h} + h_0 e^{-\kappa c}$, and $\gamma(x) = \frac{\tau x}{\tau + x}$ where $k_0 > g_0$ and $\nu > \mu$. Moreover, $\underline{k} = 0.03$, $k_0 = 0.5$, $\nu = 2.5$, $\underline{g} = 0.03$, $g_0 = 0.04$, $\mu = 0.3$, $\underline{h} = 0.03$, $h_0 = -0.03$, $\kappa = 2.5$, $\bar{g} = 0.06$, $D = 12$, $t = 2$, $p_H = 0$, $v = 5$, $\tau = 100$, and $\zeta_0 = 0.025$. The marginal cost of AV safety investment ξ_0 is a key parameter, and in large parts of the analysis we distinguish between a low value $\xi_0 = 0.001$ and a high value $\xi_0 = 0.02$.

[23] In Fig. 6 we fix the value of connectivity investment at $c = 0.7$, which is close to the equilibrium level (see Section 4.2).

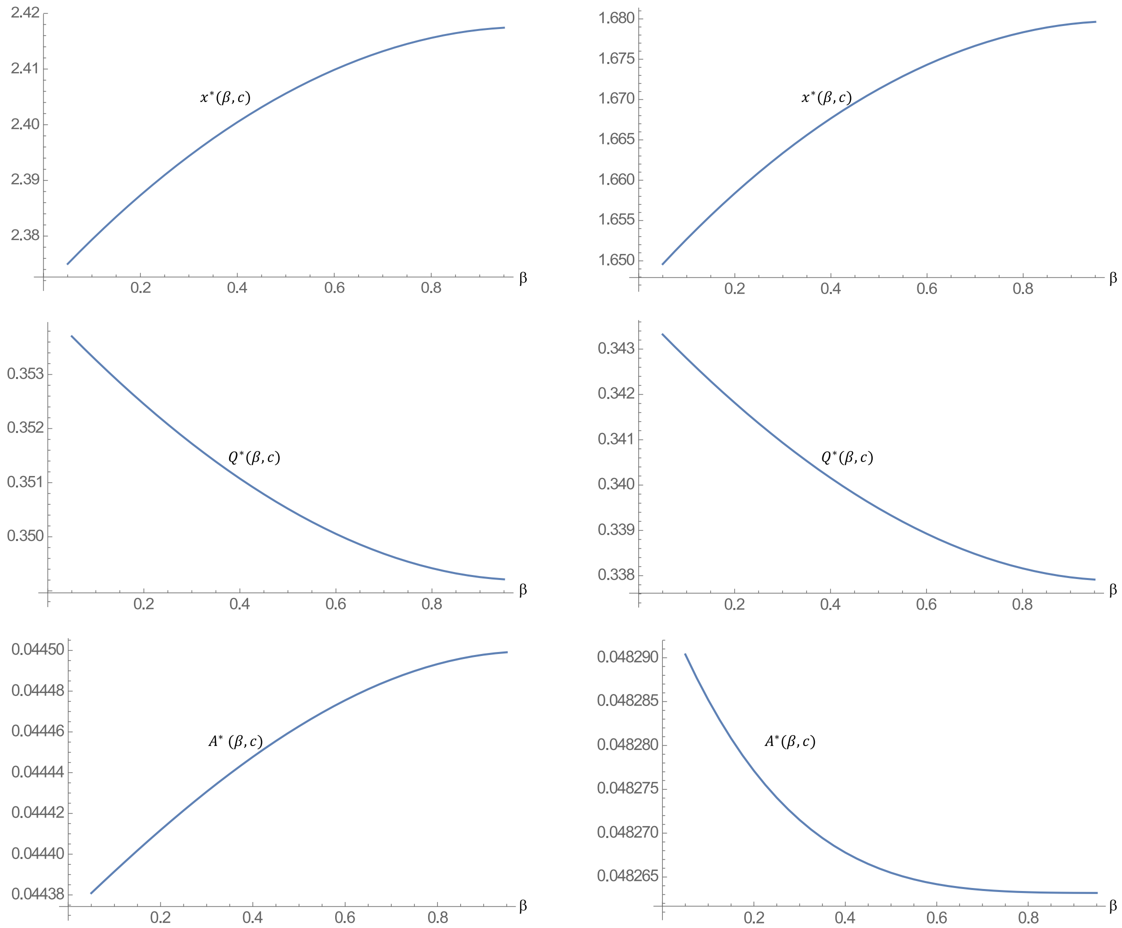

Fig. 6. Effect of product liability (β) on optimal AV investment $x^*(\beta, c)$ (first row), AV quantity $Q^*(\beta, c)$ (second row), and expected number of accidents $A^*(\beta, c)$, (third row), for low (left column) and high (right column) marginal costs of safety investment (ξ_0).
Note: The basic parameter setting applies (see Footnote 22). The low and high value for ξ_0 is 0.001 and 0.02, respectively. In addition, we set $\beta = 0$.

2. The *quantity effect* leads to a lower AV quantity as β increases (see second row of Fig. 6). Intuitively, a higher β increases the expected liability costs of the AV producer per unit of AV, which leads to a higher AV price, which reduces AV demand. At the same time, since consumers face now less liability, this increases their willingness to pay for the AV and hence AV demand. However, due to limited liability, captured by $\gamma(.)$, this effect is smaller than the price effect, so that the AV quantity decreases in β. This in turn implies that the HV quantity increases since the total number of vehicles is constant. And, because in equilibrium the AV is always safer than the HV, this *quantity effect* increases the number of accidents.

The cost parameter ξ_0 does not affect the overall shape of the safety and the quantity effect, but their relative importance. In particular, when ξ_0 is low, the AV producer's optimal investment x^* is large (see top left panel in Fig. 6). In this case, since the accident probability $k(x)$ decreases in a convex way, the marginal effect of a further increase of x on AV safety (induced by a higher β) is hence relatively small compared to the quantity effect. By contrast, when ξ_0 is high, the optimal x^* is small (see top right panel in Fig. 6), and hence the marginal effect of an increase on AV safety is relatively large.

To understand the effect of an increase of β on the number of accidents (see the two bottom panels of Fig. 6), it is helpful to distinguish between the four different interaction types (AV–AV, AV–HV, HV–AV and HV–HV). As discussed in more detail in Appendix C, for the first three types, the safety and the quantity effect go in the same direction and induce a decrease in the number of accidents. By contrast, the number of HV–HV accidents increases, which is solely driven by the quantity effect. Since the safety effect is less important relative to the quantity effect for low values of ξ_0, this explains why for this setting the change in HV–HV accidents dominates, and the overall number of accidents increases with β. By contrast, for large ξ_0 the effect on the first three types of accidents dominates and the overall number of accidents decreases with β.

2. Impact of AV connectivity. Consider next the effect of an increase in the level of AV connectivity (C) on the optimal behavior of the AV producer. This is illustrated in Fig. 7, again separately for the case with low (left column) and high (right column) marginal

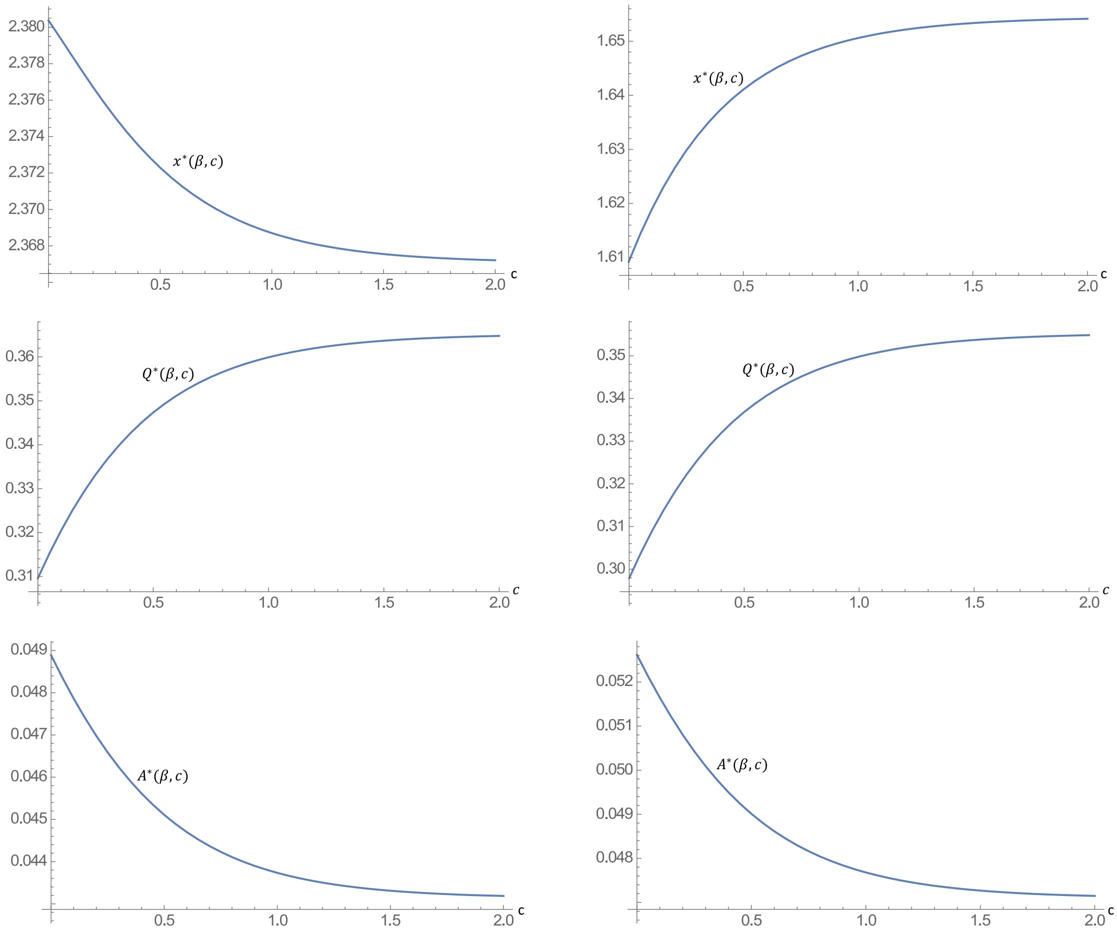

Fig. 7. Effect of V2I connectivity (c) on optimal AV safety investment $x^*(\beta, c)$ (first row), AV quantity $Q^*(\beta, c)$ (second row), and expected number of accidents $A^*(\beta, c)$, (third row), for low (left column) and high (right column) marginal costs of safety investment (ξ_0)
Note: The basic parameter setting applies (see Footnote 22). The low and high value for ξ_0 is 0.001 and 0.02, respectively. In addition, we set $\beta = 0$.

costs of improving AV safety, ξ_0.[24] Intuitively, an increase in c lowers the AV producer's expected liability costs per unit of AV sold, which in turn provides an incentive to increase the AV quantity. Whether this involves a higher or lower investment in AV safety depends on the marginal costs of the investment (see Proposition 3 above): if ξ_0 is sufficiently low, then $x^*(\beta, c)$ is large and lies in a region where AV demand is decreasing in x. Hence, an increase in Q is accompanied by a reduction of x (see upper left panel in Fig. 7). By contrast, for ξ_0 sufficiently large, $x^*(\beta, c)$ is small and lies in a region where AV demand is increasing in x. In this case, increasing Q requires an increase in x (see upper right panel in Fig. 7). Note also that in both cases, the total number of accidents $A^*(\beta, c)$ is negatively related to the AV quantity (see bottom row of Fig. 7). As discussed in more detail in Appendix C, this result is mainly driven by the fact that an increase in connectivity reduces the number of AV–AV accidents, although the AV quantity increases.

4.2. The optimal AV policy

In the final step of the backwards procedure of analysis, we consider the policymaker's optimal choice of the liability regime (β) and the level of AV connectivity (c), thereby taking into account the subsequent optimal behavior of consumers and the AV producer as characterized in the previous analysis. Recall from (2) above that the policymaker chooses β and c to minimize the total accident and connectivity infrastructure costs, denoted by $\Psi^*(\beta, c) = \Psi^*(x^*(\beta, c), Q^*(\beta, c); \beta, c)$.

[24] In Fig. 7 we fix the liability regime at $\beta = 0$, which corresponds to the equilibrium level for small values of ξ_0 (see Section 4.2). We also use this value of β in the panels showing results for high ξ_0 since we want to isolate the effect of a change of ξ_0. However, we have verified that the qualitative features of the panels in the right column of Fig. 7 do not change if different values of β are used. The same observation applies to the lower right panel of Fig. 8.

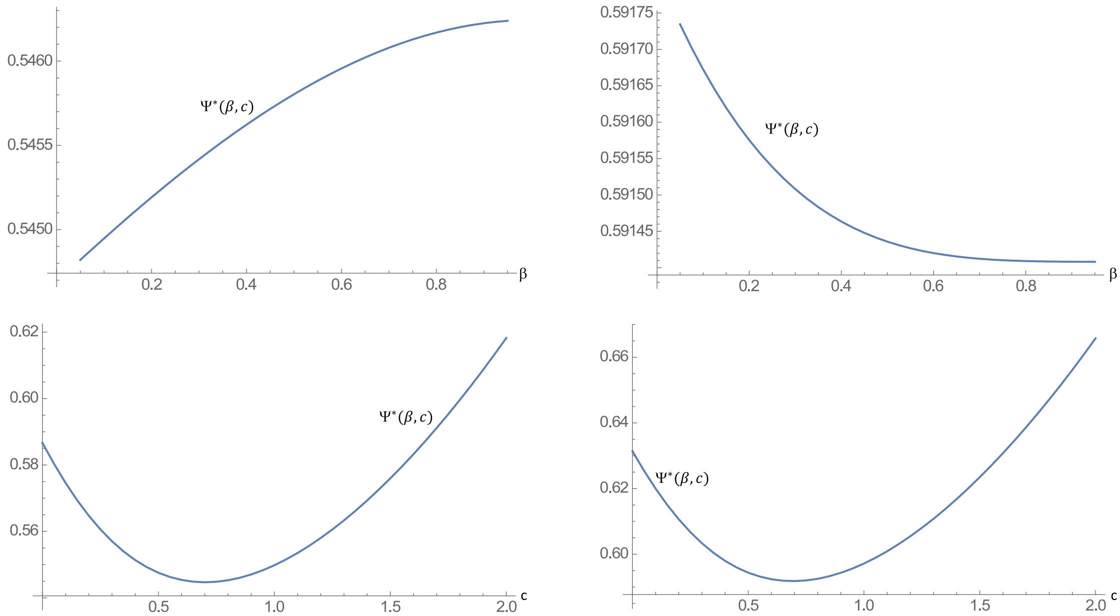

Fig. 8. Effect of product liability (β, top panels) and V2I connectivity (c, bottom panels) on policymaker's objective function $\Psi^*(\beta, c)$ for low (left column) and high (right column) marginal costs of safety investment (ξ_0).
Note: The basic parameter setting applies (see Footnote 22). The low and high value for ξ_0 is 0.001 and 0.02, respectively. In addition, we set $c = 0.7$ (top row) and $\beta = 0$ (bottom row).

To develop an intuition, Fig. 8 illustrates the effects of β and c on $\Psi^*(\beta, c)$ separately, again for low and high marginal cost of AV safety investment (ξ_0), respectively. With respect to the optimal liability regime, whether the policymaker's objective increases or decreases with β depends on ξ_0, and hence on the relative importance of the safety and the quantity effect as described above. If ξ_0 is small, the AV producer optimally chooses a high level of AV safety. In this case, the marginal effect of a further increase of x induced by β on the accident probability $k(x)$ is relatively small (see Fig. 1), and the negative effect of β on the AV quantity dominates the positive effect on AV safety investment. As a result, the total number of accidents $A^*(\beta, c)$ increases with β and so does the policymaker's cost $\Psi^*(\beta, c)$ (see upper left panel of Fig. 8). This leads to $\beta^* = 0$, i.e. the AV producer should not be subject to product liability. By contrast, when ξ_0 is large, then $x^*(\beta, c)$ is low, and increasing it has a large effect in lowering $k(x)$. In this case, the safety effect dominates the quantity effect. As a result, both the total number of accidents ($A^*(\beta, c)$) and policymaker's cost $\Psi^*(\beta, c)$ decrease with β (see upper right panel of Fig. 8), leading to $\beta^* = 1$, i.e. full liability for the AV producer. Fig. 9 (in red) shows the optimal liability regime as a function not only for two values of ξ_0, but for a whole interval. As can be seen there also exists an intermediate range of ξ_0 where neither the safety nor the quantity effect dominates, and where the safety effect becomes relatively more important as ξ_0 increases. In this range, β^* is interior and increases with ξ_0. Overall, the analysis indicates that the optimal liability policy strongly depends on the marginal costs of improving AV safety.

Consider next the optimal investment in AV connectivity infrastructure c^*. First, as long as c is not too high, there exists a negative relationship between $\Psi^*(\beta, c)$ (see Fig. 8, bottom row) and the AV quantity $Q^*(\beta, c)$ (see Fig. 7, second row). That is, an increase in c leads to both a higher AV quantity $Q^*(\beta, c)$ and a lower cost $\Psi^*(\beta, c)$ for the policymaker. Intuitively, an increase in c directly reduces the likelihood of accidents caused by each AV, $k(x) - h(c)$, so that the overall benefit from a higher c scales with the AV quantity $Q^*(\beta, c)$. As a result, the expected accident costs, and hence $\Psi^*(\beta, c)$, decrease.[25] Moreover, a higher c decreases the marginal costs per unit of AV (through lower expected liability payments), which also leads to a higher AV quantity. The policymaker weighs these benefits of higher AV connectivity against the (increasing and convex) costs, so that $\Psi^*(\beta, c)$ eventually increases for c sufficiently large.

How the optimal connectivity c^* policy depends on the marginal costs of AV safety investment (ξ_0) is illustrated in Fig. 9 (in blue). As long as the optimal liability policy β^* is constant in ξ_0 (which is the case when ξ_0 is either low or high), an increase in ξ_0 has two main effects on the policy maker's optimal choice of level of infrastructure. First, since an increase in c reduces the accident probability for each interaction between two AVs on the street, the incentive to increase c is positively related to AV quantity.[26] Second, since it is in the interest of the policy maker that the AV quantity is high, her incentive to invest in connectivity is positively related to $\partial Q^*(\beta, c)/\partial c$. For small ξ_0 the reduction in the optimal safety investment induced by an increase in ξ_0, leads to an increase

[25] Recall that in our numerical analysis, under the optimal safety investment of the AV producer, the AV is safer than the HV, i.e. $k(x^*(\beta, c)) < g(x^*(\beta, c))$.
[26] As can be seen from taking the derivative of (2) with respect to c, this effect scales with Q^2.

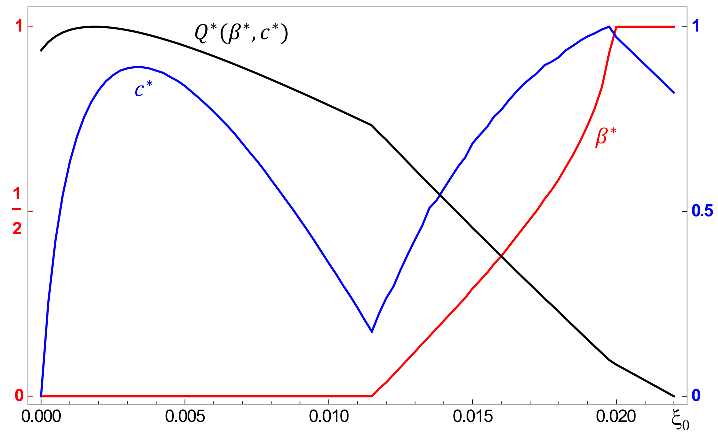

Fig. 9. Effect of costs of safety investment on firm liability (β^*, red), V2I connectivity (c^*, blue) and the resulting AV quantity (Q^*, black). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

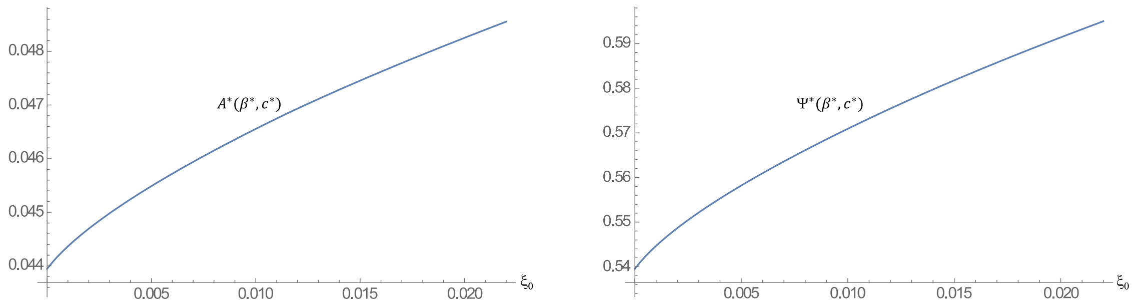

Fig. 10. Effect of marginal costs of AV safety investment (ξ_0) on equilibrium outcomes: accidents ($A^*(\beta^*, c^*)$, left) and total costs ($\Psi^*(\beta^*, c^*)$, right).

in $Q^*(\beta, c)$ (see Proposition 3) and also in $\partial Q^*(\beta, c)/\partial c$. Hence, optimal connectivity investment c^* increases with ξ_0. As ξ_0 increases further the effect on $Q^*(\beta, c)$ becomes negative, but initially the indirect effect through $\partial Q^*(\beta, c)/\partial c$ dominates such that c^* still increases with ξ_0. For even larger ξ_0 the direct quantity effect dominates such that c^* decreases with ξ_0. In the region where β^* increases with ξ_0, the optimal value c^* goes up. The intuition is that a higher c stimulates AV quantity in order to compensate the negative effect on AV quantity induced by the increase of β (see Fig. 6). Intuitively, a higher β fosters connectivity investments by increasing $\partial Q^*(\beta, c)/\partial c$.

Again, our analysis shows that the optimal AV policy crucially depends on the cost of AV safety investments. In addition, the findings highlight the interplay between the optimal liability connectivity policies, which cannot be observed when looking at these policies in isolation.

Finally, Fig. 10 illustrates behavior and payoffs along the equilibrium path as a function of ξ_0. We observe that, taking into account the optimal reactions of the AV producer and the policymaker in response to an increase in the marginal cost of AV safety investment, a positive relationship between ξ_0 and both the total number of accidents and total costs arises. This is driven by a combination of the decrease of the AV producer's safety investment and the reduction in AV quantity, as discussed above.

In Appendix B we confirm the robustness of the main findings from the numerical analysis – which we summarize in six key results – with respect to a number of variations. Firstly, we vary five parameters that are key for determining the choices and payoffs of the AV producer and the policymaker (see Appendix B.1). This leads to a total of 60 checks of robustness of our results and we establish robustness for all but one of these instances. Secondly, we analyze a model extension in which higher V2I connectivity not only improves traffic safety with respect to AV–AV interactions, but (to a lesser degree) also with respect to the other three vehicle interaction types (see Appendix B.2). We show that all our main results prevail also in this extended setting.

5. Conclusion

This paper studies a unified, game-theoretic framework (leader–follower game) of mixed traffic, thereby explicitly taking into account the fact that consumers have a choice between AVs and HVs, and the different types of accidents emerging in mixed traffic. We focus on the interaction between three crucial types of players: (i) a policymaker, who decides on the liability regime and the level of V2I connectivity, (ii) an AV producer, who decides on the AV price and safety level, and (iii) consumers, who differ in their preferences for each vehicle type.

Our analysis identifies two novel types of spillover effects: (i) An individual consumer's expected liability cost when purchasing an AV depends on the total number of AVs on the street (through the different types of accidents that may occur), which in turn results from all consumers' purchasing decisions. Therefore, each consumer's vehicle choice creates a spillover effect on all other consumers, and the determination of AV demand constitutes a fixed point problem. (ii) A higher level of AV safety might actually *reduce* the demand for AVs. Intuitively, a safer AV renders not only the AV more attractive, but also the HV, as HV–AV accidents become less likely. In this case, the AV producer's (costly) investment into AV safety creates a positive spillover on its competitors (the HV producers) by making their product more appealing to consumers (*rival externality*).

Furthermore, we show that the AV has a positive market share only if its safety level is above a minimum level. Moreover, when the marginal cost of AV safety investment is sufficiently small, the AV producer's optimal investment level is so large that this has a negative marginal effect on AV demand. In this case, despite the rival externality, the AV producer's benefit (the reduction of liability cost) outweighs the loss due to lower AV demand.

From a policy perspective, we study how the equilibrium behavior of consumers and the AV producer is affected by the two policy variables, and we highlight the crucial role of the marginal cost of AV safety investment. Our first main result in this respect is that more stringent AV (product) liability induces the AV producer to invest more in AV safety (*safety effect*), but also leads to a lower AV market penetration (*quantity effect*). The relative importance of these two effects, and whether the social harm from accidents increases or decreases as liability becomes more stringent, depends on the marginal costs of AV safety investment. Second, an increase in V2I connectivity makes AVs more attractive for consumers and reduces the expected costs of the AV producer. In equilibrium, this leads to a higher AV market penetration. Whether this increase is accompanied with higher or lower of AV safety investment depends, again, on the marginal costs of AV safety investment.

Taking these effects of the two choice variables into account, the policymaker optimally chooses a liability share for the AV producer that, starting from zero, weakly increases with the marginal cost of AV safety investment, and even full liability for the AV producer can be optimal when this cost is sufficiently large. The optimal investment in V2I connectivity is positively related with the AV market penetration, in the parameter range of marginal cost of AV safety investment where the optimal liability rule is constant. By contrast, in the (intermediate) range where the liability share of the AV producer increases, the optimal connectivity investment increases although AV market penetration decreases. Hence, from the perspective of the policymaker there is a complementarity between these two policy variables.

A further policy implication emerging from our analysis is that policymakers should carefully consider the incentives of AV producers to invest in AV safety. If these incentives are high (e.g. because the marginal investment cost is low), then the policymaker should shift the burden of liability to consumers rather than AV producers. Also, public investment into V2I connectivity need not be at very high levels, because AVs are safe enough already to limit the number of accidents. If, however, AV producers' (marginal) cost of investment are high, and hence their incentive to invest in AV safety is low, the policymakers should hold AV producers liable to a larger degree. Moreover, due to the complementarity between the policy instruments, this policy should be complemented by a large investment into V2I connectivity.

In our model, the total demand for vehicles is unaffected by the number of AVs. It has been argued that the total number of sold vehicles could decrease as the number of AVs goes up, due to the possibility of AV sharing (see e.g. Haboucha et al., 2017). Although we do not explicitly incorporate this possibility, AV sharing would not influence our findings as long as the total number of rides does not change. In our model consumers decide between the HV and the AV depending on their preference and the price to be paid for their mobility needs under both options. Whether an AV is used exclusively by one consumer or shared does not matter in this respect. Hence, in a scenario with AV sharing, p_A could be interpreted as the price for AV usage, and Q as the total number of AV rides by all AV users. Also with this alternative interpretation, the number of accidents is determined by Q even if the number of AVs sold is smaller than Q. Simulation results reported in Gurumurthy et al. (2019) indicate that the possibility of AV ride sharing does not lead to an increase of average vehicle occupancy (1.48) compared to the status quo value of 1.54 without AV sharing (see e.g. Davis and Boundy, 2022). This suggests that the number of rides is in fact not significantly reduced due to possibility of AV sharing. If this is the case, the main results and policy implications of our analysis carry over to a setting with AV sharing.

All in all, our findings provide a number of novel insights that are relevant for a fast adoption of AVs and a smooth transition from existing traffic situation to a mixed traffic environment. They provide guidance for decision making for policymakers, legal agencies, traffic operation and transportation planning agencies, as well as car manufacturers.

In future work it would be interesting to extend the model in several directions. For example, one could augment our framework to include exclusive AV lanes, which reduce interactions between AVs and HVs, as a further potentially important instrument for improving road safety in mixed traffic scenarios. Moreover, with respect to the supply side one could further explore the role of (imperfect) competition between different AV manufacturers. Finally, another interesting extension is to study a dynamic model of AV market penetration, where all agents make decisions as time progresses. This could provide further insights into how policymakers should regulate the market and decide on infrastructure investment, and how AV manufacturers should invest in AV safety, as the AV market evolves.

CRediT authorship contribution statement

Herbert Dawid: Conceptualization, Formal analysis, Methodology, Visualization, Writing – original draft. **Xuan Di:** Conceptualization, Methodology, Visualization, Writing – review & editing. **Peter M. Kort:** Conceptualization, Formal analysis, Methodology, Visualization, Writing – review & editing. **Gerd Muehlheusser:** Conceptualization, Methodology, Writing – original draft, Formal analysis, Visualization.

Acknowledgments

We are grateful for valuable comments and suggestions from three anonymous reviewers. Moreover, this paper has benefited from comments and suggestions by Cedric Argenton, Dan Klerman, Marie Obidzinski and Avi Tabbach. We also received comments from participants of the workshop "Law, economics and regulation" (Paris-Panthéon-Assas University), the conference "New research developments on autonomous vehicles" (University of Rennes), the "15th Viennese Conference on Optimal Control & Dynamic Games" (Vienna University of Technology), the 2023 Conference of the European Association of Law and Economics (Berlin), as well as from seminar audiences at the University of Hamburg. We gratefully acknowledge the hospitality and financial support by the Center of Interdisciplinary Research (ZiF) at Bielefeld University, Germany (Research Group "Economic and Legal Challenges in the Advent of Smart Products") and by the Deutsche Forschungsgemeinschaft, Germany (DFG, German Research Foundation, Project-ID 317210226, SFB 1283). Di would also like to thank the support of National Science Foundation, United States CAREER under award number CMMI-1943998.

Appendix A. Proofs

Proof of Proposition 1

We show first that for all $x \geq 0$ we have $z_1(x) - \beta Dh > 0$. Recall first from the definitions below (8) and (10) that

$$\begin{aligned} z_1(x) &= t - (r_1(x) - r_2(x)) \\ &= t - [g(x)\gamma(D) - (k(x) - h)\gamma((1-\beta)D)] + \bar{g}\gamma(D) - k(x)\gamma((1-\beta)D) \\ &= t - g(x)\gamma(D) - h\gamma((1-\beta)D) + \bar{g}\gamma(D) \end{aligned}$$

Therefore,

$$\begin{aligned} z_1(x) - \beta hD \quad &= t - g(x)\gamma(D) - h\gamma((1-\beta)D) - \beta hD + \bar{g}\gamma(D) \\ &= [t/2 - p_H - g(x)\gamma(D)] + [t/2 + p_H + \bar{g}\gamma(D) - h(\beta D + \gamma((1-\beta)D))] \\ &> 0. \end{aligned}$$

The first of the two square brackets is positive due to Assumption 3 and the positivity of the second square brackets follows from Assumption 2(ii), where we use that $h < \lim_{x\to\infty} k(x) < k(x^l)$.

Using the definition of $z_1(x)$ and $z_2(x)$ as well as (8) and taking into account that $x \geq x^l$ is fixed, the optimization problem of the firm can be rewritten as

$$\max_{p_A} \left[\left(\frac{z_2(x)}{z_1(x)} - \frac{1}{z_1(x)} p_A \right) \left(p_A - \beta D k(x) + \beta h D \left(\frac{z_2(x)}{z_1(x)} - \frac{1}{z_1(x)} p_A \right) \right) \right]$$

From the first order condition we obtain after collecting terms and multiplication with the strictly positive term $z_1(x)^2$ the following expression:

$$-p_A 2(z_1(x) - \beta hD) + \beta D(z_1(x)k(x) - z_2(x)h) + z_2(x)(z_1(x) - \beta hD) = 0$$

Solving for p_A yields expression (9). Inserting $p_A^m(x)$ into (8) yields

$$\begin{aligned} Q^m(x) &= \frac{z_2(x)}{z_1(x)} - \frac{1}{z_1(x)} \frac{z_1(x)z_2(x) + \beta D(z_1(x)k(x) - 2z_2(x)h)}{2(z_1(x) - \beta hD)} \\ &= \frac{1}{2z_1(x)(z_1(x) - \beta hD)} \left[2z_2(x)(z_1(x) - \beta hD) - \left(z_1(x)z_2(x) + \beta D(z_1(x)k(x) - 2z_2(x)h) \right) \right] \\ &= \frac{z_1(x)(z_2(x) - \beta k(x)D)}{2z_1(x)(z_1(x) - \beta hD)} \\ &= \frac{z_2(x) - \beta k(x)D}{2(z_1(x) - \beta hD)}. \end{aligned}$$

In order to show that optimal price and quantity are indeed determined by the first order condition, we still have to verify that $Q^m(x) < 1$. This inequality is equivalent to

$$\begin{aligned} & 2(z_1(x) - \beta hD) > z_2(x) - \beta D k(x) \\ \Leftrightarrow \ & 0 < \frac{3t}{2} + \bar{g}\gamma(D) - 2g(x)\gamma(D) + (k(x) - 2h)(\gamma((1-\beta)D) + \beta D) - p_H \\ \Leftrightarrow \ & 0 < \underbrace{t - 2g(x)\gamma(D)}_{>0} + \underbrace{\frac{t}{2} - p_H - h(\gamma((1-\beta)D) + \beta D)}_{>0} + \bar{g}\gamma(D) \\ & \quad + (k(x) - h)(\gamma((1-\beta)D) + \beta D), \end{aligned}$$

which holds, since all terms in the sum are positive. For the first term this is due to Assumption 3 and for second it follows from Assumption 2(ii) together with $h < k(x) \forall x$.

The expression for (11) follows directly form inserting $p_A^m(x) = z_2(x) - z_1(x)Q^m(x)$ into $\tilde{\Pi}$ and simplifying terms. ■

Proof of Corollary 1

As shown in the proof of Proposition 1 the denominator of (10) is strictly positive for $x \geq x^l$. Considering the numerator we get

$$z_2(x) - \beta k(x)D = t/2 + p_H + \bar{g}\gamma(D) - k(x)(\gamma((1-\beta)D) + \beta D).$$

By Assumption 2(ii) this expression is zero for $x = x^l$. Since $k(x)$ is strictly decreasing in x we have $z_2(x) - \beta k(x)D > 0$ for all $x > x^l$.

Assume now that $x < x^l$. In order to sell an AV quantity Q the AV producer has to choose a price p_A under which the consumers y with the distance $d_A(y) = Q/2$ and $d_H(y) = (1-Q)/2$ is indifferent between the AV and the HV. The utility of these consumers of purchasing an AV respectively HV, is given by

$$\begin{aligned} u_A(y,Q) &= v - \tfrac{tQ}{2} - p_A - [Q(k(x)-h)\gamma((1-\beta)D) + (1-Q)k(x)\gamma((1-\beta)D)] \\ u_H(y,Q) &= v - \tfrac{t(1-Q)}{2} - p_H - [Qg(x)\gamma(D) + (1-Q)\bar{g}\gamma(D)] \end{aligned}$$

From $u_A(y,Q) = u_H(y,Q)$ we obtain $p_A = \bar{p}_A(Q)$ with

$$\bar{p}_A(Q) = p_H + \frac{t(1-2Q)}{2} + Q(g(x)\gamma(D) - (k(x)-h)\gamma((1-\beta)D)) + (1-Q)\bar{g}\gamma(D) - k(x)\gamma((1-\beta)D) \tag{A.1}$$

Taking the derivative with respect to Q yields

$$\bar{p}'_A(Q) = -z_1(x).$$

In the proof of Proposition 1 we have shown that $z_1(x) > 0$ for all x. Hence, in order to sell a positive quantity the AV producer has to set a price satisfying $p_A \leq \bar{p}_A(0)$. However, since marginal cost are given by $MC = k(x)\beta D$, it follows from Assumption 2(ii) and the monotonicity of $k(x)$ that

$$p_A \leq \bar{p}_A(0) = t/2 + p_H + \bar{g}\gamma(D) - k(x)\gamma((1-\beta)D) < k(x)\beta D = MC$$

for all $x < x^l$. Hence, the AV producer would make a loss whenever selling a positive quantity and therefore the optimal AV quantity is zero. ■

Proof of Proposition 2

Expression (12) can be rewritten as

$$\frac{dQ^m(x)}{dx} = \frac{-g'(x)(\gamma((1-\beta)D) + \beta D)}{2(z_1(x) - \beta DC)}\left[\frac{k'(x)}{g'(x)} - \frac{2Q^m(x)\gamma(D)}{\gamma((1-\beta)D) + \beta D}\right].$$

Taking into account that $z_1(x) - \beta DC > 0$ and $g'(x) < 0$, this implies that $Q^m(x)$ is increasing in x if and only if

$$\frac{k'(x)}{g'(x)} > \frac{2Q^m(x)\gamma(D)}{\gamma((1-\beta)D) + \beta D}. \tag{A.2}$$

We define $w(x) = \frac{2Q^m(x)\gamma(D)}{\gamma((1-\beta)D)+\beta D}$ and hence for any x with $Q^m(x) \in (0,1)$ we have $(Q^m)'(x) < 0$ if and only if $\frac{k'(x)}{g'(x)} < w(x)$. It follows from Assumption 1 that $\frac{k'(0)}{g'(0)} > 1$ and due to $Q^m(0) = 0$ we have $\lim_{x\to 0} w(x) = 0$. Hence $\frac{k'(x)}{g'(x)} > w(x)$ for sufficiently small x (i.e. $Q^m(x)$ is increasing in x). Furthermore, according to Assumption 1, $\frac{k'(x)}{g'(x)}$ strictly decreases with x, whereas $w(x)$ strictly increases with x for any x with $\frac{k'(x)}{g'(x)} > w(x)$. The last observation follows since $w(x)$ increases for increasing $Q^m(x)$ and $(Q^m)'(x) > 0$ for all values of x with $\frac{k'(x)}{g'(x)} > w(x)$.

We now show that there has to exist a value $\tilde{x}$ with $\frac{k'(\tilde{x})}{g'(\tilde{x})} = w(\tilde{x})$ and, as a next step, we then show that $(Q^m)'(x) < 0$ for almost all $x > \tilde{x}$.

Assume that no value $\tilde{x}$ with $\frac{k'(\tilde{x})}{g'(\tilde{x})} = w(\tilde{x})$ exists. Then we must have $\frac{k'(x)}{g'(x)} > w(x)$ and therefore $w'(x) > 0$ for all $x \geq 0$ with $Q^m(x) > 0$. From Corollary 1 it follows that $Q^m(x) > 0$ for all $x > x^l$ and therefore there exists some $\epsilon > 0$ with $h(x) > \epsilon$ for all $x > x^l$. Under our assumption $\frac{k'(x)}{g'(x)} > w(x)$ for all $x > 0$ this implies $\frac{k'(x)}{g'(x)} > \epsilon$ for all $x < 0$. This contradicts Assumption 1, which requires that $\lim_{x\to\infty} \frac{k'(x)}{g'(x)} = 0$. It follows that there must exist a value $\tilde{x} > x^l$ with $\frac{k'(\tilde{x})}{g'(\tilde{x})} = w(\tilde{x})$.

As a third step we show that $w(x)$ can never cross $\frac{k'(x)}{g'(x)}$ from above at any value $x > \tilde{x}$. At $\tilde{x}$ we have $(Q^m)'(x) = 0$, which implies that $w'(x) = 0$. Taking into account that $\frac{k'(x)}{g'(x)}$ is a strictly decreasing function of x this implies that $\frac{d}{dx}\left(\frac{k'(\tilde{x})}{g'(\tilde{x})} - w(\tilde{x})\right) < 0$ and therefore $\frac{k'(x)}{g'(x)} < w(x)$ for $x \in [\tilde{x}, \tilde{\tilde{x}}]$, where $\tilde{\tilde{x}}$ is either the smallest intersection point between $\frac{k'(x)}{g'(x)}$ and $w(x)$ above $\tilde{x}$, or, if no such second intersection point exists, $\tilde{\tilde{x}} = \infty$. If a finite point $\tilde{\tilde{x}} > \tilde{x}$ with $\frac{k'(\tilde{\tilde{x}})}{g'(\tilde{\tilde{x}})} = w(\tilde{\tilde{x}})$ exists, then the same arguments as applied to $\tilde{x}$ show that $\frac{k'(x)}{g'(x)} < w(x)$ holds also for all x between $\tilde{\tilde{x}}$ and the next intersection point. Overall, this shows that $\frac{k'(x)}{g'(x)} < w(x)$ for almost all $x \geq \tilde{x}$. Hence $(Q^m)'(x) < 0$ for almost all $x \geq \tilde{x}$ and therefore $Q(x)$ is a (weakly) decreasing function of x for $x \geq \tilde{x}$. ■

Proof of Lemma 1

As shown in Corollary 1, $Q^m(x) > 0$ if and only if $x > x^l > 0$. Hence $\Pi(x) \le 0$ for all $x \le x^l$. This directly implies that $x^* > x^l$ has to hold. For $x > x^l$ the expression $\Pi(x)$ is continuous and continuously differentiable in x. Furthermore, as shown in the proof of Proposition 1, $z_1(x) - \beta h D > 0$ for all $x > x_l$. Therefore, $\frac{1}{2}Q^m(x)^2(z_1(x) - \beta h D) > 0$ for all $x > x_l$. This implies that for sufficiently small values of $\xi_0 > 0$, there exist values of $x > x_l$ such that $\Pi(x) > 0$. Consider any such value of ξ_0, then

$$\Pi'(x) = Q^m(x)Q^m(x)' \cdot (z_1(x) - \beta h D) + \frac{1}{2}Q^m(x)^2 z_1(x)' - 2\xi_0 x.$$

Since $Q^m(x)' < 0$ for x is sufficiently large (see Proposition 2), the first and the third term in this sum are strictly negative, where the third term goes to $-\infty$ for $x \to \infty$. The second term is positive, but it follows from Assumption 1 that $\lim_{x\to\infty} g'(x) = 0$. Hence $\Pi'(x) < 0$ for sufficiently large x, which implies that the value x^* maximizing $\Pi(x)$ is in the interior of the interval (x^l, ∞). Taking into account that $\Pi(x)$ is continuously differentiable on this entire interval, it follows that the optimal value of x has to satisfy the first order condition (14). ■

Proof of Proposition 3

Using the first order condition (14) we obtain by implicit differentiation with respect to ξ_0 that

$$\frac{\partial x^*}{\partial \xi_0} = -\frac{-2x^*}{\Pi''(x^*)}.$$

Since x^* is a (local) maximum of $\Pi(x)$, we must have $\Pi''(x^*) < 0$ and therefore $\frac{\partial x^*}{\partial \xi_0} < 0$.

To show the second claim of the proposition we prove that $Q^m(x^*)' < 0$ for $\xi_0 = 0$ for any value of β and c. By continuity this property also holds for positive values of ξ_0 close to 0. For ξ_0 sufficiently small we have $x^* > x^l$ and therefore $Q^m(x^*) > 0$. Taking this into account and setting $\xi_0 = 0$ we obtain from the first order condition (14) that x^* has to satisfy

$$Q^m(x^*)' \cdot (z_1(x^*) - \beta D h) + \frac{1}{2}Q^m(x^*) z_1(x^*)' = 0.$$

Hence,

$$Q^m(x^*)' = -\frac{Q^m(x^*) z_1(x^*)'}{2(z_1(x^*) - \beta D h)}.$$

Since $z_1(x^*) - \beta h D > 0$ (see proof of Proposition 1) and $z_1'(x^*) = -g'(x^*)\gamma(D) > 0$ we directly obtain that $Q^m(x^*)' < 0$.

It follows that for any value of $\beta \in [0,1]$ and $h(c), c \ge 0$ there exists a threshold $\bar{\xi}_{\beta,h(c)} > 0$ with the property that $Q^m(x^*)' < 0$ for all $\xi_0 < \bar{\xi}_{\beta,h(c)}$. Since we have assumed that $k(x) > h(c)\ \forall x, c$, we have $h(c) \le \bar{h} = \lim_{x\to\infty} k(x)$. Due to the compactness of $[0,1]\times[0,\bar{h}]$, there exists a value $\bar{\xi} = \min[\bar{\xi}_{\beta,h} | (\beta, h) \in [0,1]\times[0,\bar{h}]] > 0$ and $Q^m(x^*)' < 0$ for all $\beta \in [0,1]$ and $c \ge 0$. ■

Appendix B. Robustness

In this section we examine the robustness of our main numerical results obtained in Section 4. These can be summarized as follows:

(i) Optimal safety investment $x^*(\beta, c)$ always increases and AV quantity $Q^*(\beta, c)$ always decreases if the liability parameter β is increased. (see Fig. 6)
(ii) The number of accidents $A^*(\beta, c)$ increases with β if the marginal cost of safety investment, ξ_0, is small, but decreases with β if ξ_0 is large (see Fig. 6).
(iii) AV quantity $Q^*(\beta, c)$ always increases and the number of accidents $A^*(\beta, c)$ always decreases if connectivity c is increased (see Fig. 7).
(iv) Optimal safety investment $x^*(\beta, c)$ decreases with c if the marginal cost of safety investment, ξ_0, is small, but increases with c if ξ_0 is large (see Fig. 7).
(v) The optimal value of the liability parameter, β^*, weakly increases if the marginal cost of safety investment, ξ_0, goes up (see Fig. 9).
(vi) The optimal value of connectivity, c^*, in general changes non-monotonously with ξ_0, but strictly increases with ξ_0 whenever liability β^* strictly increases with ξ_0 (see Fig. 9).

Results (i) and (ii) refer to the effect of more stringent product liability (β), whereas results (iii) and (iv) consider the impact of an increase of V2I connectivity (c). Both (i) and (iii) refer to qualitative properties which do not depend on the size of the marginal cost of safety investment (ξ_0), whereas (ii) and (iv) refer to properties which qualitatively differ between low and high values of ξ_0. Finally, results (v) and (vi) summarize our findings about the effect of an increase in ξ_0 on the optimal policy choices (β^* and c^*).

In what follows, we first consider variations of the values of key parameters Appendix B.1, and then analyze an extension in which V2I connectivity does not only affect the probability of AV–AV accidents, but also the accident probabilities for all other vehicle interaction types Appendix B.2.

Table B.1
Robustness checks for main findings with respect to parameter variations.

Parameter values	(i)	(ii)	(iii)	(iv)	(v)	(vi)
$\nu = 2$	✓	✓	✓	✓**	✓	✓
$\nu = 3$	✓	✓*	✓	✓	✓	✓
$\mu = 0.2$	✓	✓	✓	✓	✓	✓
$\mu = 0.4$	✓	✓	✓	✓	✓	✓
$\kappa = 2$	✓	✓*	✓	✓	✓	✓
$\kappa = 3$	✓	✓	✓	✓	✓	✓
$D = 9$	✓	✓	✓	✓**	✓	✓
$D = 15$	✓	✓*	✓	✓	✓	✓
$t = 1$	✓	A^* increasing (large ξ_0)	✓	✓	✓	✓
$t = 3$	✓	✓	✓	✓	✓	✓

The table checks the robustness of properties (i) - (vi) with respect to a variation of the parameters from the baseline $\mu = 0.3, \nu = 2.5$, $D = 12$ and $t = 2$. A checkmark ✓ indicates that the property holds for the same values of ξ_0 as considered in Section 4, for those entries with a ✓* the high value of ξ_0 had to be increased compared to $\xi_0 = 0.02$ in Section 4 and for those entries with ✓** the low value of ξ_0 had to be decreased compared to $\xi_0 = 0.001$ to obtain the results (ii) respectively (iv). In particular, for $\nu = 3$ (ii) holds for high values of ξ_0 above $\xi_0 = 0.03$, the corresponding threshold for $\kappa = 2$ is $\xi_0 = 0.026$ and for $D = 15$ it is $\xi_0 = 0.045$. For $\nu = 2$ (iv) holds for low value of ξ_0 below $\xi_0 = 0.00075$ and for $D = 9$ the corresponding threshold is $\xi_0 = 0.00085$. For the entry without checkmark the type of deviation from the stated result is noted.

B.1. Robustness of main findings with respect to parameter variations

In this section, we check the robustness of findings (i)–(vi) when varying the five parameters which are key for determining the choices and payoffs of the AV producer and the policymaker:

1. ν, which determines the sensitivity of the probability that an AV causes an accident ($k(x)$ respectively $k(x) - h(c)$) with respect to the AV safety investment x;
2. μ, which determines the sensitivity of the probability that an HV causes an accident in an interaction with an AV ($g(x)$) with respect to x;
3. κ, which determines the sensitivity of the probability of an AV–AV accident ($k(x) - h(c)$) with respect to the V2I connectivity investment c;
4. D, the total damage per accident, which determines the sensitivity of the AV producer's liability cost with respect to β;
5. t, which determines the importance of (relative) prices for consumers' choice between AVs and HVs.

We vary these parameters in a symmetric interval around their baseline values, where the size of this interval is chosen such that Assumptions 1–3 remain satisfied.

The results of this robustness check are shown in Table B.1.[27] Overall, the table highlights that our findings are very robust with respect to parameter variations. In particular, five of the six results, namely, (i), (iii), (iv), (v) and (vi) are robust across all parameter variations. The only exception is (ii). Also for this result we confirm for all parameters other than t that the monotonicity of the number of accidents with respect to an increase of β differs between low and high values of ξ_0. However, for small values of t, the number of accidents increases with β no matter whether ξ_0 is low or high. Intuitively, when t is low the AV becomes less differentiated from the HV, such that the price increase induced by an increase in β leads to a large reduction in the AV quantity. Hence, for small t the quantity effect dominates the safety effect even for large values of ξ_0 such that the number of accidents always increases with β.

B.2. Generalizing the effects of connectivity

In this section, we analyze the robustness of findings (i)–(vi) with respect to a variation of the functional specifications of the accident probabilities. We now consider scenarios where connectivity investments do not only reduce the accident probability in AV–AV interactions, but also (to a lesser degree) in AV–HV interactions (see e.g Li et al., 2020). Moreover, better connectivity might even reduce the probability that an HV causes an accident.

As in our benchmark model, we assume that the AV–AV accident probability is $k(x) - h(c)$. With respect to the AV–HV accidents, better connectivity might help to give AVs advance information about approaching HVs. This effect is captured by $\alpha_0 h(c)$, such that the probability of this accident type is $k(x) - \alpha_0 h(c)$ with $\alpha_0 < 1$. Furthermore, better connectivity can also reduce the probability of accidents caused by human drivers, e.g. due to support systems in the car. We capture this effect by $\alpha_1 h(c)$, such that the accident probability is $g(x) - \alpha_1 h(c)$ in HV–AV interactions and $\bar{g} - \alpha_1 h(c)$ in interactions between two HVs. We assume that the effect of connectivity on human drivers is smaller than on AVs and hence $0 \leq \alpha_1 < \alpha_0 < 1$.

In Table B.2 we collect the outcomes of the robustness test for this model extension for $\alpha_0 = 0.5, \alpha_1 = 0$ (i.e. only AVs benefit from connectivity) as well as for $\alpha_0 = 0.5, \alpha_1 = 0.25$ (i.e. also HVs benefit from increased connectivity, although less so than AVs). As can

[27] All figures underlying the entries of Tables B.1 and B.2 are included in the online Supplementary Material file.

Table B.2
Robustness checks for main findings under generalized notion of V2I connectivity.

Parameter values	(i)	(ii)	(iii)	(iv)	(v)	(vi)
$\alpha_0 = 0.5, \alpha_1 = 0$	✓	✓	✓	✓	✓	✓
$\alpha_0 = 0.5, \alpha_1 = 0.25$	✓	✓	✓	✓	✓	✓

The table checks the robustness of properties (i)–(vi) for the model extension that generalizes the effect of V2I connectivity to other types of vehicle interactions. A checkmark ✓ indicates that the property holds for the same values of ξ_0 as considered in Section 4.

Table C.3
Effect of changes in β and c on number of accidents for different types of vehicle interaction.

Type of interaction/Accidents	ξ_0 small		ξ_0 large	
	$\beta\uparrow$	$c\uparrow$	$\beta\uparrow$	$c\uparrow$
AV–AV	↓	↓	↓	↓
AV–HV	↓	↑	↓	↑
HV–AV	↓	↑	↓	↑
HV–HV	↑	↓	↑	↓
Total	↑	↓	↓	↓

The table shows the effect of changes in β and c on the number of accidents for each of the four types of vehicle interaction, and for a low and high value of the marginal costs of AV safety investment (ξ_0). The last row gives the total number of accidents as shown in Figs. 6 and 7.

be seen all results of the analysis with our baseline model remain valid also for the extended version of the model for both parameter constellations. Moreover, numerical results not shown here indicate that the increased effectiveness of infrastructure investment in the extended model leads to higher investments and lower accident probabilities compared to our benchmark model.

Appendix C. Number of accidents under the different types of vehicle interaction

In this Appendix, we decompose the impact of the policy variables β and c on the total number of accidents (as shown in Figs. 6 and 7) into the four different types of accidents, AV–AV, AV–HV, HV–AV, and HV–HV. Table C.3 gives an overview of the qualitative effects, and Figs. C.11 and C.12 provide an illustration for the case where the marginal cost of AV safety investment (ξ_0) is low. In general, the expected number of accidents occurring in each type of interaction depends on (i) the number of interactions of this type and (ii) the respective accident probability per interaction. Clearly, the number of AV–AV interactions increases with the AV quantity $Q^*(\beta, c)$, whereas the number of HV–HV interactions decreases. The accident probability per AV–AV interaction is $k(x^*(\beta, c)) - h(c)$, while it is $\bar{g}$ per HV–HV interaction. The number of mixed interactions is given by $Q^*(\beta, c) \cdot (1 - Q^*(\beta, c))$ for each of the two types AV–HV and HV–AV, where it should be noted that in our parameter setting $Q^*(\beta, c) < 0.5$ holds (see Figs. 6 and 7), so that $Q^*(\beta, c) \cdot (1 - Q^*(\beta, c))$ increases with $Q^*(\beta, c)$. As for the accident probabilities, we have $k(x^*(\beta, c))$ and $g(x^*(\beta, c))$ per AV–HV and HV–AV interaction, respectively.

First, consider the effect of an increase of β. As discussed in the main text, safety investments $x^*(\beta, c)$ go up as β increases, such that (ceteris paribus) the accident probability for all interaction types involving the AV decreases. Furthermore, also the AV quantity $Q(\beta, c)$ decreases with β. Hence, the number of AV–AV accidents decreases as both effects go in the same direction. The same reasoning applies to AV–HV and HV–AV accidents and their number also decreases. Finally, the number of HV–HV accidents increases since there are more of such interactions, while the accident probability $\bar{g}$ is independent of β. None of these effects depends qualitatively on the size of ξ_0, however, their relative importance does. In particular, for small values of ξ_0, $x^*(\beta, c)$ is large such that the marginal effect of a change in β on the accident probabilities is small. In this case, the positive effect of an increase of β on the number of HV–HV accidents outweighs the three other effects, and the overall number of accidents goes up (see the bottom left panel of Fig. 6). By contrast, for large values of ξ_0 the effect of an increase in β on the first three interaction types is larger than the effect on HV–HV interactions, such that the total number of accidents goes down (see the bottom right panel of Fig. 6).

Consider next the impact of changes of V2I connectivity c. An increase in c directly reduces the AV–AV accident probability via $h'(c) > 0$. This direct effect dominates the safety effect (via $x^*(\beta, c)$) and the quantity effect (via $Q^*(\beta, c)$), such that the number of AV–AV accidents always decreases with c: This holds, even though the number of AV–AV interactions go up, and at least for small ξ_0 the optimal safety investment $x^*(\beta, c)$ goes down (see Fig. 7). As the AV quantity $Q^*(\beta, c)$ increases with c, this increases the number of AV–HV and HV–AV accidents, while the number of HV–HV accidents decreases. In total, in our parameter setting the negative effect of c on the number of AV–AV and HV–HV accidents is always dominant, such that the total number of accidents decreases with c.

Appendix D. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.trb.2024.102908.

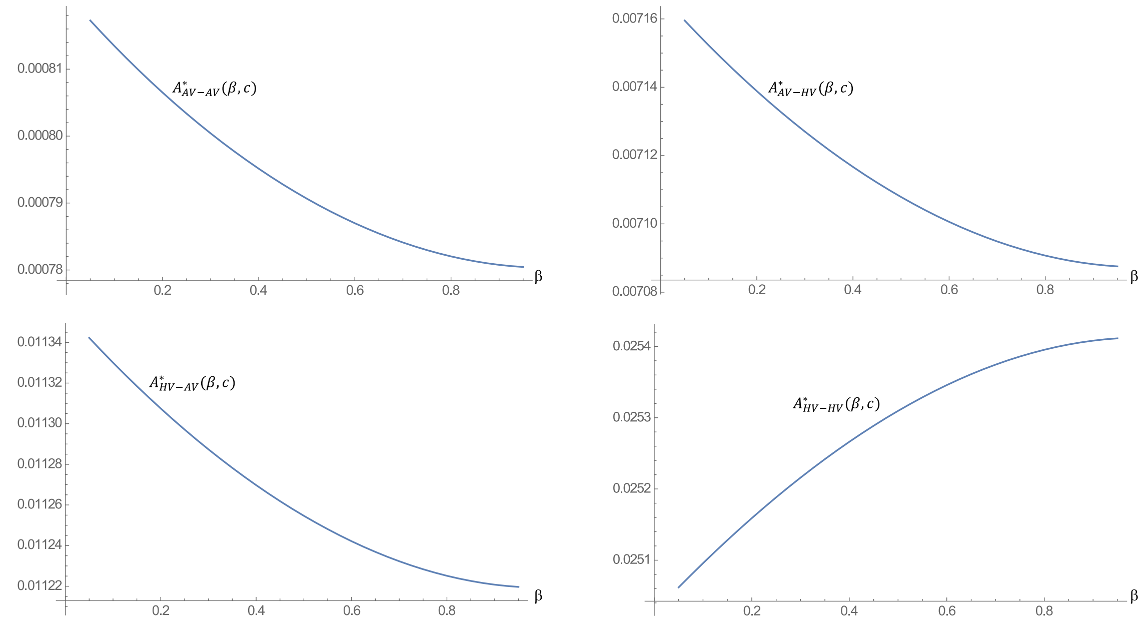

Fig. C.11. Effect of product liability (β) on the number of accidents of the four types of vehicle interaction.
Note: Results are shown for low marginal costs of AV safety investment ($\xi_0 = 0.001$). Upper panels show number of AV–AV and AV–HV accidents, lower panels number of HV–AV and HV–HV accidents. As in Fig. 6, we set $c = 0.7$.

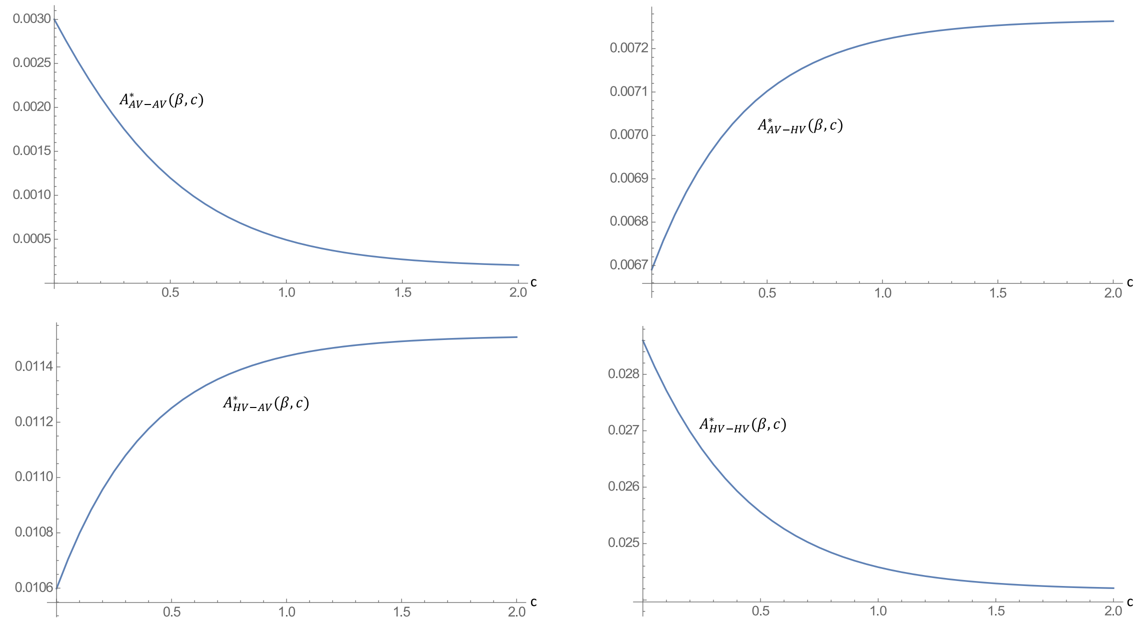

Fig. C.12. Effect of V2I connectivity (c) on the number of accidents of the four types of vehicle interaction.
Note: Results are shown for low marginal costs of AV safety investment ($\xi_0 = 0.001$). Upper panels show number of AV–AV and AV–HV accidents, lower panels number of HV–AV and HV–HV accidents. As in Fig. 7, we set $\beta = 0$.

References

Chatterjee, I., 2016. Understanding Driver Contributions to Rear-End Crashes on Congested Freeways and their Implications for Future Safety Measures (Ph.D. thesis). University of Minnesota.

Chatterjee, I., Davis, G., 2013. Evolutionary game theoretic approach to rear-end events on congested freeway. Transp. Res. Rec.: J. Transp. Res. Board (2386), 121–127.

Chen, X., Di, X., 2023. Legal framework for rear-end crashes in mixed-traffic platooning: A matrix game approach. Fut. Transp. 3 (2), 417–428.

Chen, S., Wang, H., Meng, Q., 2020. Optimal purchase subsidy design for human-driven electric vehicles and autonomous electric vehicles. Transp. Res. C 116, 102641.
Cunningham, M., Regan, M., Horberry, T., Weeratunga, K., Dixit, V., 2019. Public opinion about automated vehicles in Australia: Results from a large-scale national survey. Transp. Res. Part A: Policy Pract. 129, 1–18.
Davis, S., Boundy, R.G., 2022. Transportation Energy Data Book: Edition 40. Oak Ridge National Laboratory, Oak Ridge.
Dawid, H., Muehlheusser, G., 2022. Smart products: Liability, investments in product safety, and the timing of market introduction. J. Econom. Dynam. Control 134, 104288.
De Chiara, A., Elizalde, I., Manna, E., Segura-Moreiras, A., 2021. Car accidents in the age of robots. Int. Rev. Law Econom. 68, 106022.
Di, X., Chen, X., Talley, E., 2020. Liability design for autonomous vehicles and human-driven vehicles: A hierarchical game-theoretic approach. Transp. Res. C 118, 102710.
Di, X., Shi, R., 2021. A survey on autonomous vehicle control in the era of mixed-autonomy: From physics-based to AI-guided driving policy learning. Transp. Res. C 125, 103008.
European Commission, 2018. On the road to automated mobility: An EU strategy for mobility of the future. Report COM(2018) 283.
European Commission, 2022. Proposal for a directive on liability of defective product. Report COM(2022) 495.
Fagnant, D.J., Kockelman, K., 2015. Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. Transport. Res. Part A: Policy Pract. 77, 167–181.
Feess, E., Muehlheusser, G., 2024. Autonomous vehicles: moral dilemmas and adoption incentives. Transport. Res. Part B: Method. 181, 102894.
Freixas, X., Guesnerie, R., Tirole, J., 1985. Planning under incomplete information and the ratchet effect. Rev. Econom. Stud. 52 (2), 173–191.
Friedman, E., Talley, E., 2019. Automatorts: How should accident law adapt to autonomous vehicles? lessons from Law & Economics. Columbia University, mimeo.
Fudenberg, D., Tirole, J., 1991. Game Theory. MIT Press.
Galasso, A., Luo, H., 2017. Tort reform and innovation. J. Law Econom. 60 (3), 385–412.
Galasso, A., Luo, H., 2022. When does product liability risk chill innovation? Evidence from medical implants. Am. Econom. J.: Econom. Policy 14 (2), 366–401.
Geistfeld, M.A., 2017. A roadmap for autonomous vehicles: State tort liability, automobile insurance, and federal safety regulation. California Law Rev. 105, 1611–1694.
Gilles, S., 2006. The judgment-proof society. Washington & Lee Law Rev. 63, 603–715.
Gkartzonikas, C., Gkritza, K., 2019. What have we learned? A review of stated preference and choice studies on autonomous vehicles. Transp. Res. C 98, 323–337.
Gless, S., Silverman, E., Weigend, T., 2016. If robots cause harm, who is to blame? Self-driving cars and criminal liability. New Crim. Law Rev. 19 (3), 412–436.
Guerra, A., Parisi, F., Pi, D., 2022. Liability for robots II: an economic analysis. J. Institut. Econom. 18 (4), 553–568.
Gurumurthy, K.M., Kockelman, K.M., Simoni, M.D., 2019. Benefits and costs of ride-sharing in shared automated vehicles across Austin, Texas: Opportunities for congestion pricing. Transp. Res. Rec. 2673 (6), 548–556.
Haboucha, C.J., Ishaq, R., Shiftan, Y., 2017. User preferences regarding autonomous vehicles. Transp. Res. C 78, 37–49.
Hotelling, H., 1929. Stability in competition. Econom. J. 39 (153), 41–57.
Huang, K., Chen, X., Di, X., Du, Q., 2021. Dynamic driving and routing games for autonomous vehicles on networks: A mean field game approach. Transp. Res. C 128, 103189.
Huang, K., Di, X., Du, Q., Chen, X., 2019. Stabilizing traffic via autonomous vehicles: A continuum mean field game approach. In: 2019 IEEE Intelligent Transportation Systems Conference. ITSC, IEEE, pp. 3269–3274.
Huang, K., Di, X., Du, Q., Chen, X., 2020a. A game-theoretic framework for autonomous vehicles velocity control: Bridging microscopic differential games and macroscopic mean field games. Discrete Contin. Dyn. Syst. Ser. B 25 (12), 4869–4903.
Huang, K., Di, X., Du, Q., Chen, X., 2020b. Scalable traffic stability analysis in mixed-autonomy using continuum models. Transp. Res. C 111, 616–630.
Jing, P., Xu, G., Chen, Y., Shi, Y., Zhan, F., 2020. The determinants behind the acceptance of autonomous vehicles: A systematic review. Sustainability 12 (5), 1719.
Kyriakidis, M., Happee, R., de Winter, J., 2015. Public opinion on automated driving: Results of an international questionnaire among 5000 respondents. Transp. Res. Part F: Traff. Psychol. Behav. 32, 127–140.
Li, Y., Chen, Z., Yin, Y., Peeta, S., 2020. Deployment of roadside units to overcome connectivity gap in transportation networks with mixed traffic. Transp. Res. C 111, 496–512.
Luo, Q., Saigal, R., Chen, Z., Yin, Y., 2019. Accelerating the adoption of automated vehicles by subsidies: A dynamic games approach. Transp. Res. B 129, 226–243.
McFadden, D., 1973. Conditional logit analysis of qualitative choice behavior. In: Zarembka, P. (Ed.), Frontiers in Econometrics. Academic Press, New York, pp. 105–142.
McFadden, D., 1974. The measurement of urban travel demand. J. Publ. Econom. 3 (4), 303–328.
McGuire, E., 1988. The impact of product liability. The Conference Board Report 908.
Mo, D., Chen, X.M., Zhang, J., 2022. Modeling and managing mixed on-demand ride services of human-driven vehicles and autonomous vehicles. Transp. Res. B 157, 80–119.
Polinsky, M., Shavell, S., 2010. The uneasy case for product liability. Harv. Law Rev. 123, 1437–1492.
Rahmati, Y., Talebpour, A., 2017. Towards a collaborative connected, automated driving environment: A game theory based decision framework for unprotected left turn maneuvers. In: 2017 IEEE Intelligent Vehicles Symposium. IV, IEEE, pp. 1316–1321.
SAE International, 2021. Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles. Report J3016-202104.
Salop, S., 1979. Monopolistic competition with outside goods. Bell J. Econ. 141–156.
Schwartzstein, J., Shleifer, A., 2013. An activity-generating theory of regulation. J. Law Econom. 56 (1), 1–38.
Schweizer, U., 2023. Liability for Accidents between Road Users whose Activity Levels are Verifiable. University of Bonn, mimeo.
Shabanpour, R., Golshani, N., Shamshiripour, A., Mohammadian, A.K., 2018. Eliciting preferences for adoption of fully automated vehicles using best-worst analysis. Transp. Res. C 93, 463–478.
Shavell, S., 2008. On optimal legal change, past behavior, and grandfathering. J. Legal Stud. 37 (1), 37–85.
Shavell, S., 2020. On the redesign of accident liability for the world of autonomous vehicles. J. Legal Stud. 49 (2), 243–285.
Smith, B.W., 2017. Automated driving and product liability. Mich. St. L. Rev. 1.
Talebpour, A., Mahmassani, H.S., Hamdar, S.H., 2015. Modeling lane-changing behavior in a connected environment: A game theory approach. Transp. Res. Procedia 7, 420–440. http://dx.doi.org/10.1016/j.trpro.2015.06.022.
Tirole, J., 1988. The Theory of Industrial Organization. MIT Press.
USDOT, 2019. Connected vehicle: Benefits, roles, outcomes. United States Department of Transportation https://its.dot.gov/research_areas/WhitePaper_connected_vehicle.htm (Online; Accessed 31 March 2022).
Viscusi, K., Moore, M., 1993. Product liability, research and development, and innovation. J. Polit. Econ. 101 (1), 161–184.
Wagner, G., 2018. Robot liability. SSRN Working Paper No. 3198764.
Wang, S., Li, Z., Levin, M.W., 2022. Optimal policy for integrating autonomous vehicles into the auto market. Transp. Res. C 143, 103821.

Yoo, J.H., Langari, R., 2012. Stackelberg game based model of highway driving. In: ASME 2012 5th Annual Dynamic Systems and Control Conference Joint with the JSME 2012 11th Motion and Vibration Conference. American Society of Mechanical Engineers, pp. 499–508.
Yoo, J.H., Langari, R., 2013. A stackelberg game theoretic driver model for merging. In: ASME 2013 Dynamic Systems and Control Conference. American Society of Mechanical Engineers, V002T30A003–V002T30A003.
Yu, H., Tseng, H.E., Langari, R., 2018. A human-like game theory-based controller for automatic lane changing. Transp. Res. C 88, 140–158.
Zhang, Q., Langari, R., Tseng, H.E., Filev, D., Szwabowski, S., Coskun, S., 2019. A game theoretic model predictive controller with aggressiveness estimation for mandatory lane change. IEEE Trans. Intell. Veh. 5 (1), 75–89.