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Net-societal and Net-private Benefits of Some Existing Vehicle Crash Avoidance Technologies

Abdullah Khan
Research Assistant
John H. Heinz III College of Public Policy and Information Systems
Carnegie Mellon University
Hamburg Hall
5000 Forbes Avenue
Pittsburgh, PA 15213 USA
Email: makhan1@alumni.cmu.edu

Corey Harper, PhD Corresponding Author
Transportation Systems Engineer
Booz Allen Hamilton
20 M St SE
Washington, DC 20003 USA
Email:cdharper@alumni.cmu.edu

Chris T. Hendrickson, PhD
Hamerschlag University Professor
Carnegie Mellon University
Hamburg Hall 3050
5000 Forbes Avenue
Pittsburgh, PA 15213 USA
Email: cth@cmu.edu

Constantine Samaras, PhD
Associate Professor
Civil and Environmental Engineering
Carnegie Mellon University
Porter Hall 103
5000 Forbes Avenue
Pittsburgh, PA 15213 USA
Email: csamaras@cmu.edu

ABSTRACT

Most light-duty vehicle crashes occur due to human error. Many of these crashes could be avoided or made less severe with the aid of crash avoidance technologies. These technologies can assist the driver in maintaining control of the vehicle when a possibly dangerous situation arises by issuing alerts to the driver and in a few cases, responding to the situation itself. This paper estimates the societal and private benefits and costs associated with three crash avoidance technologies, blind-spot monitoring, lane departure warning, and forward-collision warning, for all light duty passenger vehicles in the U.S. for the year 2015. The three technologies could collectively prevent up to 1.6 million crashes each year including 7,200 fatal crashes. In this paper, the authors estimated the net-societal benefits to the overall society from avoiding the cost of the crashes while also estimating the private share of those benefits that are directly affecting the crash victims. For the first generation warning systems, net-societal benefits and net-private benefits are positive. Moreover, the newer generation of improved warning systems and active braking should make net benefits even more advantageous.

Keywords: Crash avoidance technologies, Active safety, Cost-benefit analysis; Forward collision warning, Lane departure warning, Blind Spot Monitoring

1 INTRODUCTION

Most light-duty vehicle (LDV) crashes occur due to human error. The National Highway Safety Administration (NHTSA) reports that nine percent of fatal crashes in 2016 were distraction-affected crashes, while close to ninety-four percent of all crashes occur in part due to human error (Singh, 2015) (NHTSA, 2018). Crash avoidance features could reduce both the frequency and severity of light and heavy-duty vehicle crashes, primarily caused by distracted driving behaviors and/or human error by assisting in maintaining control or issuing alerts if a potentially dangerous situation is detected (Insurance Institute for Highway Safety, 2014).

As the automobile industry transitions to partial vehicle automation, newer crash avoidance technologies are beginning to appear more frequently in non-luxury vehicles such as the Honda Accord and Mazda CX-9. Toyota has announced that by the end of 2017, nearly all models and trim levels in the US will be equipped with autonomous emergency braking (AEB), lane departure warning, and automatic high beam active safety technologies as standard features (Toyota, 2016). A number of automakers such as GM, Audi, Ford, and Nissan as well as many other companies in the automotive indiustry have agreed to make AEB a standard feature on all new cars by 2022 (Insurance Institute for Highway Safety, 2016).The availability of Forward Collision Warning (FCW), Lane Departure Warning (LDW), and Blind Spot Monitoring (BSM) technologies could reach 95% of all registered vehicles anywhere between the years 2039 and 2045 (Highway Loss Data Institute, 2015a). Federal mandates could accelerate the market penetration rate of these technologies by as much as 6 years (Highway Loss Data Institute, 2015a). In 2015 NHTSA proposed changes to its New Car Assessment program that would give favorable ratings to vehicles that are equipped with rear-visibility cameras, LDW, and FCW crash avoidance systems. This change in regulation could encourage manufacturers to equip their vehicles with these technologies (NHTSA, 2015).

This paper estimates the annual net-societal benefits and net-private benifits of fleet-wide deployment of BSM, LDW, and FCW, crash avoidance systems within the U.S. light-duty vehicle fleet. Societal benefits are estimated from observed reductions in crash frequency and severity for vehicles equipped with warning devices coupled with NHTSA estimates of crash costs (Blincoe et al. 2015). Private benefits are the fraction of these societal benefits received by vehicle owners. Costs are the annualized costs of equipping vehicles with these warning devices.

2 EXISTING LITERATURE

Several researchers have analyzed the effectiveness of crash avoidance technologies in reducing crash frequency and severity. Cicchino (2017) evaluated the effectiveness of FCW alone and FCW with AEB in reducing rear-end crashes in 27 U.S. states during 2010-14, using poisson regression analysis was to compare rates of police-reported crashes of passenger vehicles equipped with these technologies. Cicchino (2017) concluded that FCW alone and FCW with AEB systems could reduce rear-end crash involvement by 27% and 50%, respectively. More recent studies by Cicchino found that vehicles with LDW were involved in 18% fewer relevant crashes of all severities and 24% fewer lane-departure relevant crashes with injuries, while BSM could reduce lane-change crash frequency by 14% (Cicchino, 2018a, 2018b). Isaksson-Hellman and Lindman (2018) used insurance claim data on Volvo car models to estimate the effectiveness of BSM. Isaksson-Hellman and Lindman (2018) found that in crashes with a repair cost exceeding $1,250, BSM could provide significant reductions in crash rates and cars that have BSM have

30% lower claim cost on average, indicating reduced crash severity (Isaksson-Hellman and Lindman, 2018). In a separate study of fatal car crashes in Sweden in 2010, Sternlund et al. (2017) showed a positive effect of LDW systems in reducing head-on and single-vehicle crashes. In a study of simulations adapted from crash data and crash scenarios on advance collision avoidance technologies (ACAT), Blower (2014) estimated that FCW could prevent about 38% of all rear-end crashes. The Insurance Institute for Highway Safety (IIHS) in a recent report shared new findings on the effectiveness of BSM technology using 2015 crash data. IIHS concluded that BSM lowers the rate of all lane-change crashes by 14 percent and the rate of lane-change crashes with injuries by 23 percent. If all passenger cars were equipped with BSM technologies, up to 50,000 police reported crashes could be prevented each year (Insurance Institute for Highway Safety, 2017). Results of the same report indicate that LDW lowers rates of single-vehicle, sideswipe and head-on crashes of all severities by 11 percent and lowers the rates of injury crashes of the same types by 21 percent. That means that if all passenger vehicles had been equipped with LDW, nearly 85,000 police-reported crashes and more than 55,000 injuries would have been prevented in 2015 (Insurance Institute for Highway Safety, 2017). Penmetsa et al. (2018) assessed the effectiveness of LDW using state-level crash data and vehicle registration information and found that by 2020 if 8.5% of the LDV fleet were equipped with LDW systems that are 20% effective, 2.7% of single-vehicle lane departure crashes could be avoided. Yue et al. (2018) estimated the effectiveness of connected vehicle and driver assistance technologies by comparing the estimated effectiveness between studies. Yue et al. (2018) estimates that FCW could reduce 35% of near crash-events in fog conditions.

Researchers have also attempted to estimate the economic benefits of crash avoidance technologies. For a consistent comparison, the authors used the consumer price index (CPI) to convert all benefits in previous literature to $2015 (Bureau of Labor Statistics, 2017). In a recent study Li and Kockelman (2016) estimated that FCW along with adaptive cruise control can save more than $53 billion in economic costs and 497,100 functional person-years (Kockelman & Li, 2016). Mangones et al. (2017) concluded that side collision warning avoidance systems are economically justifiable in New York City's transit buses. In that study, the expected crash reduction frequencies for forward and side collision warning safety features were estimated using expert elicitation. Harper et al. (2016) estimated that equipping all three technologies (FCW, LDW, and BSM) on light-duty passenger vehicles can provide annual lower and upper bound benefits of $18 and $202 billion, respectively. The net benefit in both instances was positive (Harper, et al., 2016). This paper makes a contribution to the literature by starting with a method similar to Harper et al. (2016) but using more recent insurance and crash data and contributing estimates of private net benefits in addition to overall societal net benefits.

3 DATA

In this paper, the authors provide two estimates of potential societal benefits: 1) the total annual societal benefits based on observed insurance data from the Highway Loss Data Institute (HLDI) and 2) the upper bound crash prevention cost savings by assuming all relevant crashes are avoided. In order to estimate the total annual societal benefits of fleet-wide deployment of LDW, FCW, and BSM systems, the authors estimate the changes in crash frequency and severity from vehicles equipped with these systems. To estimate the upper bound crash prevention cost savings, the authors identify which types of crashes could potentially be prevented or made less severe by each technology. The primary sources of data used are the 2015 General Estimate System (GES) which provides information on crashes of all severities, the 2015 Fatality Analysis

Reporting System (FARS) which provides information on fatal crashes, and insurance data from various reports written by HLDI.

3.1 Background on the General Estimate System (GES), Fatality Analysis Reporting System (FARS), and Highway Loss Data Institute Insurance Data

NHTSA collects information annually on both fatal and nonfatal motor vehicle crashes in the United States in order to aid researchers and other transportation professionals in evaluating the number of different crashes involving all types of vehicles and any relevant information regarding the crash that could be used to find and diagnose problems within traffic safety. Along with accident data, the 2015 GES and FARS datasets also include person and vehicle level data.

The 2015 GES represents the crash characteristics of the United States population, within the sampling errors of the GES sampling design, and includes crashes of all severities. This dataset is the best national representation of vehicle crashes the authors are aware of. A weighting factor is provided for each person, vehicle, and accident included in the datasets. This weighting factor is the computed inference factor, which is intended to represent the total population from which the sample was drawn. The system has a population sample of about 57 thousand accidents that is representative of about 6.3 million crashes nationwide. All of the results presented in this report for non-fatal accidents were found using the full sample weights for the 2015 GES.

The 2015 FARS data contains information on every fatal crash occurring on a public roadway in the year 2015. In order for a crash to be included in the FARS dataset, the crash must result in the death of an occupant of a vehicle or a pedestrian within thirty days of the crash due to injuries suffered from the accident. Unlike the GES database, the FARS dataset does not include any weighted estimates since each fatal accident that meets the criteria outlined above is included in the dataset. All of the results presented in this reported related to fatal accidents were found using the 2015 FARS.

HLDI reports contain insurance loss information on crash avoidance systems for different vehicle manufacturers. HLDI derives its data by comparing the insurance records for a sample set of vehicles with crash avoidance system against vehicles of the same model year and series assumed not to have any of the systems. The two metrics from HLDI's report that were used to inform the analysis were observed changes in: 1) collision claim frequency and 2) collision claim severity. Collision claims cover damage the at-fault party does to their own vehicle, while collision claim severity refers the average loss payment per claim. HLDI reports insurance statistics in terms of an expected value within a 95% confidence interval. No crash type or crash injury severity (e.g., maximum abbreviated injury scale (MAIS) 1, MAIS2, etc.) data could be ascertained from the dataset. The expected values were utilized to estimate the changes in collision claim frequency and severity for this analysis. HLDI reports from 2011-2015 were used for this analysis (Highway Loss Data Institute, 2011a, 2011c, 2011b, 2012a, 2012b, 2015a, 2015b, 2015c).

3.2 Overview of crash avoidance systems

There are a number of crash avoidance systems that have been introduced over the years to enhance vehicle safety. Some auto manufacturers package these technologies in bundles or with other crash mitigation technologies which are not focused in this paper, but are commercially available and in some cases (e.g., autonomous emergency braking), represent an early form of vehicle automation as defined by the Society of Automotive Engineers (SAE) (SAE, 2016). BSM systems are intended to alert the driver when another vehicle enters his/her blind spot. LDW systems monitor the lane markings in the roadway and helps the driver avoid unintended lane departure by issuing an alert if he/she departs his/her travel lane. FCW systems are installed to detect other vehicles and objects ahead that are stationary or moving at a slower speed and issue a warning to the driver if his or her closing speed represents risk of impending collision. Some manufacturers pair this technology with AEB, which actives the vehicle's braking system if the driver does not respond to the initial warning. The three technologies are discussed in detail in their respective sections below.

3.3 Data Selection Methodology

To be eligible for analysis, the authors have truncated all crashes that do not involve at least one light-duty passenger vehicle in both FARS and GES datasets. One-and two-vehicle crashes make up 93% of all vehicle crashes in 2015; evaluating three or more vehicle crashes adds complexity to the analysis and as a result these were not considered. Additionally, crashes that were attributed to loss of control were removed from the analysis. Crashes in the GES that were coded as fatal were excluded from the analysis since the authors were only interested in examining property damage only and injury-related crashes from this dataset. In order to account for any missing data, imputed data were used where available.

Target crash populations for each technology were established in order to sort crashes into identifiable categories, making it easier to estimate the relevant number crashes for each technology. For this analysis the three target populations are: lane-change crashes which are most closely related to BSM, lane-departure crashes which are related to LDW, and front-end collisions which are attributed to FCW. These technologies are activated at certain functional speeds, and can vary by manufacturer. In order to identify vehicles that were traveling at speed greater than or equal to the functional speed of the technologies, the vehicle speed was considered. In cases where the vehicle speed was unknown or unreported, the roadway speed limit was considered due to the large percentage of unreported travel speeds. If the vehicle speed was unreported it is assumed that when the crash occurred, the vehicles involved were traveling at a speed greater than or equal to the reported speed limit. The functional speeds established for this analysis are 20, 40, and 10 miles per hour (MPH) for BSM, LDW, and FCW, respectively (HLDI, 2012, 2011a). Crashes that took place in inclement weather were excluded from the dataset, since these systems use sensors that may not be able to detect other vehicle movements or accurately identify objects in rain, sleet, snow, or fog (Jermakian, 2011).

3.3.1 Blind Spot Monitoring (BSM)

BSM systems are comprised of a camera or sensor-based technology that alerts the driver when there is a vehicle encroaching into the blind spot area of the driver's side view that one might not be able to see. The way BSM systems interact with the driver varies slightly from automaker to automaker where some systems provide only visual alerts while others provide a combination of both visual and audio alerts. BSM systems are useful in preventing crashes or reducing the severity of lane change crashes. A lane-change crash was defined as where two vehicles were initially traveling along parallel paths in the same direction and the encroachment of one vehicle into the travel lane of another vehicle, was the primary reason for the crash occurring. For crashes that involve loss of control or where it was not clear whether or not two vehicles were traveling in the same or opposite direction, or if two vehicles were initially traveling in the same lane, these entries were excluded from the analysis. The filtering of lane change crashes was done by using the pre-crash movement (p_crash1), critical event (p_crash2), crash type (acc_typ), number of motor vehicles in transport (ve_form), atmospheric conditions (weather), speed limit (vspd_lim), and travel speed (trav_sp) variable codes. This target crash population includes only two-vehicle crashes. The method used to identify lane-change crashes is outlined in Table 1. More information regarding lane-change crashes can be found in Basav et al.'s Analysis of Lane Change Crashes report (Basav et al., 2003).

Table 1 Filtration method used to identify Lane Change crashes

Filter	Description	Filter Code
1	Identify crashes involving at least one passenger car	Identify crashes involving at least one passenger car
2	Selects crashes Involving two vehicles	if ve_form = 2
3	Selects accident types that a lane change could fall under	if 44<= acc_typ<=49 or 70<=acc_typ<=75
4	Remove crashes involving loss of control	if not 1<= p_crash2 >= 9
5	Remove crashes involving pedestrians, animals, or other objects	if not 80<=p_crash2 = 92
6	Remove Opposite direction	if not p_crash2 = 54, 62, 63, 67, 71, 72
7	Remove crashes where it is not clear if vehicles were initially traveling in the same direction	if not p_crash2 = 59, 68, 73, 78
8	Remove crashes that do not conform to the definition of lane change crashes	if not (acc_typ = 74 or 75 and p_crash2= 15 or 16) or (p_crash1=10 or 11)
9	Remove vehicles initially traveling in the same lane	if not p_crash2 = 50, 51, or 52 for one vehicle and p_crash2= 18 or 53 for other
10	Travel speed of more than 20 mph and if unknown then posted speed limit more than 20 mph	If (trav_sp>= 20 mph) or (trav_sp = 998 and vspd_lim>=20)
11	Eliminates crashes that took place in inclement weather	If weather not = 2, 3, 4, or 5

Source: Adapted from Basav et al.'s Analysis of Lane Change Crashes report (Basav, et al., 2003)

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Note: p_crash1= pre-crash movement, p_crash2= critical event, acc_typ = crash type , ve_form = number of motor vehicles in transport, weather = atmospheric conditions, vspd_lim = speed limit, and trav_sp = travel speed

3.3.2 Lane Departure Warning (LDW)

LDW systems monitor a vehicle's position in the lane of travel and warns the driver in the event of imminent or actual lane departure. Lane-departure crashes are defined as one where the vehicle inadvertently departs its travel lane and the driver of the vehicle is not actively maneuvering the vehicle other than the general intent of lane keeping. While LDW (similarly to BSM) warn of sideswipe crashes, the FARS and GES datasets do not indicate the driver's intention (drift out of lane or active lane change), and as a result crashes with the pre-crash movement: "changing lanes" were not considered for the lane departure crash population. The method used to identify lane departure crashes is outlined in Table 2. This target crash population includes both single and two-vehicle crashes. More information regarding LDW system crashes can be found in Gordon et al.'s Safety Impact Methodology for Lane Departure Warning report (Gordon et al., 2010).

Table 2 Filtration Method used to identify Lane Departure Crashes

Filter	Description	Filter Code
1	Identifies crashes involving at least one passenger car	Identify crashes involving at least one passenger car
2	Travel speed of more than 40 mph and if unknown then posted speed limit more than 40 mph	if trav_sp >= 40 or (trav_sp = 998 and vspd_lim>=40)
3	Selects single vehicle road departure crashes	if ve_form=1 and p_crash1 = 1, 14, or 15 and p_crash2 =12 or 13
4	Two vehicle, prior lane-keeping, lane departure crashes	if ve_form=2 and p_crash1 =1 or 14 and p_crash2 = 10 or 11
5	Two Vehicles; Changing lanes, lane departure	if ve_form>2 and p_crash1 = 15 and p_crash 2 = 10 or11
6	Other lane or road departure, prior lane-keeping crashes	if p_crash1 = 1, 14, or 15 and 10 <= p_crash2 <= 13
7	Eliminates crashes that a lane change could fall under	if not 44<= acc_typ<=49 or 70<=acc_typ<=75
8	Remove crashes involving loss of control	if not 1<= p_crash2 >= 9
9	Eliminates crashes that took place in inclement weather	If not weather= 2, 3, 4, or 5

Source: Adapted from Gordon et al.'s Safety Impact Methodology for Lane Departure Warning report (Gordon et al., 2010).

Note: p_crash1= pre-crash movement, p_crash2= critical event, acc_typ = crash type , ve_form = number of motor vehicles in transport, weather = atmospheric conditions, vspd_lim = speed limit, and trav_sp = travel speed

3.3.3 Forward Collision Warning (FCW)

FCW systems are designed to prevent crashes or reduce the severity of front-end collisions by using a camera or radar to detect whether a vehicle is approaching an object at an unsafe speed and issues an alert to the driver. Some FCW systems are combined with autonomous emergency braking (AEB), which is applied if the driver fails to react to the initial warnings. In both FARS and GES datasets front-end collisions were identified using the crash type, pre-event movement, and critical event variables. Crash type variable codes in GES 10-29 correspond to front-end collisions and were used to filter out crashes where FCW could become active. Vehicles that were backing up at the time of collision were excluded from the analysis. This target crash population includes one- and two-vehicle collisions. Single vehicle front-end collisions involving pedestrians, animals, and bicyclist are included in this target crash population. Only rear-end collisions are considered in this target crash population for vehicles involving two vehicles. The method used to identify front-end collision crashes is outlined in Table 3.

Table 3 Filtration Method Used to Identify Front End Collisions

Filter	Description	Filter Code
1	Identifies crashes involving at least one passenger car	Identify crashes involving at least one passenger car
2	Selects accident types that a front-end collision could fall under	if 11 <= acc_typ<= 31
3	Travel speed of more than 10 mph and if unknown then posted speed limit more than 10 mph	if trav_sp >= 10 or (trav_sp = 998 and vspd_lim>=10)
4	Prior to critical event position of the object / vehicle	if 1 <= p_crash1 <= 5
5	Two vehicle crashes that align with the rear-end crash scenario	if ve_form = 2 and 50 <= p_crash2 <= 53
6	Single vehicle crashes with pedestrian, pedacyclists, animal, or other object that align with front-end collision crash scenario	if ve_form = 1 and 80 <= p_crash2 <= 92
7	Remove crashes involving loss of control	if not 1<= p_crash2 >= 9
8	Eliminates crashes that took place in inclement weather	If not weather= 2, 3, 4, or 5

Note: p_crash1= pre-crash movement, p_crash2= critical event, acc_typ = crash type, ve_form = number of motor vehicles in transport, weather = atmospheric conditions, vspd_lim = speed limit, and trav_sp = travel speed

3.4 Estimation of Reduction in Crash Frequency and Crash Cost Due to Warning Systems

Using a similar methodology to Harper et al. (2016), the authors gathered changes in collision claim frequencies and collision claim severity from insurance data published by HLDI for major automakers between 2011 and 2015. Two major assumptions are made here to establish population parameters. First, it is assumed that change (positive or negative) in collision claim frequency is the equivalent change in crash frequency for single and multiple-vehicle crashes. While not all accidents are reported to insurance companies and collision claim frequency does not perfectly reflect crash frequency, there is a relationship between the two statistics. Second, it is assumed that a change in collision claim severity, whether positive or negative, is the equivalent change in crash cost for crashes that are not prevented. Crash avoidance technologies could reduce crash severity, which should, in turn, reduce crash costs.

HLDI provides information on the number of insured years for each type of technology by vehicle make and model as vehicle exposure. To convert all reported values into a single value for each technology, a weighted average was calculated based on the total vehicle exposure. For each technology, higher exposure of one automaker is weighted greater than another automaker with lower exposure. For example, Mazda with BSM has a total exposure of 788,000 insured vehicle years and Mercedes with BSM have a total exposure of 33,000 insured vehicle years, therefore the change in collision claim frequency for Mazda would contribute more to the final weighted average claim frequency for BSM than that of Mercedes. The datasets contain estimates for coupled systems that were always packaged together, where two separate estimates for each system could not be produced. In order to produce separate estimates for such systems, it was assumed that the benefits are equally distributed for each system. For example, on the Honda Accord, LDW and FCW were always packaged together and vehicles with both of these systems are estimated to reduce collision claim frequency by 1.7%. Based on this assumption both Honda's FCW and LDW systems are assumed to reduce collision claim frequency by 0.85% each. A similar process was followed for Buicks LDW system, which is coupled with BSM. Once all estimates are converted to a single value for each technology, the summation of these three values are assumed to be the real-world reduction in collisions claim for a light-duty vehicle equipped with LDW, BSM, and FCW. Because, these are separate systems that work largely on different crash types, the authors believe that that summing these values was an appropriate approach for the analysis, as opposed to averaging these values. Table 4 shown below, provides an overview of the data before they were combined.

Table 4 Details of Collision Claim Frequency, Severity, and Exposure by Car Make and Model

	Manufacturer	Additional Technologies[1]	Change in Collision Frequency	Change in Collision Severity ($ 2015)	Collision Exposure
Blind Spot Monitoring	Volvo		1.3%	$ (170)	96,158
	Mercedes		-0.1%	$ (463)	33,115
	Acura		-5.4%	$ 337	5,624
	Buick	LDW	2.1%	$ (36)	29,202
	Honda		-5.0%	$ (61)	334,122
	Mazda		-3.1%	$ (9)	788,556
Forward Collision Warning	Volvo		-6.6%	$ 476	6,504
	Mercedes		-3.1%	$ 870	99,484
	Honda	LDW	-0.85%	$ (147)	282,353
	Mazda		1.9%	$ (89)	18,712
Lane Departure Warning	Mercedes		5.6%	$ 1,080	29,433
	Buick	BSM	2.1%	$ (36)	29,202
	Honda	FCW	-0.85%	$ (147)	282,353
	Mazda		-3.7%	$ 351	13,561
	Subaru		0.5%	$ 4	35,556

Source: Collection of Collision Avoidance Features Reports published for Volvo, Mercedes, Acura, Buick, Honda, Mazda, and Subaru. (Highway Loss Data Institute, 2011a, 2011c, 2011b, 2012a, 2012b, 2015a, 2015b, 2015c).

[1]Additional technologies refer to technologies that are coupled together and estimates in collision claim frequency and severity cannot be separately distinguished.

4 SOCIETAL AND PRIVATE BENEFIT-COST ANALYSIS

In this section the authors provide the framework for estimating the total annual costs, societal and private benefits, and societal and private net-benefits.

The total annual costs are the annualized technology purchasing cost of equipping all light-duty vehicles with the three technologies and is expressed below in Eq. (1):

$$TC = (A/r\,,n)\,TP_C \tag{1}$$

Where TC is the total annual cost for equipping light-duty vehicles with BSM, LDW and FCW crash avoidance systems and TP_C is the technology purchasing cost and $(A/r\,,n)$ is the equivalent uniform annual amount at a discount rate of r over a period of n years.

Total annual societal benefits are the sum of the cost savings from a reduction in crash frequency and cost savings from less severe crashes due to fleet-wide deployment of BSM, FCW, and LDW and is expressed below in Eq. (2):

$$SB = CS_{CP} + CS_{LS} \tag{2}$$

Where SB is the total annual benefits, CS_{CP} the cost savings from crash prevention, and CS_{LS} is the cost savings from less severe crashes.

The cost of a motor vehicle crash is borne by every stratum of the society including the crash victims. The authors have categorized the overall societal benefits into private benefits and public benefits and is expressed below in Eq. (3):

$$SB = SB_{Pvt} + SB_{Pub} \tag{3}$$

Where SB is annual societal benefits to the society, SB_{Pvt} is the share of societal benefits to private individuals, and SB_{Pub} is the share of societal benefits reaped by the public at large.

The framework for assessing net-societal benefits of crash avoidance technologies is the difference between overall societal benefits and total costs as expressed in Eq. (4):

$$NSB = SB - TC \tag{4}$$

Where NSB is the annual net-societal benefit, SB the total annual societal benefits, and TC is the total annual technology purchasing costs.

The estimation of net-private benefits follows a similar formula and is the difference between the share of societal benefits to private individuals and the total annual technology purchasing costs and is expressed below in Eq. (5):

$$NPB = SB_{Pvt} - TC \tag{5}$$

Where NPB is the annual net-private benefit, SB_{Pvt} the share of societal benefits to private individual, and TC is the total annual technology purchasing costs.

4.1 Total Annual Costs

The total cost (TC) of equipping all LDVs with crash avoidance technologies are the technology purchasing costs associated with purchasing FCW, LDW, and FCW systems, as shown in Eq. (1). This cost is annualized over the average lifespan of a vehicle in order to compare annual fleet-wide costs and benefits. Changes in vehicle sales and miles traveled over time are not taken into consideration for this analysis. Most auto manufacturers offer crash-avoidance systems as an add-on option to their customers for an additional price. Toyota is the first manufacturer in the U.S. the authors are aware of to announce offering these technologies as a standard feature with no additional cost by the end of 2017 (Toyota, 2016). However, for our analysis in 2015, the cost of equipping a vehicle with BSM, LDW and FCW were offered by numerous automakers with varying prices. The authors have taken the median price offering of Toyota Safety Sense (TSS) of $575 (Lienert, 2015) in 2015 as to equip a new vehicle with the three technologies. While many manufacturers offer these systems at a higher price, the authors assume that other manufacturers will eventually reduce their price to remain competitive in the market.

In order to annualize the technology purchasing costs, the authors assumed an average vehicle lifespan of 11.5 years (Walsworth, 2016) and an average car loan interest rate of 4.63% (Zabritski, 2015). The total annual cost assumes these systems will be equipped on new vehicles and the cost to purchase these technologies will be distributed over the lifetime of the vehicle on the road. The estimation of the total annual technology purchasing cost is derived as follows (Harper, et al., 2016):

$$Total\ Cost\ (TC) = LDV\ \times\ VT\ \times\ [r/(1 - (1 + r)^{-n})] \tag{1}$$

$$= 243\ million\ vehicles\ \times\ \$575\ per\ vehicle\ x\ [4.63\%/(1 - (1 + 4.63\%)^{-11.5})]$$
$$= 243\ million\ vehicles\ \times\ \$575\ x\ 0.114$$
$$= 243\ million\ vehicles\ \times\ \$66$$
$$= \$16\ billion$$

$where,$
$LDV\ =\ the\ total\ number\ of\ light\ duty\ vehicles\ in\ the\ U.S.$
$VT\ =\ purchasing\ cost\ of\ the\ technology$
$r\ =\ the\ rate\ of\ return\ for\ a\ new\ automobile\ loan$
$n\ =\ the\ average\ lifetime\ of\ a\ vehicle\ considered\ for\ the\ period$

In 2015, the total number of registered light-duty vehicles in the national fleet was 243 million (Bureau of Labor Statistics, 2015). The total annual cost, as per Eq. (1), for equipping all LDVs with the three crash avoidance technologies is about $16 billion.

4.2 Total Annual Societal Benefits

As mentioned earlier, the authors provide two estimates of potential societal benefits: 1) total annual societal benefits and 2) upper bound crash prevention cost savings. The annual societal benefits of fleet-wide deployment of the three technologies comes from a reduction in crash frequency and severity. To estimate the total annual societal benefits, the authors use current insurance data for vehicles with these technologies and project the savings across assumed fleet-wide technology diffusion. The estimates from HLDI are interpreted as the actual effectiveness of these systems on an individual vehicle, thus it is assumed that if every vehicle in the fleet were equipped with the three crash avoidance technologies, the total number of crashes would be reduced by HLDI's estimate. As a result, the authors use the total number of crashes that occurred in 2015, including those crashes that occurred in inclement weather and applied this number to HLDI's estimates of changes in collision claim frequency and collision claim severity to estimate the total annual societal benefits. The upper bound crash prevention cost savings assumes that the technologies are 100% effective and could prevent all relevant crashes (i.e. those crashes identified in the data analysis). The upper bound crash prevention cost savings does not make use of HLDI's data and is meant to provide an assessment of the maximum potential benefits that could be realized as these technologies increase in effectiveness.

Vehicles with BSM recorded the greatest reduction in collision frequency as well as severity by 3% and $45, respectively. This was followed by FCW, which lowers the claim frequency by 0.34% but increases the claim amount by $165. Lastly, LDW has the lowest reduction in claim frequency and the second highest reduction in crash frequency. LDW lowers collision clam frequency and severity by about 0.12% and $40, respectively. Combined, we see that the three technologies lowers collision claim frequency by about 3.54% but increases crash costs by $160. Compared to the 2012 results, crash severity is higher and collision frequency is lower. The higher average claim amount can be attributed to the different mix of vehicle make and models assessed in this study. In particular, some of the manufacturers in this study paired expensive headlights (that are vulnerable to damage when a crash occurs) with FCW sensors, which contributed to the increase in collision claim severity. The lower collision claim frequency can be mainly attributed to the different methodologies used to estimate the combined effectiveness of the three warning systems. Because Harper et al. (2016) did not separate the effectiveness of coupled systems[1], the authors of that study averaged the effectiveness of the three warning systems, since cumulating the results would overstate technology effectiveness. In this study, the authors have attempted to separate the effectiveness of coupled systems and since these technologies work largely on different crash types, the cumulative effectiveness of the three warning systems is assumed to be the expected change in crash frequency and severity for a vehicle equipped with LDW, FCW, and BSM. The total number of insured years or vehicle exposure has increased since Harper et al.'s (2016) paper, which can be mainly attributed to the additional data sources and reports with higher convenience samples published by HLDI since the previous work. Updated reports on Mazda and Honda with higher collision exposure were included in this paper along with an updated entry of Subaru in the analysis. In addition, the authors have separated FCW alone and FCW with AEB; our analysis will only consider the crash avoidance potential of warning systems, without any associated automated features. Table 5 summarizes these changes in crash frequency and severity for each of the three technologies.

Table 5 Observed Changes in Crash Frequency, Cost Severity ($2015) and Collision Exposure by Crash Avoidance Technology from Actual Insurance Reports (2011 – 15)

Crash Avoidance Technology	Change in Collision Frequency [a]	Change in Collision Severity [a]	Collision Exposure [c]
Blind Spot Monitoring	-3.08%	-$45	1,286,800
Forward Collision Warning [b]	-0.34%	$165	407,053
Lane Departure Warning	-0.12%	$40	396,100
Sum	-3.54%	$160	N/A

Source: Collection of Collision Avoidance Features Reports published for Volvo, Mercedes, Acura, Buick, Honda, Mazda, and Subaru (HLDI, 2011a) (HLDI, 2011b) (HLDI, 2012a) (HLDI, 2012b) (HLDI, 2015a) (HLDI, 2015b) (HLDI, 2015c).

[a] Weighted average based on vehicle exposure

[b] Vehicles in this estimate do not include those equipped with autonomous emergency braking (AEB)

[c] This represents total exposure for each technology, measured in insured vehicle years

In a detailed study of societal and economic costs of motor vehicle crashes in 2010, the aggregate amount equates to $836 billion, out of which $594 billion is attributed to the loss of life and decreased quality of living while the remaining $242 billion in economic costs (Blincoe, et al., 2015). From the total number of crashes in 2010, the authors estimate each crash costing approximately $154,000. The authors have used the Consumer Price Index (CPI) to adjust this cost to 2015 monetary value (Bureau of Labor Statistics, 2017). This gives us the societal cost of

[1] HLDI studies include estimates that were always packaged together for many manufacturers. For example, on the Honda Accord, LDW and FCW were always packaged together so separate estimates were not reported. Harper et al. (2016) double counted the effectiveness of these systems (once for FCW and once for LDW), whereas this study attempts to separate their effectiveness based on the methodology outlined in Section 3.4.

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$168,600 in 2015, with $119,706 for quality-adjusted-life-years (QALYs) and $48,894 in economic costs. The direct measure of benefits from crash avoidance technologies is the cost saved from crash prevention and changes in severity of crashes. The estimation of cost savings from crash prevention is based on the following formula:

$$\begin{aligned} \mathit{Cost\ Savings\ from\ Crash\ Prevention}\ (CS_{CP}) &= NC \times CF \times SC \\ &= 6.3\ \mathit{million\ crashes} \times 3.54\% \times \$168{,}600 \\ &= 222{,}975 \times \$168{,}600 \\ &= \$37.6\ \mathit{billion} \end{aligned}$$

$where,$
$NC = \mathit{Number\ of\ total\ crashes\ in}\ 2015$
$CF = \mathit{Change\ in\ collision\ claim\ frequency}\ (\mathit{listed\ in\ column}\ 2\ \mathit{of\ Table}\ 5)$
$SC = \mathit{Societal\ cost\ of\ a\ single\ crash}$

Less severe crash cost savings describe the savings to private insurers due to lower claim collision amounts. Because this paper assumes 100% deployment of crash avoidance technologies, it is assumed that all relevant crashes not prevented will have a change in average severity. Our insurance calculations from Table 5 show that the average claim amount has increased by $160. The estimation of cost savings from less severe crashes is based on the following formula:

$$\begin{aligned} \mathit{Cost\ savings\ from\ less\ severe\ crashes}\ (CS_{LS}) &= NO \times CS \\ &= (6.3\ \mathit{million\ crashes} - 222{,}975) \times \$160 \\ &= \$970\ \mathit{million} \end{aligned}$$

$where,$
$NO = \mathit{Number\ of}\ 2015\ \mathit{crashes\ still\ expected\ to\ occur}$
$CS = \mathit{Change\ in\ the\ average\ collision\ claim\ severity}\ (\mathit{listed\ in\ column}\ 3\ \mathit{of\ Table\ 5})$

The total annual societal benefits (SB) from cost savings due to less severe and prevented crashed as highlighted in Eq. (2), is estimated to be about $36.6 billion. The primary contributor of total benefits is from the crash prevention amount of $37.6 billion whereas the increase in the amount of claim severity of $970 million insignificantly dilutes this savings to the final total amount of $36.6 billion. The estimation of the total annual societal benefits is based on the following formula:

$$\begin{aligned} \mathit{Total\ Annual\ Societal\ Benefit}\ (SB) &= CS_{CP} + CS_{LS} \\ &= \$37.6\ \mathit{billion} + (-\$970\ \mathit{million}) \\ &= \$36.6\ \mathit{billion} \end{aligned} \tag{2}$$

$where,$
$CS_{CP} = \mathit{Cost\ savings\ from\ prevented\ crashes}$
$CS_{LS} = \mathit{Cost\ savings\ from\ less\ severe\ crashes}$

Using the 2015 FARS and GES datasets, the authors have estimated the upper bound number of crashes (shown below in Table 6) that could be avoided or made less severe by the three crash avoidance technologies, given system limitations. The authors estimate that approximately 25% of the 6.3 million police reported crashes are relevant to at least one of the three technologies. With 100% deployment, the combination of all three technologies could prevent or reduce the severity of as many as 1.6 million crashes including 7,200 fatal crashes. The largest number of non-fatal accidents occurs due to front-end collisions, followed by lane change and lane departure collisions. For the fatal accidents, the authors see that LDW could prevent or reduce the severity of the highest number of fatal crashes out of all three technologies, followed by FCW and BSM, respectively.

Table 6 Relevant Crashes from 2015 GES and FARS Data Representing the Upper Bound that can Potentially Prevent or Become Less Severe Annually by Crash Avoidance Technologies

Crash Avoidance Technology	Non-Fatal Crashes	Fatal	Total
Blind Spot Monitoring	392,000	150	392,000
Forward Collision Warning	804,000	2,900	807,000
Lane Departure Warning	373,000	4,100	377,000
Sub-total	1,569,000	7,200	1,575,000
Percent of total crashes	25%	20%	25%

Source: 2015 National Automotive Sampling Survey (NASS) General Estimate System (GES) and Fatality Analysis Reporting System (FARS) datasets; National Highway Traffic Safety Administration (NHTSA).
Note: Numbers may not sum exactly due to rounding.
Note: The estimates shown in this table are utilized to estimate the upper bound crash prevention cost savings. Highway Loss Data Institute observed insurance data are not applied to the estimates in this table.

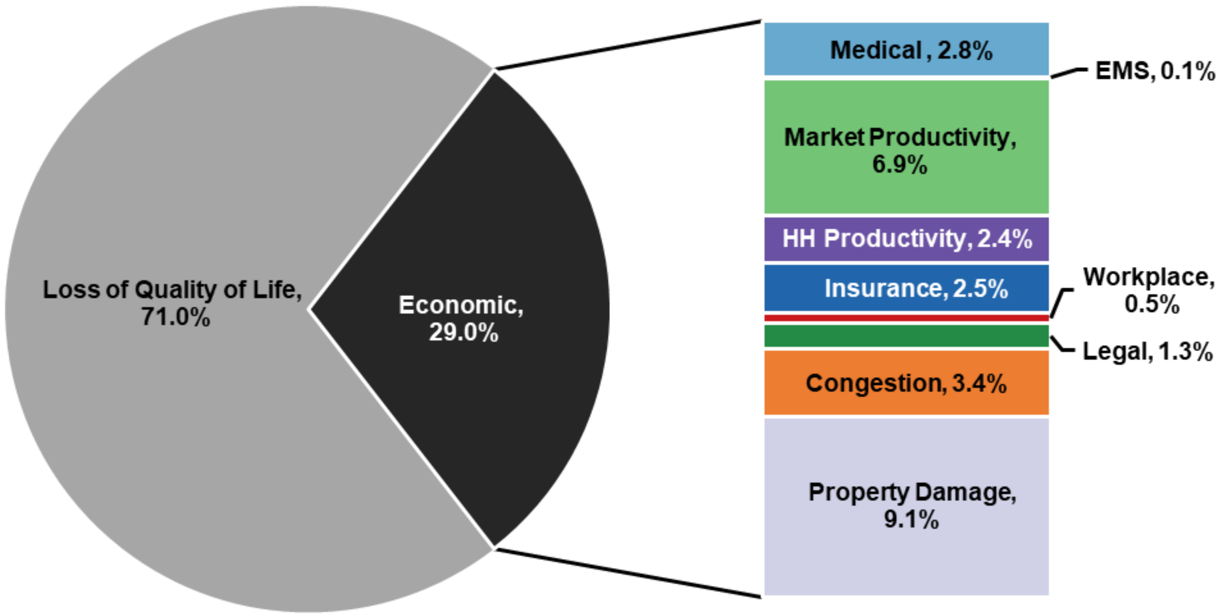
If these technologies were 100% effective and could prevent all relevant crashes, this would provide an upper bound annual benefit of $264 billion. This estimation of the annual upper crash prevention cost savings is based on the following formula (Harper et al., 2016):

$$\begin{aligned} Upper\ bound\ crash\ prevention\ cost\ savings &= M \times SC \\ &= 1.6\ million\ crashes \times \$168{,}600\ per\ crash \\ &= \$264\ billion \end{aligned}$$

$where,$
$M = upper\ bound\ estimate\ of\ crashes\ that\ could\ be\ prevented\ or\ made\ less\ severe$
$by\ the\ three\ crash\ avoidance\ technologies\ (listed\ in\ column\ 4\ of\ Table\ 6)$
$SC = Societal\ cost\ of\ a\ single\ crash$

4.3 Private Costs and Payments

The value of societal harm from motor vehicle crashes includes the economic costs that are mostly the monetary outflows, and the remaining share is attributed to the valuation for quality-of-life. Lost quality-of-life represents 71 percent of the societal cost and the remaining 29 percent constitutes the economic costs, as shown in Figure 1. It is difficult to put a price tag on the intangible consequences such as pain and suffering, but there have been studies undertaken on this subject to estimate the how society values risk reduction (Blincoe, et al., 2015). The societal cost is factored completely from the indirect and intangible cost of QALYs. However, the societal and economic costs are a mixture of direct and indirect monetary costs that are paid from four major sources: government, private insurers, individual crash victims, and other third parties. In order of significance, private insurers incur more than half of all economic costs by being the primary source for medical care, insurance administration, legal costs, and property damage. Individual crash victims contribute a modest portion of medical care but absorb significant portions of property damage as well as market and household productivity losses. Third parties absorb all costs related to workplace and congestion. Lastly, tax dollars cover a significant portion of medical care, lost market productivity and the entire cost of emergency medical service (EMS). In this section the authors focus on the private benefits to individuals since the decision to pay for the additional cost of the systems is taken by private individuals.



Source: Adopted from NHTSA's Economic and Societal Impact of Motor Vehicle Crashes (Blincoe, et al., 2015)

Figure 1 Composition of the Societal Cost of Motor Vehicle Crashes into Quality-Adjusted-Life-Years (QALYs) and Economic Costs Including its Nine Cost Components

It is challenging to disaggregate costs across the payment categories because according to Blincoe (2015), ultimately it is individuals who pay for these costs through insurance premiums, taxes, out-of-pocket cost, or higher charges for medical care. However, a distinction can be made between costs borne by private individuals and the public at large. Private costs are those that are borne by private individuals and consist of direct costs as a result of fatal and non-fatal crashes. For this analysis, private costs are those costs to individual crash victims as well as to private insurers. Public costs are primarily intangible and indirect costs that arise from lost market productivity, congestion, and emergency medical services (EMS). For this analysis, costs to government entities and third-parties (e.g., uninvolved motorists) are considered to be public costs. Using Blincoe et al.'s (2015) distribution of source of payment for economic costs by cost component, which shows the portion of related crash costs borne by private insurers, governmental, sources, individual crash victims and other sources, the economic cost of a crash can be disaggregated into public and private benefit categories. To allocate the cost of QALYs into public and private costs, the authors have used Blincoe's et al.'s (2015) relative incidence crash scenarios to establish a 10% share of public costs from the overall societal costs. Therefore, QALYs are allocated 90% to private vehicle occupants since 10% of all societal harm are incurred by bicycle or pedestrian crashes (Blincoe, et al., 2015). As shown in Table 7, private costs make up about 86% of the societal cost of a crash, while public costs make up only about 14%.

Table 7 Distribution of Private, Public, and Societal Costs for Economic and Quality Adjusted Life Years Costs by Cost Component

Cost Component	Private Cost	Public Cost	Societal Cost
Medical	1.90%	0.90%	2.80%
EMS	-	0.10%	0.10%
Market Productivity	5.10%	1.80%	6.90%
Household Productivity	2.40%	-	2.40%
Insurance Admin.	2.40%		2.40%
Workplace Costs	-	0.50%	0.50%
Legal Costs	1.30%	-	1.30%
Congestion Costs	-	3.40%	3.40%
Property Damage	9.10%	-	9.10%
QALYs	64.00%	7.00%	71.00%
Sub-total	86.20%	13.80%	100.00%

To estimate the private benefits, the authors use the information from Table 7 to estimate the share of private and public benefits from the overall societal benefits.

$$\begin{aligned} SB &= SB_{Pvt} + SB_{Pub} \\ 100\% &= 86.2\% + 13.8\% \end{aligned} \tag{3}$$

Hence, the share of private benefits from the overall societal benefits is as follows,

$$\begin{aligned} SB_{Pvt} &= 86.2\% \times SB \\ &= 86.2\% \times \$36.6\ billion \\ &= \$31.6\ billion \end{aligned}$$

Where SB is annual societal benefits to the society, SB_{Pvt} is the share of benefits to private individuals, and SB_{Pub} is the share reaped by the public at large. The distribution of public and private benefits across each cost component is shown below in Table 8.

Table 8 Distribution of Total Public and Private Benefits for Fleet-Wide Deployment of Lane Departure Warning, Forward Collision Warning, and Blind Spot Monitoring ($2015 Billion)

Cost Component	Private Cost	Public Cost	Societal Cost
Medical	$0.70	$0.33	$1.03
EMS	-	$0.04	$0.04
Market Productivity	$1.87	$0.66	$2.53
Household Productivity	$0.88	-	$0.88
Insurance Admin.	$0.88	$0.00	$0.88
Workplace Costs	-	$0.18	$0.18
Legal Costs	$0.48	-	$0.48
Congestion Costs	-	$1.25	$1.25
Property Damage	$3.33	-	$3.33
QALYs	$23.44	$2.56	$26.00
Sub-total	$31.57	$5.05	$36.62

Note: Numbers may not sum exactly due to rounding.

4.4 Net-Societal and Net-Private Benefits

In order to analyze the economic feasibility of our analysis, the authors laid out the benefit-cost framework in Eq. (4) to estimate the annual net- societal benefits. The total annual societal benefits (SB) are the total annual benefits from crash prevention and severity. The total cost of equipping the three technologies on 100% fleet of light duty vehicles in the U.S. annualized over the average lifetime of a vehicle is the total cost (TC). The net-societal benefit is the difference between the societal benefits (SB) and total costs (TC).

$$\begin{aligned} Annual\ Net\ Societal\ Benefits\ (NSB) &= SB - TC \\ &= \$36.6\ billion\ - \$16\ billion \\ &= \$20.6\ billion \end{aligned} \tag{4}$$

Similarly, to assess net-private benefits, the percentage share of private benefits of the overall societal benefits was estimated based on the source of paying for the costs to derive at the private benefits. The difference between the private benefits (SB_{Pvt}) and the total costs (TC) gives us the net-private benefits, as shown in Eq. (5).

$$\begin{aligned} Annual\ Net\ Private\ Benefits\ (NPB) &= SB_{Pvt} - TC \\ &= \$31.6\ billion\ - \$16\ billion \\ &= 15.6\ billion \end{aligned} \tag{5}$$

The net-societal benefit of equipping light-duty vehicles with the BSM, LDW, and FCW systems is $20.6 billion. On a per-vehicle basis, this amount translates to an approximate net benefit of $360 per light-duty vehicle. This net positive estimate should serve as a lower-bound estimate as these technologies are likely to improve over time and cost reduced with economies of scale. Similarly, the net-private benefits show a positive beneficial change of $270 per vehicle. As these technologies become more effective in terms of crash prevention and less severe crashes, there is opportunity for greater societal and private net-benefits, as shown by the upper bound crash prevention cost savings estimate.

5 DISCUSSION

This paper assesses the net-societal benefits and net-private benefits of equipping all light-duty vehicles with these technologies, based on the best available insurance information on crash avoidance technologies. Assuming fleet-wide deployment of these systems within the light-duty vehicle fleet while extrapolating the changes in insurance claim and severity, the authors have estimated the cost savings from crash prevention with adjustment for the increase in the average amount of insurance claim. Insurance data was obtained from HLDI's published reports on these technologies, relevant crash data were obtained from the 2015 GES/FARS datasets, and economic data was sourced from NHTSA's report on societal and economic impact.

In 2015, approximately 25% of crashes were relevant to one of the three technologies: BSM, LDW or FCW. With fleet-wide deployment, 1.6 million police reported crashes a year could be prevented or made less severe, including 7,200 fatal crashes. LDW could address the largest number of fatal crashes, while FCW system could address the greatest number of crashes overall.

To estimate the net-societal benefit, it was assumed that collision claim frequency and severity mirrored changes crash frequency and costs, respectively. If all three technologies were equipped on all light-duty vehicles this would provide an annual benefit of about $36.7 billion with the significant portion of this benefit going towards the indirect cost of QALYs amounting to $26 billion. Although we see increases in the average crash costs for vehicles with these technologies, the marginal increase does not dilute the annual benefits from prevented crashes. The remaining direct monetary benefits are shared among government sources, private insurers, third parties, and private households for about $0.7 billion, $5.9 billion, $1.8 billion, and $2.5 billion, respectively. The purchase price of the technology is fixed at $575 per vehicle and with an annualized costing method, the total cost of equipping all vehicles sums to $16 billion. The net-societal benefits are approximately $360 per vehicle or $20.6 billion in aggregate. If all three technologies could prevent all crashes in their respective target crash populations, this would provide an upper bound crash prevention cost savings of $264 billion. Indicating that as these systems improve in effectiveness, there is opportunity for greater economic benefits.

The aggregate societal benefits are divided between private individuals and the public at large. The benefits for private individuals form an 86.2% share of the overall societal benefits. Net-private benefits are the costs saved by private individuals who could have avoided these costs with the use of the crash avoidance technologies. Again, adjusting for the purchase price of equipping all light-duty vehicles with the technology, the net-private benefits out of the aggregate are $15.6 billion or approximately $270 per vehicle. The positive net-private benefits confirm the favorable benefit that private individuals can reap by installing these systems. In this paper, the authors focus on the private benefits since the decision to pay for the additional cost for the systems is taken by private individuals.

This paper is an update of work published by Harper et al. (2016), which estimated the net benefits of fleet-wide deployment of crash avoidance technologies using 2012 GES and FARS data. While some of the findings of the technology and insurance information is in line with the previous paper, there are some notable differences worth mentioning. 2015 saw the highest rise in fatal accidents in a one-year time span over the last 50 years, but our findings suggest that the number of fatalities related to the three technologies have reduced from 10,100 to 7,200 over the course of three years. Harper et al. (2016) estimated that LDW could prevent or reduce the severity of about 9,000 fatal crashes compared to about 4,100 in this study. Part of this decrease could be attributed to the more conservative estimate in this paper, as Harper et al. (2016) only considered snow as a system limitation to LDW whereas the authors of this study considered snow, fog, rain, and sleet as system limitations. Still, such a large decrease in the number fatalities requires further work to understand the pressing factors behind it. In comparison, the number of fatal crashes relevant to FCW increased significantly, from 750 crashes in the previous study to 2,900 in this study. This is mainly due to the fact that the authors included single and two-vehicle front-end collisions in the FCW target crash population whereas Harper et al. (2016) only considered two-vehicle crashes.

Another difference between this paper and Harper et. al.'s (2016) is that FCW alone and FCW with AEB were separated in this initial analysis whereas Harper et al. (2016) combined these two estimates. FCW with AEB has proven to be more effective than FCW alone (Cicchino, 2017) and as a result the authors consider two separate scenarios in this paper. The first scenario is the analysis conducted earlier, where all light-duty vehicles are assumed to have FCW, LDW, and BSM, without any associated automated features. A second scenario, that should be considered, is where AEB, a Level 1 automated feature as defined by SAE, is introduced to the light-duty vehicle fleet in addition to the warning systems. If the same methodology is followed, the introduction of AEB would lower collision claim frequency from -3.54% to -7.17%, increasing the annual societal benefits by about 62%, from $36.6 billion to $59.2 billion.

The authors also compare the estimates in this paper to other studies that have attempted to estimate the crash avoidance potential of FCW, BSM, and/or LDW using national crash data. Jermakian (2010) extracted crash data from the 2004–08 GES and FARS and used crash descriptors such as time of day, location of damage on vehicle, and road characteristics to determine if BSM, FCW, and LDW could have prevented the crash. Jermakian (2010) estimates that the three systems could collectively, prevent or reduce the severity of about 1.8 million or 30% of crashes annually. Li and Kockelman (2016) extracted crash data from the 2013 GES to estimate the effectiveness and potential economic benefits of BSM, FCW, and LDW using Najm et al. 's (2007) pre-crash scenario typology and Blincoe 's (2015) MAIS injury severity economic cost translator, respectively. Li and Kockelman (2016) estimates that there are about 2 million crashes that are relevant to the three systems, resulting in $83 billion in potential economic savings annually. The difference in crash potential between this study, Jermakian (2010), and Li and Kockelman (2016) can be in part attributed to the different versions of GES and FARS used, system limitations considered, and overall methodologies applied to estimate crash relevance. For example, Li and Kockleman (2016) did not consider any system limitations in their estimates, while Jermakian (2010) considered snow and rain as system limitations.

The authors also examined the involvement of alcohol (both within and outside of permissible limits) and other drugs (e.g., narcotics, depressants, stimulants, and hallucinogens) by the individuals involved in crashes relevant to BSM, LDW, and FCW. The majority of these warning systems flash a visual and/or audio warning to the drivers, and few of the systems are paired with automated action by the system like AEB. The reaction of the driver from witnessing the warning could be less effective due to the use of alcohol or drugs. According to the 2015 FARS, about thirteen and six percent of fatal front-end collisions involved a driver under the influence of alcohol and drugs, respectively. Further work could be undertaken to assess the effectiveness of human reaction to these warnings.

Our analysis of the crash data excluded crashes in inclement weather that covered conditions like rain, sleet, and snow. The basis for this exclusion was the fact that sensing and perception technologies (e.g., sensors, radars, and cameras) generally have different performance in inclement conditions. According to the 2015 GES, 7.4% of front-end injury crashes occur in inclement weather conditions. Similarly, 9.1% of fatal lane departure crashes occur in inclement weather. These numbers are significant enough to suggest that further research in this direction would be beneficial to ascertain either improving the sensing technologies or complementing the sensing technology with other forms of effective support mechanisms.

While the results from this paper offer an understanding of the overall net-societal benefits and net-private benefits of crash avoidance technologies, there are several opportunities for improvement. Instead of estimating benefits of fatalities and injuries by a single crash estimate, future analysis should take crash severity into account. The effectiveness of the systems could also be modelled to closely represent real world outcomes where crash avoidance systems may not work properly and can be disabled by the user. In addition, market adoption of these technologies in the overall fleet can be incorporated to reflect how changes in consumer demand could impact overall net-benefits. Policymakers and engineers have already begun to consider the safety benefits and impacts of these warning systems and as more advanced and more highly automated systems become more common in the light-duty vehicle fleet, there could be even greater societal and private benefits from prevented and less severe crashes.

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