Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles

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HELP OR HINDRANCE? THE TRAVEL, ENERGY AND CARBON IMPACTS OF HIGHLY AUTOMATED VEHICLES

Abstract

Experts predict that new automobiles will be capable of driving themselves under limited conditions within 5-10 years, and under most conditions within 10-20 years. Automation may affect road vehicle energy consumption and greenhouse gas (GHG) emissions in a host of ways, positive and negative, by causing changes in travel demand, vehicle design, vehicle operating profiles, and choices of fuels. In this paper, we identify specific mechanisms through which automation may affect travel and energy demand and resulting GHG emissions and bring them together using a coherent energy decomposition framework. We review the literature for estimates of the energy impacts of each mechanism and, where the literature is lacking, develop our own estimates using engineering and economic analysis. We consider how widely applicable each mechanism is, and quantify the potential impact of each mechanism on a common basis: the percentage change it is expected to cause in total GHG emissions from light-duty or heavy-duty vehicles in the U.S. Our primary focus is travel related energy consumption and emissions, since potential lifecycle impacts are generally smaller in magnitude. We explore the net effects of automation on emissions through several illustrative scenarios, finding that automation might plausibly reduce road transport GHG emissions and energy use by nearly half – or nearly double them – depending on which effects come to dominate. We also find that many potential energy-reduction benefits may be realized through partial automation, while the major energy/emission downside risks appear more likely at full automation. We close by presenting some implications for policymakers and identifying priority areas for further research.

Keywords

vehicle automation; energy demand; travel demand; carbon emission; energy intensity; self-driving vehicle, autonomous car

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1 Introduction

Automated vehicles are defined as those in which at least some of the safety critical control functions (e.g. steering, throttle, or braking) occur without direct driver input (NHTSA 2013). While there has always been substantial interest and continuous innovations in vehicle automation through various advanced driving assistance (ADA) technologies, vehicle longitudinal and lateral control systems, and navigation systems, Google's demonstration of a fully automated, autonomous vehicle in 2012 appears to herald a new era of automation. Most automobile manufacturers are already marketing vehicles with some automation features, and working to develop more highly automated and self-driving vehicles. A recent survey of self-identified experts in vehicle automation found a median estimate of 2019 (interquartile range: 2018-2020) as the initial date at which vehicles would be capable of driving themselves on freeways, with drivers available to take over as required. The same group predicted that vehicles would be capable of driving themselves on urban and rural surface roads and highways by 2025 (interquartile range: 2024-2030), and doing so in a failsafe manner (without a human driver backup) by 2030 (interquartile range: 2027-2035) (Underwood, 2014). Optimistic estimates predict that around 30% of the trucks in the UK could be automatically driven by 2022 (Wardrop 2009), while up to 75% of the vehicles on road could be fully automated by 2040 (IEEE 2012). Four cities in the UK will be hosting a fully automated vehicle demonstration, while the city of Gothenburg in Sweden is expected to pilot 100 fully automated vehicles in urban conditions in 2017. Regulators are attempting to keep pace, with four U.S. states (Nevada, California, Florida, and Michigan) plus the District of Columbia already legalizing the testing of driverless vehicles on their roads (CIS, 2015), and the UK government also allowing testing of automated vehicle recently. The U.S. National Highway Traffic Safety Administration (NHTSA, 2013) has also developed a taxonomy of levels of automation ranging from level 0 (no automation) to level 4 (full automation), to which we will refer frequently throughout this paper.

Automation *per se* is unlikely to significantly affect energy consumption, but is expected to facilitate myriad other changes in the road transportation system that may significantly alter energy consumption and GHG emissions. For example, automated vehicles may enable the adoption of energy-saving driving practices, and facilitate changes in the design of individual vehicles or the transportation system as a whole that enable reductions in energy intensity. Fully automated, self-driving cars can offer on-demand mobility services and change vehicle ownership and travel patterns. However, they are also likely to substantially change the in-vehicle experience and the cost of drivers' time in the vehicle (perceived cost for private drivers, and actual cost for commercial drivers), which could lead to more demand for travel by car and modal shift away from public transport, passenger train and air travel. Freight truck travel could also increase. These travel demand and energy intensity related changes would have large total energy and carbon implications.

Researchers, analysts, and policymakers must begin considering the impacts of vehicle automation on future travel and energy demand, and on the efficacy of different policies and technologies intended to mitigate the effects, if they are adverse from societal perspectives. Given the potentially large influence of vehicle automation on travel behaviour, mobility, traffic capacity and end-use energy efficiency, any study on mitigating energy consumption or carbon emissions from the transport sector is likely to miss the mark if the impacts of vehicle automation are not understood. As such, there is a need to get a sense of how automation may affect travel and energy use, by how much, and to identify opportunities to support and guide an environmentally beneficial transition toward vehicle automation.

1.1 Prior work

To date, few studies have quantified the system-wide energy or carbon impacts of automated vehicles. Fagnant and Kockelman (2013) note the potential for reduced per-km emissions and increased travel demand with automated vehicles, but offer few numbers. Their discussion of travel demand effects focuses mainly on the effects of extending mobility to underserved groups and induced demand from capacity improvements. Anderson et al. (2014) mention eco-driving, traffic smoothing, and vehicle lightweighting as potential mechanisms by which automation could reduce energy consumption and emissions per kilometer. They also suggest that vehicle automation might facilitate a transition to alternative fuels, by enabling self-refueling, increasing annual distance traveled per vehicle (accelerating payback periods), and reducing the up-front costs of alternative powertrains (through lighter vehicles the consume less energy overall). Finally, they note that automation could affect travel demand, as a shift to a shared vehicle system could reduce car ownership and travel demand, while several other factors (reduced energy cost per kilometer, increased urban sprawl, the growth of automated taxi services, and decreased use of public transportation) would tend to increase travel demand.

Recent work by Brown, Gonder, and Repac (2014) quantified many potential effects of automation on energy consumption, seeking "to estimate upper-bound effects." They considered platooning, eco-driving, efficient routing, and lighter vehicles as potential sources of reduced fuel consumption per kilometer, and faster travel speeds as a source of increased fuel consumption. They also consider the potential for increased travel demand from currently underserved groups and from demand induced by higher travel speeds and reduced congestion. They model the effects of induced demand using a travel time budget framework, assuming that vehicle kilometers traveled (VKT) increases so as to maintain total time spent traveling. Finally, they consider less time spent searching for parking and higher occupancy enabled by shared mobility services as potentially reducing VKT.

In addition to the above studies, there is a broad literature addressing many of the potential changes that automation could enable. Most papers consider these changes in isolation, and impacts on energy demand or emissions are often specific to the particular conditions being considered. We refer to this literature throughout this paper.

1.2 Objectives and organization of this paper

The objectives of this paper are to:

1. review key mechanisms through which automation may affect transportation energy consumption, including travel demand as a major mechanism;
2. quantitatively estimate the potential magnitudes of these effects, providing bounds on these effects in the context of total road transport energy demand and emissions;
3. develop several scenarios to illustrate plausible ranges of overall future energy and carbon impacts of vehicle automation;
4. identify key leverage points for policymakers at which vehicle automation can be directed toward the goal of reducing energy consumption and carbon emissions

We do *not* attempt to definitively predict changes in energy consumption due to vehicle automation; we believe that confidently answering that question deserves a sizeable, dedicated research effort.

With the exception of the work by Brown et al. (2014), no prior work has addressed these questions systematically. This paper addresses some of the same effects considered by Brown et al. (2014), with several additional contributions. First, we have developed ranges of estimates for each mechanism, rather than a single value. Second, we have drawn upon additional literature sources and used different methods to estimate the potential energy and emissions impacts of vehicle automation. For example, we have used a generalized cost approach to estimate changes in travel demand, and modeled the tradeoff between fuel cost and time cost to estimate potential increases in highway travel speeds. Finally, we have included several mechanisms that were not included in their analysis, including reductions in acceleration performance, separate estimates of the effects of improved crash avoidance and vehicle right-sizing, the potential for increased comfort and convenience feature weight, and reductions in the embodied energy of transportation infrastructure.

The paper is organized as follows. Section 2 explains our methodology in greater detail. Section 3 develops estimates of changes in per-kilometer energy consumption due to changes in vehicle design and operations. Section 4 explores how automation may change the distances that vehicles are driven, while Section 5 describes the potential of vehicle automation to reduce carbon intensity of fuel. Section 6 develops several illustrative scenarios to assess the potential range of net energy and emissions impacts from automation. Section 7 concludes and discusses some implications for policy and future research needs.

2 Methodology

The primary contribution of this paper is to review a wide range of potential mechanisms through which vehicle automation may affect transportation energy use and emissions, consolidating a wide-ranging literature and expressing potential impacts in comparable terms. The paper is structured around the widely-used “ASIF” framework, which expresses transport carbon emissions in terms of the major drivers. (Schipper, 2002). The formulation is summarized in the following equation:

$$Emissions = \boldsymbol{A}ctivity\ Level \cdot Modal\ \boldsymbol{S}hare \cdot Energy\ \boldsymbol{I}ntensity \cdot \boldsymbol{F}uel\ Carbon\ Content \qquad (1)$$

The ASIF framework makes explicit the fact that use-phase emissions from a transportation mode depend on the overall level of travel activity, the fraction of that travel conducted that mode, the average energy consumption per kilometer in that mode, and the carbon intensity of fuels used by that mode. Holding all else equal, changes in any of these factors will lead to a proportional change in overall emissions from that mode. The impacts of multiple independent factors can be readily multiplied together to estimate an overall impact on energy consumption or emissions. It is thus a convenient and intuitive tool for structuring one’s thinking about transportation energy and emissions. The framework is used by a number of influential studies on modeling energy consumption in the transportation sector, e.g. Greene and Plotkin (2013) and Schipper (2002).

We employ the ASIF framework in this paper first as a tool to help organize the various potential mechanisms through which vehicle automation may affect energy consumption and emissions. Each of the four driving factors on the right hand side of Eq. 1 can be substantially affected by vehicle automation and thus energy consumption and carbon emissions. We identified the ways in which vehicle automation could alter the transportation system via a review of relevant scholarly and grey literature (including websites and online discussion forums, popular press articles, and consultants’ reports) and conversations with subject area experts. We then considered whether these changes would be likely to affect VKT (through changes in overall travel demand or mode shares), energy intensity (through changes in vehicle design or operations), and/or fuel choices. Table 1 summarizes these key mechanisms, along with our judgments as to how each mechanism may affect the four driving factors and eventually energy use and emissions. Table 1 also shows our judgment about the level of vehicle automation and penetration of these automated vehicles in the vehicle stock at which the changes could be realized.[1] For example, demand from new user groups can increase the travel activity and alter the existing modal share, but this can be realized only at a high level (levels 3-4) of automation which would encourage new type of users. These impacts, however, can be immediately realized (after the vehicles are on road), even with a low level of penetration of automated vehicles in the overall vehicle fleet.

[Table 1 here]

We next estimated multipliers for the relevant ASIF components for each mechanism identified in Table 1. We began by reviewing the literature for estimates of the individual impacts of each mechanism. Where suitable data or modeling results could not be found in the literature, estimates of the effects were developed using basic engineering and economic analysis, travel survey data, and reasonable assumptions. In all cases, we expressed the potential impact as a fractional change in the applicable driving factors, after considering different types of driving for a typical light-duty vehicle (or, where applicable, a typical freight truck) in the United States: for example, a mechanism such as vehicle platooning may be relevant to only highway driving and not urban driving and such differences are accommodated while deriving the overall multipliers for the mechanisms. The development of these estimates is described in detail in Sections 3, 4 and 5. We also considered some potential lifecycle impacts of vehicle automation: fewer vehicles scrapped due to accidents, and a physically smaller transportation infrastructure due to increased lane capacity, reduced lane width, and reduced parking requirements in Appendix A.

Finally, we developed several scenarios to explore the potential range of overall impacts that automation may have on energy consumption and carbon emissions over the long term. We combine the effects of the various ASIF factors multiplicatively, using a spreadsheet tool based on Greene and Plotkin's (2013) recent study of prospects for reducing U.S. transportation energy consumption and carbon emissions. The scenarios are not meant to be predictions, but plausible, internally consistent alternative visions of how the transportation system may evolve in the presence of automation. These scenarios underscore the substantial uncertainty and large range of potential impacts that an unmanaged transition to automation could produce.

[1] We use NHTSA (2013) definition on the level of vehicle automation: Level 0 - no automation; Level 1 - one or more functions are automated but operate independently of one another; Level 2 - multiple automated system operate in concert, but driver must pay attention to roadway and be prepared to take over control immediately; Level 3 - limited self-driving - vehicle is fully automated under certain traffic or environmental conditions and driver can disengage from driving, but must be available for occasional control, but with sufficiently comfortable transition time; Level 4 - full automation - vehicle navigates entire trip from origin to destination with no involvement from the driver, in an occupied or unoccupied state

2.1 Scope and limitations

Given the breadth of the potential mechanisms and interactions amongst them, it is important to understand the limitations and scope of our analytical approach. Our focus is on *first order impacts*, and the ASIF framework is less amenable to modeling non-independent effects, higher-order interactions, and equilibrium feedbacks. For example, more travel will increase congestion, which will take back some of the increased travel demand, but also lead to increased energy intensity. These nuances can be lost with the simple ASIF formulation, nevertheless it remains useful for aggregating the main effects of automation. It is still possible to include some secondary interactions through developing multipliers that are functions of other multipliers, as long as there is no circularity. We do this in the case of energy intensity and its effect on travel demand, a particularly important interaction effect (known as the 'rebound effect' in energy literature).

The quantitative estimates at this stage focus on the energy impacts through activity (A), modal share (S) and energy intensity (I). Impacts on activity and modal share are combined into a single multiplier for changes in VKT. The study excludes the potential changes in energy use and carbon emissions in other transport modes as a result of vehicle automation (e.g. modal shift from air to highly automated automobiles might reduce aviation energy demand in the long run, but is beyond the scope of this paper). A key assumption is the absence of any disruptive technological innovations in these other modes, keeping the costs of traveling by these modes constant. Potential changes in fuel mix and the carbon content of fuel (F) are discussed only qualitatively, since the impact of automation in this area is little studied.

Our estimated impacts are premised on a nearly complete penetration of automated vehicles in the light duty and heavy duty fleets. We do not make any predictions of when that might happen, but use 2050 as the basis for our scenarios. We also limit our focus on 'vehicle' automation, and do not encompass the full range of intelligent transportation systems (ITS) and connectivity technologies, since they can work as standalone systems without automation of the driving task *per se*.

3 Energy Intensity Effects

Vehicle automation may reduce the energy intensity of vehicle travel, by enabling more efficient operations, facilitating a shift away from the owner-driver model of personal mobility, and altering the size, weight, and efficiency of vehicles. In the sections that follow, estimates of these effects are developed based on simple analyses and reviews of the relevant literature.

3.1 Congestion mitigation

Vehicle automation may reduce the energy wasted by congestion, by improving traffic flow and reducing accident frequency (both are sources of congestion). Schrank, Eisele, and Lomax (2012) have estimated the annual volume of fuel wasted in the U.S. due to congestion for each year since 1982. Dividing their estimates by total on-highway gasoline and diesel consumption (from the Energy Information Administration) indicates that the fraction of fuel wasted on congestion rose steadily from 0.5% in 1984 to 1.8% in 2005, and is expected to reach 2.6% by 2020. Extrapolating this trend suggests that 4.2% of fuel would be wasted due to congestion in 2050. So, the complete elimination of congestion might decrease the energy intensity of road vehicle travel (light-duty and heavy-duty combined) by about 2% today and a little over 4% in 2050.

3.2 Automated Eco-driving

Automation may facilitate the broad implementation of so-called "eco-driving," a set of practices that tend to decrease in-use fuel consumption without changing vehicle design. One way to reduce energy consumption is to drive so that the engine can spend as much time as possible at its most efficient operating points, which typically means high load and moderate speed. Another is to minimize repeated braking-acceleration cycles, since braking represents wasted energy (Barth and Boriboonsomsin, 2008).

One branch of the eco-driving literature focuses on driving practices that reduce fuel consumption, and the efficacy of training drivers in these methods. Barth and Boriboonsomsin (2009) concluded that providing real-time advice to drivers could reduce energy consumption by 10-20%. Human drivers in a simulator reduced their energy consumption by between 0 and 26% when provided with real-time guidance on optimal acceleration and deceleration behavior (Wu, Zhou, and Ou, 2011). Degraeuwe and Beusen (2013) found that without continual reminders, drivers who took an eco-driving course reverted to less-efficient habits over time. Berry (2010) showed that many eco-driving studies found savings averaging 20% in the short run, but closer to 10% in the long run.

A second branch of the literature focuses on optimizing the driving cycle to minimize fuel consumption, while respecting technical and legal (e.g. speed limit) constraints and maintaining travel time. The potential is greatest in urban conditions, which include more stop-and-go traffic. In heavily congested conditions, optimal drive cycles may reduce energy consumption by 35-50% (He at al., 2012), but such conditions are only occasionally encountered in practice. For a Renault Clio, an optimized drive cycle was found to reduce energy consumption by 16% compared with the New European Driving Cycle (NEDC) while maintaining travel time and respecting speed limits (Mensing, Trigui, and Bideaux, 2011). Compared with a real-world drive cycle, the potential reduction was found to be as much as 34%. However, the presence of other vehicles on the road constrains the ability of drivers to follow an energy-minimizing drive cycle, and depending upon the acceptable following distance from other vehicles, energy savings were found to drop to just 15% (Mensing et al., 2013). For a Toyota Prius hybrid, an optimized drive cycle was found to save just 10% relative to a real-world drive cycle (Mensing, Trigui, and Bideaux, 2012). This is not surprising since hybridization both enables regenerative braking and permits the engine to operate at higher efficiency more of the time.

Considering this body of work, it appears that while Berry's (2010) short run reduction of 20% for human drivers can be sustained by automation in the long run. An additional complication in evaluating eco-driving comes from the effects that these practices (particularly slower speeds and gentler accelerations) have on road capacities and congestion levels. As a result, several investigators have reported that system-wide fuel consumption may remain unchanged, or even increase, when eco-driving practices are widely used more (Orfila, 2011; Qian and Chung, 2011; Kobayashi, Tsubota, and Kawashima, 2007) found that this take-back effect is most significant when driving in already-congested conditions. In light of these findings, and the fact that realizing these benefits depends upon eco-driving algorithms being engineered into automated vehicles, it is also possible that eco-driving practices will deliver little system-wide benefit, which is the lower bound of our estimate.

3.3 Platooning

Platooning refers to the practice of multiple vehicles following one another closely, leading to reductions in aerodynamic drag for all of the vehicles, but particularly for the vehicles in the middle of the pack. Platooning may also increase roadway capacity, helping to reduce congestion as discussed above, and reducing the need for roadway capacity expansions. Platooning in tight formations is unsafe without automation, because of the delays in human drivers perceiving and reacting to speed changes of the vehicles ahead.

Drag reductions from platooning depend on the shapes of the vehicles in the platoon, their ordering, and their following distances. Since savings are bigger for vehicles in the middle of the pack, average savings increase with the number of vehicles in the platoon. For two sedans 1 m apart, the average reduction in drag has been estimated to be 10% (Zhu and Yang, 2011). For platoons containing mixed vehicle types, drag reductions between 20% and 60% have been reported (Schito and Braghin, 2012; Duan et al., 2007). For a long platoon of vans (five or more vehicles) separated by 0.5-1.0 vehicle lengths, average drag reductions between 45% and 55% have been reported (Schito and Braghin, 2012), while reductions of up to 60% have been reported for the vans in the middle of a platoon with short following distances (less than half a vehicle length) (Zabat et al., 1995).

To estimate the effect of platooning on energy intensity, we consider the fraction of energy use that goes to overcoming aerodynamic drag, and the fraction of kilometers in which platooning could deliver a benefit. Since aerodynamic losses increase with speed, and because it is more practical to keep cars in formation at constant speeds, platooning offers significant potential for energy savings mainly in highway driving. Based on FHWA travel statistics, highway travel comprises between 33% (counting only interstates and expressways) and 55% (also including principal arterial roads) of all kilometers traveled in the U.S. Kasseris (2006) shows that on the U.S. Highway Fuel Economy Test cycle, about 50% of tractive energy goes to overcoming drag, and that for steady-speed travel at more typical highway speeds (90-120 km/h), drag accounts for about 75% of tractive energy requirements. Combining the above factors suggests that if platooning were universally adopted during highway travel for light-duty vehicles, it might reduce energy intensity by anywhere from about 3% (20% drag reduction * 50% of load * 33% of kilometers) up to 25% (60% drag reduction * 75% of load * 55% of kilometers).

For freight trucks, Tsugawa (2013) has reported a 10% reduction in energy consumption for a 3-truck platoon at 80 km/h, with a 20m gap between trucks (15% reduction at 5 m gap). Extrapolating his results toward zero gap implies a 25% reduction for the middle truck. This represents a plausible upper bound for the middle vehicles in a long platoon. Lu and Shladover (2013) reported savings of 4%, 10%, and 14% in fuel use for first, second, and third trucks, respectively, in a 3-truck platoon with 6 m spacing. Since the large majority of freight kilometers are on the highway, we can use these energy savings estimates directly and estimate an upper range of 10-25% energy intensity reduction from platooning of heavy trucks.

3.4 Changing highway speeds

Automation may lead to increased highway travel speeds, if human attention and reaction times are no longer limiting factors in determining safe speeds. Since aerodynamic losses increase with speed, this could increase the energy intensity of vehicle travel.

To bound this effect, it is necessary to predict how much faster people might travel in the absence of speed limits. Currently, speed limits on most U.S. interstates and other limited-access highways range from 88-113 km/h (55-70 mph), and actual interstate speeds average 105-113 km/h (65-70 mph) (White, 2010). To estimate speed in the absence of speed limits, we assume that drivers will increase their speed until the marginal value of time saved just matches the marginal cost of increased fuel consumption. Assuming a value of travel time of $18 per hour (Trottenberg, 2011) and a fuel price of $0.92 per liter ($3.50 per gallon), and the speed – fuel consumption relationship of a typical car (Berry, 2010), suggests that light-duty vehicle speeds might increase to 127 km/h (79 mph) on U.S. highways in the absence of speed limits and safety considerations. This matches well with an average speed of 140 km/h (88 mph) on sections of Germany's Autobahn system that do not have speed limits (Scholz, Schmallowsky, and Wauer, 2007). Increasing highway speeds to these levels would increase energy intensity by 20-40% on the highway. These faster speeds are applied to between 33% and 55% of all distance traveled (i.e. all highway travel using FHWA metrics), yielding average energy intensity increases of 7-22% for light-duty vehicles.

On interstate highways, freight trucks currently average between 80 and 97 km/h (50 and 60 mph). Similar calculations as above, using the weight, drag, and other characteristics of a class 8 truck and assuming a cost of $25 for the driver's time (Trottenberg, 2011), show an optimum travel speed of 84 km/h (52 mph). This suggests that truck travel speeds would not necessarily be expected to increase even if speed limits were increased, particularly if advanced automation decreased the hourly cost of drivers' time.

3.5 De-emphasized performance

Today's new cars and trucks can accelerate from 0-97 km/h (0-60 mph) about twice as quickly as new vehicles in the early 1980s (MacKenzie and Heywood, 2012). Taking drivers "out of the loop" may reduce the demand for acceleration capabilities in light-duty vehicles, since hard acceleration may become more a source of discomfort than of visceral satisfaction.

If historic trends continued, the average acceleration of new vehicles would fall from about 8.8 seconds currently, approaching 7.8 seconds (MacKenzie & Heywood 2012). MacKenzie (2013) has estimated that (holding other vehicle attributes constant) a 1% increase in the 0-97 km/h acceleration time decreases per-kilometer fuel consumption by 0.44%. If instead of continuing historic trends, acceleration capabilities stabilized at current levels, future energy intensity could be reduced by about 5%. If acceleration capabilities reverted to 1982 levels, fuel consumption could be reduced by 23%. Vehicles delivering 1982-level performance would likely have sufficient power to maintain highway speeds in excess of 160 km/h. However, larger reductions in acceleration performance, entailing larger reductions in engine power, could come into conflict with the power requirements of increased highway speeds, as discussed in Section 3.4.

3.6 Improved crash avoidance

More than 90% of accidents are commonly attributed to human error (NHTSA, 2008). Automation can dramatically lower crash rates, and render crashworthiness of the vehicles much less important in the future. In this situation, vehicles could become smaller and potentially shed safety equipment. These effects are speculative and seem unlikely to materialize until traffic risks are radically and convincingly reduced.

MacKenzie et. al. (2014) have estimated that safety features contributed 112 kg out of 1452 kg (7.7%) of the average new U.S. car's weight in 2011. Based on common estimates of the relationship between weight and fuel consumption (MacKenzie 2013), removing this safety weight would decrease fuel consumption by 5.5%.

A more extreme reaction to improved crash avoidance might be consumers shifting into smaller vehicle classes, which might be perceived as insufficiently safe today.[2] In 2010-2012, average fuel economy of new light-duty vehicles in the U.S. was 28.8 miles per gallon (mpg) (8.17 l / 100 km), while that of compact cars was 35.3 mpg (6.66 l / 100 km) (EPA, 2013). If improved crash avoidance could make everyone willing to switch to a compact car, it could reduce average per-kilometer fuel consumption by about 18%. Combined with the reduction of safety equipment, this could yield an estimated maximum 23% reduction in fuel consumption. Since safety is certainly not the only reason that people choose larger vehicles, this is very much an upper-bound estimate of this effect.

3.7 "Right-sizing" of vehicles

Despite the fact that most light-duty vehicles in the U.S. seat at least four people, the average occupancy of these vehicles was just 1.67 in 2009 (Davis, Diegel and Boundy, 2012). This slack capacity implies that if vehicle capacity could be matched to individual trip requirements, considerable reductions in average energy intensity could be realized. This practice would be promoted by the availability of some sort of automated carsharing or on-demand mobility model, in which a traveler requests a vehicle sized to match the needs of a certain trip, and said vehicle (with Level 4 automation) delivers itself to the traveler.

To assess the potential reductions in energy intensity from this approach, the average energy intensity under current travel patterns can be compared with that which could result from matching trip-specific passenger requirements to vehicle size. Based on the 2009 National Household Transportation Survey (NHTS), the distance-weighted average fuel economy for private vehicle travel was 24.8 MPG (9.50 l / 100 km).

One possible scenario is that trips are met with currently-available vehicles. Assume that all private vehicle trips with 1-2 travelers are met with compact cars (32.1 MPG, 7.33 l / 100 km), those with 3-4 travelers are met with midsize cars (29.4 MPG, 8.00 l / 100 km), and those with 5-7 passengers are met with minivans (24.2 MPG, 9.72 l / 100 km). Assume that those (very few) trips with more than 7 passengers were met with whichever vehicle that was actually reported by the NHTS respondents (no right-sizing). This would increase the distance-weighted average fuel economy to 31.3 MPG (7.49 l / 100 km), a 21% reduction in energy intensity.

Since many trips are made by single-occupancy vehicles, a more ambitious scenario presupposes the development of a new class of single-person vehicles. Predicting the fuel consumption of such a hypothetical vehicle is difficult. However, motorcycles are estimated to consume a little more than half as much energy per kilometer as an average car (2881 BTU/mile or 1889 kJ/km versus 5342 BTU/mile or 3502 kJ/km) (Davis, Diegel and Boundy, 2012). Let us assume that the hypothetical

[2] For example, 4-wheel drive SUVs are often perceived as safer by the consumers (Gladwell, 2004).

vehicle would achieve double the fuel economy of a compact car, holding the level of technological sophistication constant. Assume further that this hypothetical single-person vehicle serves all trips with a single occupant, while a compact car serves all trips with two occupants. Again assuming that 3-4 person trips use midsize cars and 5-7 person trips use minivans, the distance-weighted average fuel consumption would be reduced by 45% in this case.

While the potential is impressive, it is very optimistic. Full right-sizing benefits may only be achieved with automated car-sharing. The estimated potential considers passenger movement as the only goal of vehicle travel, ignoring cargo-carrying, towing and other requirements. It ignores other reasons that some users may have for keeping personal vehicles, such as the option to keep child seats or bicycle racks installed. It omits the above mentioned safety considerations, but may be more feasible in conjunction with safety-enabled downsizing. Finally, this approach ignores potential correlations in demand for different vehicle sizes between different households over time. That is to say, trips requiring large vehicles may be a relatively small share of the total, but if they tend to occur on certain days or times (e.g. summer long weekends), the number of large vehicles on the road would not decrease as much.

3.8 Increased Feature Content

Automating driving tasks may lead to travellers devoting more time to other activities in their vehicles. Additionally, as discussed in section 4, travellers may travel greater distances and spend more time in their vehicles. These changes could lead to increased consumer demand for vehicle features and in-vehicle comfort, which could lead to heavier vehicles that consume more fuel. MacKenzie et al. (2014) estimated that the addition of safety, emissions, and comfort and convenience features added approximately 200 kg to the weight of the average new car in the U.S. between 1980 and 2010. If greater demand for comfort and convenience features doubled this rate of increase, it could add an additional 240 kg of weight to the average new car by 2050 (beyond any business-as-usual increases in feature weight). Assuming a base vehicle weight of 1,452 kg, this additional weight would increase fuel consumption by about 11% in 2050. It is also conceivable that level 4 automobiles could become larger and less fuel efficient to provide added comfort and relaxing opportunities (e.g. space for a fully reclining seat).

4 Travel Demand Effects

Despite significant interest in the energy saving benefits of vehicle automation, the potential countervailing energy impacts are often overlooked. Vehicle automation could increase transportation energy consumption by increasing vehicle travel, as a response to a sharp reduction in generalized travel costs for automated vehicles. Travel demand may also grow as automation makes private vehicle travel accessible to demographic groups who do not drive now or drive less than they might like. Automation can also allow wider-scale adoption of carsharing or on-demand mobility services. All of these mechanisms are represented in our ASIF framework in Eq. 1 through the 'road travel activity' term, which combines the effects on *A* and *S*.

4.1 Increased travel from reduced cost of driver's time

Automation can alter the generalized travel costs for driving personal vehicles substantially in several ways. Firstly, vehicle automation (levels 2-4) is expected to substantially reduce accidents on road, 90%-95% of which are caused by driver error (NHTSA, 2008). This should reduce vehicle insurance costs per kilometer. Secondly, vehicle automation will relieve - to varying degrees, depending on the level of automation - driving related stresses and demands on attention, and thus reduce the perceived discomfort costs of driving. We view this as a reduction in the cost per hour of the driver's travel time, implying a reduction in driver's time-cost per kilometer, one of the largest components in the full generalized cost of travel (Table 2). Finally, automation reduces per-kilometer energy costs, which is an interaction effect ('rebound' effect), but is included in our calculations.[3]

Beyond reducing driver burden, highly automated vehicles (levels 3-4) can actually permit productive use of in-vehicle time. Therefore the cost of a private driver's travel time can be substantially diminished in automated vehicles, to below the cost of time for passengers in rail or taxi travel, in the limiting case of level 4 vehicles. Although there are no studies yet on how the perceived costs of travel time may change due to automation of vehicles, there is evidence in the UK that rail users value their travel time on trains as more productive, i.e. the travel time costs on trains are less than that in cars (Batley et al. 2010, Lyons et al. 2007). Ian Wallis Associates Ltd (2014) reviewed the (relatively sparse) literature on how car passengers' value of time compares to that of drivers, finding estimates that ranged from a negligible difference to approximately a 40% lower value of time for passengers than for drivers. These numbers appear to be sensitive to trip purpose. The effects on heavy-duty vehicles may also be similar, with reduced energy, insurance and driver related costs playing an important role (for level 4, long-haul driver cost could approach zero), which would make trucking more attractive than other transport modes. Apart from issues of labor relations and industrial organization, the heavy-duty assessment is conceptually simpler: driving behavior is more governed by economics, and driver cost is clearly defined by labor costs.

In order to quantify the impact on travel activity, we estimate changes in the various vehicle cost components due to automation and apply published estimates of the elasticity of vehicle travel (VKT) with respect to generalized travel costs. Thus, in our ASIF computation, activity *A* is endogenously determined from an economic response to estimated shifts in travel cost components, and energy

[3] Although we have focused mainly on first-order effects in this work, we included this particular interaction effect because energy costs are a large fraction of the generalized travel cost, and are particularly sensitive to automation.

intensity appears both as the separate factor *I* and a variable contributing to the endogenous cost-based determination of activity.

Although there is a large literature on elasticities of VKT or fuel demand with respect to fuel prices, estimates for light duty VKT elasticities with respect to generalized travel costs per kilometer are few. FHWA (2005) suggests a long-run elasticity of -1.0 to -2.0, while Graham and Glaister (2002) recommends -2.3. For heavy vehicles, freight demand elasticities with respect to total costs range from -0.5 to -1.75 (Cambridge Systematics, 2009, Graham and Glaister, 2004, Winebrake et al. 2012), with a choice of -0.97 to -1.0 as a central value by HDR/ICF (2008) and Cambridge Systematics (2009). Since these are long run elasticities, the corresponding changes in road travel distance include a range of responses to reduced travel cost, such as modal shift from rail or aviation, increased trip frequencies and distances, as well as increased travel resulting from altered residential and business location choices. Moreover, since these are long-run responses, average costs (such as the average insurance cost per kilometer) are appropriate, as insurance rates will ultimately adjust based on distances that people are driving. We calculate the present day vehicle running and fixed costs per kilometer for light duty vehicles and heavy duty trucks, which are presented in Table 2, and apply the elasticities to total costs given posited changes in key cost components.

[Table 2 here]

We account for several changes in fuel costs per kilometer based on the estimated changes in energy intensity discussed in section 3. In order to understand the maximum potential change in insurance costs due to vehicle automation, we use Celent's (2013) estimate of a 60%-80% reduction in insurance costs resulting from an estimated 90% reduction in accidents. Although it is widely believed that automation will reduce the cost of in-vehicle time, no estimates are available at the moment (Small 2012). We therefore assume a range of 5% (for Level 2) up to 50%-80% (for levels 3 and 4) reduction in cost of travel time. This allows us to modify the generalized travel costs per kilometer due to vehicle automation and quantify the travel impacts through the following relationship, which is then used to derive the ASIF multiplier for travel activities:[4]

$$VKT_{auto} = VKT_{pre-auto}\left(\frac{generalized\ cost_{auto}}{generalized\ cost_{pre-auto}}\right)^{elasticity} \quad (3)$$

This results in a wide range of changes, from a 4% increase for low-level automation to around 60% increase for level 4 automation for light duty travel. The wide range reflects the uncertainty regarding the changes in the costs of travel time from automation. Inclusion of any uncertainty in the long run elasticity of travel demand for large changes in generalized cost would increase this range further.

[4] note that for this work, we did not modify vehicle purchase costs, as our assumption is a wide-scale adoption of automated vehicles, which will not take place unless vehicle prices are near to current prices in real term.

While we have incorporated secondary interactions between per kilometer costs related to energy efficiency improvements resulting from automation as described Section 3 (rebound effect), some other secondary impacts are not included. These might include lower driver time per kilometer due to higher speed or reductions in parking costs if level 4 vehicles can park themselves to low-cost (or even zero-cost) parking areas. Our approach of using elasticities should also be interpreted carefully given these elasticities were determined over a relatively narrow range of observed costs. The elasticity approach also fails to appreciate the role of travel time budgets (e.g. Marchetti (1984) and Schafer et al. (2011) argue that commuting time budget has remained constant over centuries). But this is less of an issue for levels 3-4 since the travel time budget itself is likely to change if in-vehicle time becomes productive.

4.2 Increased travel due to new user groups

Vehicle automation may increase travel by specific user groups not actively driving, increasing demand beyond that captured by the response of current drivers as in the previous section. Indeed, planners and vehicle manufacturers identify enhanced mobility for older or driving-restricted demographic groups as a major motivation for automation (Bigman 2014). There is a noted decline in vehicle license holding and vehicle travel for the elderly, due to both stage-of-life factors and age-induced disabilities which make driving risky. To bound the increase in travel among these individuals, we consider both the potential for more drivers among the elderly and the young, and for more travel per elderly driver.

NHTS (2009) data shows that the age group with the largest fraction of drivers is the 35-55 group. We assume that automation could lead to the same share of drivers across all age groups (16 and above), which provides the increased number of drivers resulting from vehicle automation. NHTS (2009) also shows that vehicle kilometers travelled per driver peaks at age 44, then declines steadily through age 62 and more steeply after that. This is believed to result from multiple factors, including retirement or reduced working week as well as age-related disabilities. In order to determine increased driving per elderly driver, we assume that the decline between ages 44 and 62 represents the 'natural' rate of decline in travel needs, and that the accelerated decline after age 62 represents travel that is foregone due to impaired driving abilities. We calculate the latent demand that could be filled through automation as the difference between the actual age-driving curve and the linear extrapolation of the age 44-62 trend (Fig. B1 in Appendix B). We note that the post-62 decline also includes retirement, but argue that the retirement age itself can be a function of driving ability, which will be enhanced substantially by level 3-4 automation. Also, the natural decline (44-62) - at least partially - captures some of the fall in driving due to retirement.[5] As an upper bound, we assume everyone aged 62 and

[5] If retirement is not a function of driving ability, then the blue line would be closer to the green line in Fig. A1. Note also, our estimates are on the higher side since there is a self-selection issue in NHTS data - only those

above drive as much as those 62 years old. These result in an increase of 2%-10% in overall personal vehicle travel, after considering the current aggregate age-wise travel distribution. For this work, we do not include any potential increase in driving distances or changes in vehicle ownership arising from those younger than 16 year old.

For heavy duty vehicles, whose primary purpose is to transport goods, automation may create new categories of demand outside those included in the estimated economic response to generalized cost, but we do not identify any here.

4.3 Changes in mobility service models

New service models of mobility, such as car-sharing (through car clubs or peer to peer) and on-demand mobility, can be revolutionized by vehicle automation. Such services typically charge consumers on a per-trip (per-mile and/or per-minute) basis, and there is some evidence that such marginal-cost pricing can reduce demand for travel compared with the high-fixed-cost / low-marginal-cost model of personal car ownership. Car-sharing through commercial car-clubs is becoming increasingly popular, and there is some evidence that it results in reduced vehicle travel activities by members (Cervero et. al. 2007; Martin and Shaheen 2011). However, one impediment to broad adoption of the car-club model is that there is often not enough access to cars to attract new users, and not enough users to justify deploying more cars. Level 4 automation may mitigate this access barrier by allowing vehicles to deliver themselves to the user on-demand, reducing the need for geographic concentration of vehicles. The need to own a vehicle may diminish significantly, and perhaps entirely, if the availability of such on-demand vehicles can be ensured in future. It is also quite possible for traditional taxi services to merge with car-sharing type mobility services.

Spieser et al. (2014) show that a fully automated taxi fleet one-thirds the size of passenger car fleet in Singapore can meet all its travel needs, but do not focus on VKT or energy implications. Martin and Shaheen (2011) estimate that the net effect of using car-clubs is a reduction of 0.84 t CO_2 per household, which represents an 8.8% reduction in CO_2 emissions, and, by extension, energy use from personal vehicle travel. Given that shared cars are generally more fuel efficient than average household vehicles, the vehicle travel reduction is less than 8.8%. While the final calculations on energy implications will not necessarily be different, we cannot decompose the reported net reduction from car sharing into activity and fuel intensity effects.

The 8.8% reduction in CO_2 emissions and energy use is a result of an increase in vehicle travel by previously non-motorized travellers (increase of 0.13 t by 53% of members) and a decrease in travel by those who owned vehicle(s) previously. We therefore estimate that vehicle owners reduced their

elderly drive, who currently has a great 'need' to drive. The rest of the elderly may not have such 'need' even if self-driving become available.

emissions by 1.93 t ((0.84*100 - 0.13*53)/47), which is around 20% of total emissions and energy use. Although non-vehicle owners may increase their travel, we neglect that impact for our upper bound estimate of 20% reduction. This estimate may reflect self-selection bias (i.e. households which were planning to reduce their travel join the car-clubs) and can inflate the reductions. Despite the potential for a decline in vehicle kilometers, the possibility of increased travel activity cannot be completely ruled out, either, as level 4 automated vehicles would spend some time deadheading (traveling empty to pick up passengers) in an on-demand mobility system. Fagnant and Kockelman (2014) show that shared automated vehicles could increase VMT as much at 10% compared with privately owned vehicles. Therefore, our lower bound assumes the personal demand reduction due to shared mobility is cancelled out by the increased travel due to deadheading.

5 Fuel mix changes

Beyond altering energy demand and emissions through activity, mode share and energy intensity, there is a prospect that automation could alter carbon emissions by encouraging a change in the carbon intensity of fuels used. We identify three mechanisms here by which automation could make advanced alternative fuel technologies (e.g. electric vehicles, hydrogen fuel cell vehicles, or compressed natural gas vehicles) more competitive, and possibly speed their introduction.

First, highly automated vehicles could travel to an alternative fuel station and refuel in unattended mode. This would sharply reduce the user-perceived cost and inconvenience of fuels such as electricity or hydrogen with limited station availability and long refuel/recharge times. These factors, and the implied high cost of the necessarily widespread refueling infrastructure are widely cited as significant barriers to the introduction of alternative fuels (Greene 1998, Nicholas et al. 2004, Melaina et al. 2012.) Considering limited station availability alone (not refueling time), Melaina et al. 2012 estimated that the consumer inconvenience for an alternative fuel with very low (1%) station share is equivalent to $1500 to $4000 per vehicle. Fully automated alternative fuel vehicles could largely avoid this penalty.

Second, most low-carbon alternative fuels have low volumetric energy density, and high storage costs (electricity, H_2, CNG), leading lower vehicle operating range. Low range is thought to be an important barrier to electric vehicles, for example (NRC 2013). One line of reasoning suggests that automated vehicles – by refueling/recharging themselves frequently, automatically and with little user inconvenience – can circumvent this important barrier.

Third, many advanced fuels and vehicles are very capital intensive, involving expensive batteries, fuel-cells, storage tanks, etc., but offering greater energy efficiency, lower emissions, and/or lower energy costs per kilometer. As mentioned earlier, highly automated vehicles may be well suited to the carsharing or mobility-on-demand service models. Automated shared vehicles are likely to be moved from task to task, driven far more kilometers per year than current private vehicles which spend most of their time parked. Such high-utilization rates call for vehicle types that have low operating costs, are durable, more energy efficient, and ideally use lower-cost fuels like electricity or natural gas. Thus automated vehicles that are driven a lot, particularly for carsharing, seem good candidates for high-capital-cost advanced vehicles optimized for high-efficiency, either conventional or alternative fuel drivetrain.

Together these three mechanisms suggest that automation may be favorable to the introduction of advanced and alternative fuels, and may lead to a reduction in fuel emissions intensity, *F*. We leave quantitative analysis of this topic for separate work.

6 Scenarios and Net Energy Effects

Following the discussions in Sections 3 and 4, Figure 1 summarizes the range of potential energy impacts for each mechanism. Figure 1 not only provides an understanding of the relative magnitude of the impacts through various mechanisms, but also shows the uncertainties around these estimates. It is clear that while a number of mechanisms can result in a substantial reduction in energy use and carbon emissions in future, there are also a few which can have an opposite effect. The substantial technical, behavioral, and regulatory uncertainty around vehicle automation mean that it would be unwise to 'predict' the precise impacts of automation on transportation energy consumption or carbon emissions. The overall energy and environmental implications of automation in future will depend upon:

- The degree to which energy-saving algorithms and design changes are implemented in practice;
- The degree to which automation actually leads to system-wide changes that facilitate energy savings, e.g. shared vehicles, adoption of alternative propulsion technologies and fuels;
- The degree to which reduced driver burden (and reduced cost of time spent in the vehicle) lead private travelers to spend more time and travel greater distances in their vehicles, or lead to greater commercial roadway activity;
- Policy responses at the federal, state, and local levels.

[Figure 1 here]

Given the uncertainties in predicting the above factors, we present several scenarios to illustrate how the transportation system might evolve in the coming decades in response to vehicle automation. Rather than being predictions, these four scenarios are meant to illustrate how plausible responses to vehicle automation could lead to dramatically different energy and environmental impacts. Table 3 provides a description of each scenario, along with ASIF multipliers corresponding to each of the effects outlined in Sections 3 and 4. The scenarios vary in terms of the levels of automation achieved, effectiveness of the mechanisms listed in Figure 1 in altering energy intensity, the degree of achieved cost reductions (including the cost of driver's travel time), and the magnitude of demand response.

[Table 3 here]

Figure 2 shows the results for the four scenarios, illustrating a broad range of plausible outcomes. In the optimistic “Have our cake and eat it too” scenario, all of the energy intensity benefits develop and travel demand increases only slightly, yielding around 45% reduction in total 'road' transportation energy demand. Given road transport is responsible for nearly three-fourths of all transport energy consumption, this represents an approximately 40% reduction in total transport energy demand.[6] In the “Stuck in the middle” scenario, energy intensity benefits are partially offset by higher travel demand, yielding a modest 9% reduction in total road transport energy (7% for all transport energy). In “Strong responses,” all of the envisioned mechanisms deliver maximum effects, yet these cancel out to leave transportation energy essentially unchanged. “Dystopian nightmare” is a pessimistic case in which no energy intensity improvements actually materialize, but travel time costs fall, travel demand increases significantly, and highway speeds actually increase energy intensity, more than doubling transportation energy demand. Such a scenario is highly unlikely given other constraints that will possibly limit such an increase, but it is still useful to highlight the potential increases in energy demand due to automation. The variability of our scenarios is instructive, emphasizing both the opportunity for significant energy and transportation benefits, and the need for more careful analysis to identify net effects, and guard against adverse outcomes, especially as we move toward level 4 automation. [Figure 2 here]

7 Conclusions and Policy Implications

Several key insights have emerged from this work. First, vehicle automation offers the potential for substantial reductions in energy consumption and emissions. Second, these reductions are not assured, since they generally are not direct consequences of automation *per se*. Instead, they follow from other changes in vehicle operations, vehicle design, or transportation system design, which may be facilitated by automation. Thirdly, some of these reductions may be enabled by greater connectivity in vehicles, even without full automation. Finally, total automobile travel and fuel consumption could increase significantly, if automation sharply reduces the cost of drivers’ time and sufficient energy intensity benefits are not realized.

[6] ignoring the important modal substitution effects, which is beyond the scope of current work

One of the major findings of this study is the potential for different energy efficiency and travel impacts resulting from different levels of automation. In the nearer term, at relatively low levels of automation, many of the energy intensity saving mechanisms could be realized, which would most likely outweigh the modest increases in travel activity. Many initial savings may also come from vehicle connectedness, in concert with or apart from automation. Yet at a high level of automation, some conditions lead to very different energy outcomes, with a possibility of substantial increases in travel activities and energy consumption. This suggests that policymakers may wish to focus their energies less on accelerating Level 4 automation (which may come in due course), and more on measures that promote the application of automation toward socially desirable objectives.

Policymakers should be considering early actions to mitigate possible negative outcomes from vehicle automation, while encouraging the realization of its potential energy benefits. Among the changes more directly influenced by automation, eco-driving and platooning appear to offer substantial energy intensity reductions: in the range of 5-20% from each, if universally adopted. Platooning is likely to require some coordination between vehicles, since drag reductions and travel cost savings depend on a vehicle's ability to drive safely in a tight formation. Regulations to mandate and standardize V2X communication capabilities and protocols may be a necessary enabler. In addition, "off-cycle" credits (for fuel economy or GHG emissions improvements that are achieved when driving in more efficient ways than simulated by the test-cycles) can provide an additional incentive for automobile manufacturers to develop energy-saving automated vehicle control algorithms. The off-cycle credit regulations do not yet directly address automation. Greater clarity is needed on the mechanisms by which manufacturers can reliably generate obtain off-cycle improvements and gain verifiable credits for vehicle partial-automation technologies. In the near-to-medium term, new CAFE/GHG test driving cycles may be needed for automated vehicles.

A shift over time from privately owned, privately used vehicles to a shared-use system with some automation might decrease energy, vehicle travel and emissions in several ways. On-demand mobility services could decrease demand by exposing travelers to full marginal-cost pricing. Widespread use could also create a market for small, 1- or 2-passenger vehicles, or could get more travelers into a larger shared vehicle (as with uberPOOL or Lyft Line today). Finally, it is hoped that shared-use vehicles, given their higher annual VMT and utilization factors than private vehicles, could more easily amortize the high capital cost of many efficient, low-carbon vehicle and fuel technologies that offer lower operating costs per mile. Local policymakers may therefore wish to consider the energy and travel demand benefits of permitting these services to operate within their jurisdictions. The operation of current on-demand mobility providers also provides an opportunity to learn and better prepare for a future in which automated taxi services are widespread.

At present, the long-term potential for automation to increase travel and energy demand is not widely appreciated. If the cost of in-vehicle time falls dramatically over the longer term due to automation, policies like road pricing will become much more important as a means to control VMT and congestion. This will be especially true if on-road energy intensity per km also falls, which would render energy-based (gasoline) taxes less effective for managing travel demand. Under current U.S. federal regulations, vehicle emissions are primarily controlled on a grams-per-mile basis. These regulations may also need to be reconsidered if automation induces greater demand. Fortunately, vehicle automation can also facilitate the implementation of policies that efficiently manage vehicle travel. For example, dynamic road pricing to control local congestion or to reduce overall travel demand could be implemented readily in self-driving vehicles by taking advantage of the vehicles' built-in navigation and communication systems. Implementation of other innovative policies directed at total emissions, such as personal carbon trading (Wadud 2011), or total travel, like VMT trading (Wadud 2008), would also be facilitated with connected and automated vehicles.

In the longer term, radical reductions in accident rates could render conventional crashworthiness much less important to safety outcomes. Smaller vehicles with less safety equipment and occupant protection mass could significantly reduce vehicle weight and per-km energy consumption. While it would be premature to relax crashworthiness requirements for automated vehicles at this time, regulators should monitor the crash rates of highly automated vehicles and consider appropriate changes in the future.

This work has highlighted some critical issues and uncertainties regarding the energy implications of automation. The way drivers value their time is crucial to predicting changes in both travel demand and desired highway speeds, but may vary widely around the central value investigated here. Future research should investigate the distribution of value of time, particularly among likely adopters of automated vehicles. The reduction in the cost of driver's time from automation is similarly important but almost entirely unexplored, and would benefit significantly from further research. We also did not account for competitive responses and any energy/cost reductions in other modes such as air and rail. Finally, automation can enable dramatic shifts in mobility models, vehicle design, fuel choices, and vehicle use patterns, but we are only beginning to gather the information to assess how these changes might actually materialize over time. Research that improves our understanding of these individual responses and integrates them in a coherent framework would be most beneficial for future policymaking.

Ultimately, we should not view vehicle automation through rose-colored glasses. The ultimate effect of automation on travel and energy demand may be positive or negative, and we cannot yet say which. Clear-headed analysis, evaluation, and adaptive policymaking provide the greatest chance of realizing the full benefits of automation and minimizing the costs.

Appendix A: Life cycle effects

While our primary focus is the first-order impacts of vehicle automation on energy consumption, many second or higher-order effects may also prove to be relevant. For example, smaller and lighter vehicles, and fewer vehicles destroyed in collisions, could mean less manufacturing and disposal energy. Higher effective road capacity and fewer accidents could mean narrower roads and less new construction. On-demand mobility services and self-parking vehicles could mean less energy invested in building parking facilities.

Argonne National Laboratory's GREET 2 lifecycle model indicates that about 90% of the lifecycle energy use of a light-duty vehicle is associated with fuel production and use. GREET 2 attributes about 100 GJ of energy use to the manufacturing, assembly, disposal, and recycling of a conventional vehicle. Approximately 3 million vehicles are declared total losses in the U.S. each year.[7] Even if no vehicles were declared total losses, the manufacturing and disposal energy saved each year would be the equivalent of only about 1.4% of annual on-road fuel use (approximately 640 billion liters, 170 billion gallons, or 2.2×10^{19} J). Since the vehicles declared total losses have an average age of 9-10 years, the actual energy savings would be somewhat less than 1.4% of on-road fuel use.

Automated vehicles could operate on infrastructure systems with significantly less embodied energy. With more precise control than manually operated vehicles, automated vehicles might be able to operate safely in narrower lanes. Although most light-duty vehicles are 1.6-2.0 m (5-6.5') wide, a typical class 8 tractor is 2.6 m (8.5') wide. Thus, 2.7 m (9') appears to be an absolute minimum for lane width even with automated vehicles. Current standards call for lane widths of 3.6 m (12') on freeways, 3.3-3.6 m (11-12') on rural arterials, 3.0-3.6 m (10-12' on urban arterials and all collector routes, and 2.7-3.6 m (9-12') on local roads. Assuming that the average width for each road class falls in the middle of the respective range, and weighting by the total length of each class of road in the U.S. (as reported by the Federal Highway Administration), it is estimated that narrowing all lanes to 2.7 m (9') could reduce the footprint of the U.S. road system by 16%.

In addition to enabling narrower lanes, automated vehicles could also reduce the total number of lane kilometers required, by increasing lane capacity. Here it is assumed that automated vehicles can double lane capacity (Shladover, Su, and Lu, 2012). We further assume that with this doubling of capacity, 3- and 4-lane roads could be reduced to 2 lanes, roads with 5 to 8 lanes could be reduced to 4 lanes, those with 9-12 lanes could be reduced to 6 lanes, and so forth. One- and 2-lane roads were assumed to maintain the same number of lanes, even with automated vehicles using them. Weighting these reductions by the lengths of each road type in the U.S. today indicates that this reduction in

[7] Personal communications with Susanna Gotsch (CCC Information Services) and John Yoswick (CRASH Network).

lane-kilometers could decrease the footprint of the U.S. road system by about 5%. This reduction may appear small for a doubling of lane capacity, but is due to the fact that 2-lane roads account for 95% of road length and 91% of lane kilometers in the U.S.

Combining the above estimates of reductions in lane-kilometers and reductions in lane widths suggests that the footprint of the road system could be reduced by about 20% while maintaining mobility and accessibility in a system comprising automated vehicles. Prior investigators have concluded that road construction accounts for the large majority the energy embodied in the transportation infrastructure, representing about 8-18% of total lifecycle energy use, or the equivalent of 11-23% of the energy used by vehicles operating on those roads (Chester & Horvath, 2009; Nichols & Kockelman, 2014). This suggests that automation could reduce the lifecycle energy use of the road system by about 2-4%, equivalent to cutting operational energy use by up to 5%. These investigators also found that parking infrastructure accounts for no more than 4% of lifecycle energy use, and considerably less than this in less dense environments. Given these effects are minor, we do not consider them further while developing the scenarios and net effects.

Appendix B: Increased driving by the elderly

[Figure B1 here]

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Figures

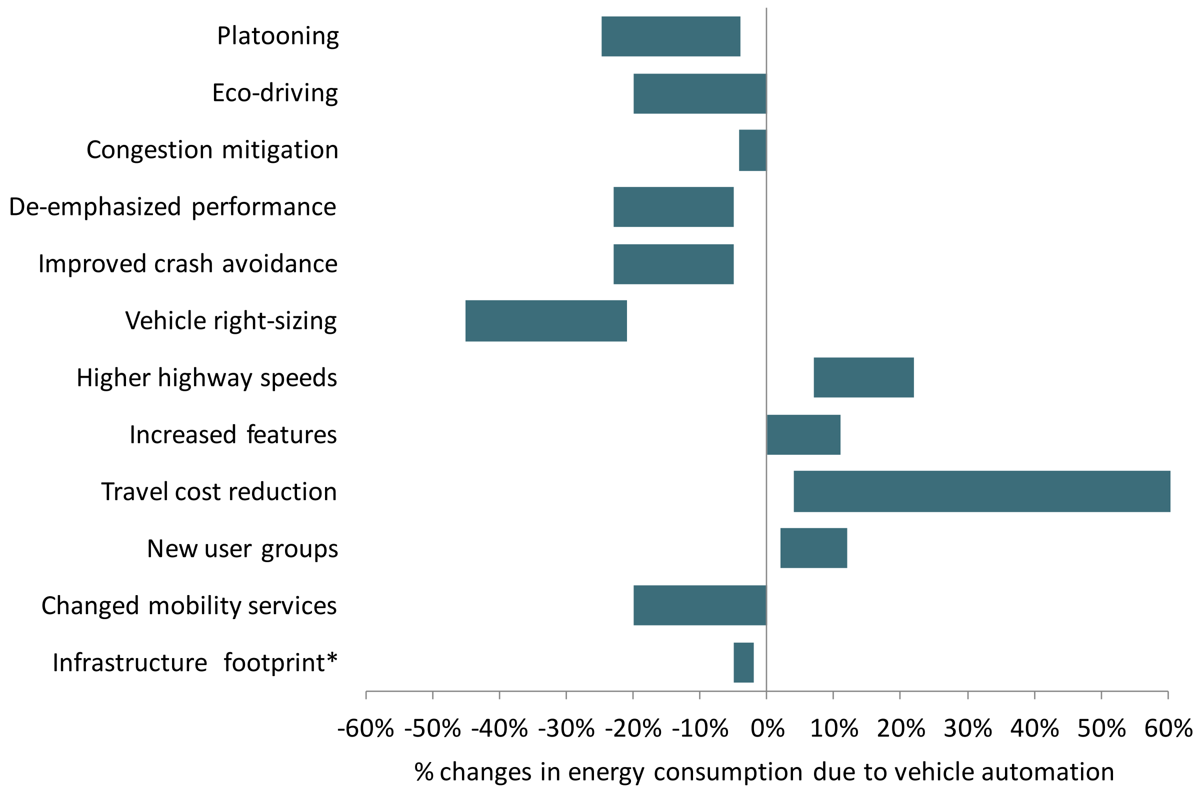

Figure 1: Summary of estimated ranges of operational energy impacts of vehicle automation through different mechanisms. (* please see Appendix B for lifecycle infrastructure impacts, which has not been considered in later calculations due to our focus on operation impacts)

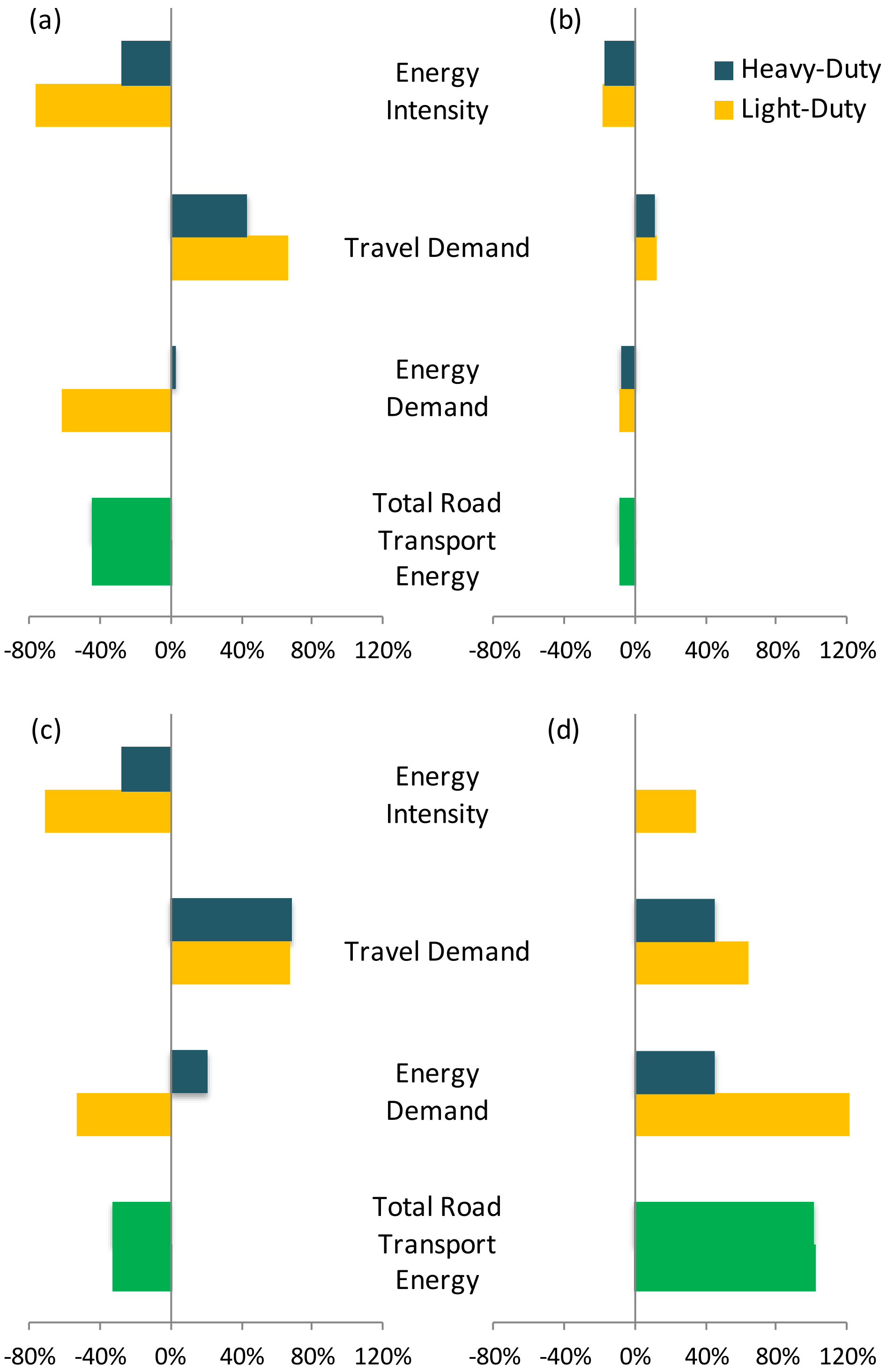

Figure 2: Changes in energy intensity per kilometer, travel demand, and total road transport energy consumption for light-duty (LDV) and heavy-duty vehicles (HDV) under varying automation

scenarios: (1) “Have our cake and eat it too” (2) “Stuck in the middle at Level 2” (3) “Strong responses” (4) “Dystopian nightmare.”

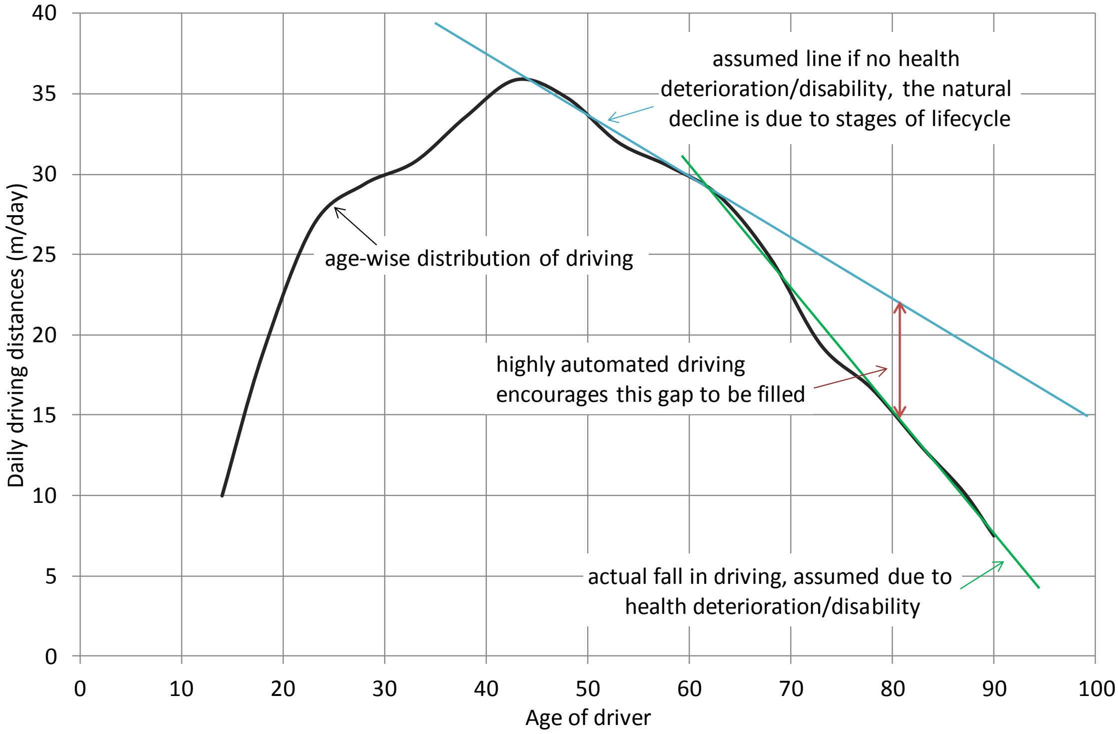

Fig. B1. Distribution of age-wise driving and increased driving by the elderly

Tables

Table 1. Potential mechanisms for energy impacts of automated vehicles

Mechanisms	**ASIF**/ Kaya element	**V**ehicle or **N**etwork effect	Direction of effect	Automation level	Penetration level	Comments
Congestion mitigation	I	N	-	1-4	Moderate to high	
Eco-driving	I	V+N	-	1-4	Any	Could have adverse network effect
Platooning	I	V+N	-	2-4	Any	Platoons affect road capacity
Higher highway speeds	I		+	1-4	Moderate to high	Step change for levels 3-4
De-emphasized performance	I	V	-	3, 4	Any	
Improved crash avoidance	I	V	-	2-4	Very high, near 100%	Safety allows size-weight reductions
Vehicle right-sizing	I	V+N	-	3, 4	High to very high	Smaller size affects congestion
Increased features	I	V	+	3,4	Any	Further demand for comfort
Demand due to travel cost reduction	A, S		+	1-4	Any	Step change for levels 3-4
Demand from New user groups	A, S		+	3, 4	Any	
Changed mobility services	A, S		-	3, 4	Any	
Potential for low carbon transition	F	V+N	-	3, 4	High	Through automated refueling/charging

Table 2. Cost components per kilometer for driving LDVs and HDVs

Cost item	2011 Cost per kilometer (US cents)			Posited 2050 real changes due to vehicle automation
	Car	SUV	HDV	
Fuel	9.1	12.2	36.7	Costs change as system efficiency improves as described earlier
Maintenance	3.4	3.8	12.1	Unchanged
Insurance	5.3	5.3	4.2	Cost decreases by 60% to 80%
Wear and ownership	18.6	27.0	11.7	Unchanged
Parking and tolls	1.3	1.4	3.4	Unchanged
Time	31.1	31.1	38.0	Costs of time decreases by 5% to 50%, 80% in extreme case
Registration	3.2	4.5	0.0	Unchanged
Total	71.9	85.3	106.0	

Based on: AAA (2012), FHWA (2005), Davies et al. (2013), EPA (2008), ATRI (2012), Trottenberg (2011). Converted to per-kilometer from original per-mile estimates.

Table 3: Description of automation scenarios and estimated ASIF multipliers for each effect.

		LDV Energy Intensity								LDV Travel Demand			HDV Energy Intensity		HDV Demand
Scenario	Description	Platooning	Congestion	Eco-driving	Performance	Crash Avoidance	Right-Sizing	Highway Speeds	Increased Features	Generalized Cost*	New user groups	Car-sharing	Platooning	Congestion	Generalized Cost
Have our cake & eat it too	*Virtually all of the potential benefits of automation are realized through coordinated policy actions and cooperation with the private sector, with little downside. Level 3 automation enables much smoother traffic and vastly fewer accidents, all but eliminating congestion. Eco-driving is widely adopted, since it no longer relies on drivers modifying their behaviors. On the highways, speed limits continue to keep traffic to about 115 km/h (70 mph), and platooning is widespread. With drivers largely out of the loop and acceleration no longer important, engine power is greatly dialed back. As accidents become a rarity, vehicles become smaller and shed safety equipment. Despite the reduction in driver burden, people cannot fully disengage from driving tasks, limiting reductions in the costs of drivers' time.*	0.75	0.96	0.80	0.77	0.95	0.55	1.00	1.00	1.56	1.07	1.00	0.75	0.96	1.43
Stuck in the middle at Level 2	*Automation advances to Level 2, but many states balk at permitting Level 3 and 4 vehicles onto their roads, effectively shutting these vehicles out of the market. Mid-range benefits are obtained from platooning (both LDVs and HDVs) and low-end benefits from eco-driving in LDVs, mainly through driver-coaching systems and energy-saving systems that operate the vehicle in select conditions. Accident rates fall, lowering insurance costs, and more elderly people drive longer, but the cost of in-vehicle time changes only slightly for most drivers.*	0.86	1.00	0.95	1.00	1.00	1.00	1.00	1.00	1.09	1.00	1.02	0.83	1.00	1.11

Scenario	Description	LDV Energy Intensity								LDV Travel Demand			HDV Energy Intensity		HDV Demand
		Platooning	Congestion	Eco-driving	Performance	Crash Avoidance	Right-Sizing	Highway Speeds	Increased Features	Generalized Cost*	New user groups	Car-sharing	Platooning	Congestion	Generalized Cost
Strong responses	*Automation shakes up car travel in a big way. Most of the envisioned responses are large in magnitude -- we see big operational improvements and many fewer accidents. Automated eco-driving and platooning take over, and safety equipment and power become much less important. But at the same time, highway speeds increase markedly and travel demand grows substantially due to lower perceived costs of travel. Widespread adoption of mobility-on-demand services means that vehicles are "right-sized" for each trip.*	0.75	0.96	0.80	0.77	0.95	0.55	1.20	1.10	1.89	1.11	0.80	0.75	0.96	1.68
Dystopian nightmare	*Policymaker and industry's eagerness leads to broad adoption of Level 4 automation, which totally redefines what it means to travel by car. Drivers totally disengage from driving responsibilities, and the perceived cost of the their time plummets. On the highways, vehicles travel safely at higher speeds, creating continued demand for big, powerful engines. Platooning is forestalled by a regulatory and liability quagmire, and policy inaction. In the cities, congestion relief from operational improvements is swamped by the sheer increase in traffic volume. Automated eco-driving fails to catch on, as drivers value shorter travel times over energy savings. Vehicle designs and ownership models are largely unchanged from today, as consumers buy for their peak requirements.*	1.00	1.00	1.00	1.00	1.00	1.00	1.20	1.10	1.49	1.11	1.00	1.00	1.00	1.45

*This includes interaction effects due to changes in energy intensity