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People's attitudes to autonomous vehicles

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ABSTRACT

We analyse people's attitudes to autonomous vehicles (AVs), i.e. driverless cars and trucks, using Eurobarometer data relating to November/December 2014 on approximately 1000 people in each EU country. People tend to be lukewarm to AVs, particularly driverless cars. However, a simple average hides the fact that many people, young and old, are totally hostile to the concept and a smaller number totally in favour. AVs are part of a technological development linked in general to robots, and regression analysis finds attitudes tend to be linked to both general attitudes to robots and individual self-interest relating specifically to AVs. Consistent with the literature, we find the young to be more in favour than the elderly. There are other differences, with males, those in cities and the more educated being more in favour, as well as differences between countries. There is also some evidence that support for AVs is greater in countries with high accident rates.

1. Introduction

Driverless cars have been on the radar of automobile companies since 1939, when the concept appeared at the New York World's Fair. But now this concept is turning to reality with, e.g., Google's driverless car having been driven more than five million miles on city streets by February 2018.[1] Autonomous vehicles (AVs) can be driven without human involvement. But there are variations on this and at one level it is now common that automated cars assist drivers in parking. The supporters of AVs claim many benefits, not least the ability to reduce the number of road accidents, 90% of which are down to human error in the EU.[2] The EU Parliament, in a recent briefing document (Pillath, 2016), gives more details both on this and other advantages. AVs may be linked to a central control system which facilitates 'platooning', i.e., the linking of several vehicles, automatically moving together. Information on future road conditions can then lead the platoon to change speed appropriately. All of this should improve traffic management both in large towns and on major highways, and may reduce fuel consumption and pollution (Mersky and Samaras, 2016; Bhavsar et al., 2014). Obviously too, they allow travelers to spend their time in other ways than driving, and also potentially allow people who cannot drive to travel. These and other advantages have been emphasized by many researchers (e.g. Thrun, 2010; Burns, 2013; Le Vine et al., 2015, Fagnant and Kockelman, 2015).

But it is not a one way street, and as the EU briefing document details there are various legal, financial, ethical, economic and technical issues which need further consideration. Some are merely technical problems on which agreement needs to be reached on relatively straightforward matters, e.g. the technical standards for international compatibility and interoperability. Other issues are

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† Prof. John Hudson passed away on 13. July, 2018.
[1] https://waymo.com/ontheroad/.
[2] http://ec.europa.eu/transport/themes/its/road/index_en.htm.

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less easy to resolve. For example, there is the potential for recording individual movements, thus threatening privacy. Even more concerning is the possibility that criminals or terrorists may hack the software causing, or threatening to cause, mass accidents (Grunwald, 2016). Wadud et al. (2016) emphasise that increased road usage, as a consequence of AVs, may increase, rather than reduce, energy usage and carbon emissions. Also on the negative side, as with other forms of automation, driverless cars will replace jobs, particularly those of taxi drivers. Much of the focus has been on cars, but there are, in many cases similar, benefits to freight transportation (Fagnant and Kockelman, 2015). When extended to trucks, the job replacement effects could be substantial. There are several differences between driverless cars and trucks, e.g. trucks tend not to drive into residential areas, driverless trucks do not replace the individual behind the wheel of their car, and the impact on cheaper prices because of reduced transportation costs relates mainly to trucks.

With respect to safety, AVs are being continuously tested on the roads and in other ways. However, Kalra and Paddock (2016) emphasise that it may be impossible to fully establish the safety of AVs prior to making them available for public use. This both presents significant liability and regulatory challenges for insurers and policymakers, and will cause concern among the public. Katrakazas et al. (2015) analyse some of the problems. They emphasise that AVs operate in a complex, dynamic and uncertain transport environment, with constantly changing road signals and other road users, as the vehicle moves at potentially high speeds. Human drivers maintain safe separation from other road users by both understanding their actions and also anticipating future ones. This is the problem facing AVs, and more research is needed, e.g., in tracking and anticipating the movements of pedestrians, bikes and other vehicles.

1.1. Prior work

There has only been a limited, although growing, amount of work done on people's attitudes to AVs. Bansal et al. (2016) detail some of the surveys that have been carried out into such attitudes. Their study is one of the few to use regression techniques to analyse the impact of socio-economic and demographic variables on attitudes. In a study of people in Austin, Texas, they found that the most common concerns with respect to AVs related to system failure, the problems of interacting with other, conventional, vehicles and affordability. The main perceived benefits were fewer crashes and better fuel economy. They also found that higher-income, technology literate males, living in urban areas had a greater interest in AVs and also a greater willingness to pay. Experience of crashes also had a positive effect on attitudes. Yap et al. (2016) estimated a discrete choice model which showed that first class train travellers, on average, prefer the use of AVs in egress mode, compared to the use of bicycles or the bus/tram/metro. This suggests that income may be an important factor in determining such attitudes. Their results also showed that attitudes regarding trust are relevant. In doing this research, they use factor analysis to investigate the underlying, latent attitudinal factors related to AVs in last mile transport. They selected 23 indicators which were relevant for exploring attitudes regarding the use of AVs as last mile transport. For example, the first 8 indicators were related to the service provided by AVs in this context.

Kyriakidis et al. (2015) use an Internet-based survey to analyse 5000 responses to AVs from 109 countries. This is a little problematic as the responses will be biased towards Internet users, who may not be representative of the population as a whole. They found that 22% of the respondents did not want to pay for a fully automated driving system. However, 33% responded that it would be highly enjoyable, although more felt manual driving to provide greater enjoyment. Concerns focused on software hacking/misuse, legal issues and safety. Respondents from more developed countries were less comfortable with the transmission of data from the vehicle. Howard and Dai (2014) using a small sample of people in California, found safety and convenience to be the most attractive features about automated driving, with liability and cost as the least attractive elements. Almost half, 40%, were favourable to having this technology for themselves in the near future. Schoettle and Sivak (2014) in a larger sample, analysed attitudes in the US, the UK, and Australia, finding that a majority had favourable views of driverless cars. The main perceived benefits related to safety, emissions reduction and fuel consumption. Concerns related to equipment failure, the ability of vehicles to deal with unexpected situations, legal liability, systems hacking and privacy issues. They also found men to be more favourable than women. Payre et al. (2014) found French drivers to be substantially in favour, at least to some degree, with men again being more in favour than women. There also seem to be rather strong cultural differences with some nationalities significantly more positive about AVs than others (Yerdon et al., 2017; Haboucha et al., 2017). Schoettle and Sivak (2014) and Payre et al. (2014).

There has also been some research done on shared autonomous vehicles (SAVs). Haboucha et al. (2017) analysed a sample of Israelis and North Americans, comparing SAVs with non-sharing AVs. They found that, even if the usage of SAVs were to be free of charge, 25% of individuals would not be willing to use this service. According to their results, it is mostly the young, students and better educated people who tend to be more in favor to AVs. With respect to SAVs, Krueger et al. (2016), found that young people and those with multimodal travel patterns are more likely to pay for SAVs. Bansal and Kockelman (2016) whose sample was focused only on Texas also found that approximately 41% of individuals were not yet prepared to use SAVs. Using a regression based approach, they found that Texans were willing to pay from $2910 to $7589 for AVs, a value which increased with the level of automation. This contrasts with Daziano et al. (2017) who estimate that the average household in the US is willing to pay $3500 for partial automation and $4900 for a fully automated car. However, there were significant differences among households. Those households which were not willing to pay anything for automation, had significantly less knowledge about this technology compared to those who wanted to pay a significant amount.

Driverless cars are a form of automation and may be linked to other forms of automation such as robots on which there is also some literature. It has indicated that a number of factors determine people's attitudes to robots. Moon et al. (2012) found that a majority of people they studied were favourable to the contribution that robots could make in caring for the elderly, however they were also concerned that robots should be used to assist, rather than replace, human care. Hudson et al. (2017) found that older people, with some qualification, tend to be more hostile, and gender is a further factor influencing attitudes, with women tending to be more hostile than men. There is also some, although not much, research on the effects of education on attitudes towards robots, with the literature suggesting that more educated people tend to have more favourable attitudes to robots (Hudson et al., 2017). More generally, Nomura et al. (2009) argue that research suggests that attitudes to robots are affected by gender, culture and experience of robots. In their own research, which related to Japan, they found educational background to be significant, particularly having a background in natural sciences and technologies. More generally, much of the literature tends to find a relationship between attitudes to technology and socio-economic characteristics, with younger people, men and the well educated tending to be more in favour than others (Hudson and Orviska, 2011)

1.2. Objectives and organisation of the paper

The main objective of the paper is to test, using regression analysis, the hypotheses that attitudes to AVs are determined both by general attitudes to robots, and socio-economic variables reflecting specific AV attitudes based on self-interest calculations. The two dependent variables will be people's attitudes to driverless cars and driverless trucks respectively. The independent variables will be both socio-economic variables and underlying attitudes to robots. There is an enormous variation in robots, but they are characterized by three key characteristics: maneuverability, a sense of location awareness via sensors, and artificial intelligence. People may not tend to think of AVs as robots because of their development from vehicles which have been on our roads for more than a hundred years. However, AVs possess all three of the characteristics noted above. In this respect AVs are likely to be one of the first robots that people regularly come into contact with on a personal basis. There is one other characteristic that they share with many other types of solo robots, and that is that they may be hacked. Because of all this it is likely that people's attitudes to AVs will be determined by both their attitudes to robots in general and also their specific attitudes to AVs. The possibility of the former is strengthened by the fact that many of the characteristics such as gender, age, education have a similar impact on both attitudes to robots on dimensions such as surgery, care for the elderly and education, and attitudes to AVs. This suggests that some common factor, such as robot technophobia (Nomura et al., 2007), is driving both sets of attitudes. We will be testing this hypothesis. But people are also likely to be influenced by how they are impacted upon by the specific characteristics of AVs. These are likely to impact on people in different ways according to, e.g. how much they use cars, and these differences will be captured by individual socio-economic and demographic characteristics.

In terms of the direct impact of the socio-economic and demographic characteristics, i.e. in addition to any indirect impact via their basic attitudes to robots, poor people are likely to be less in favour of driverless cars due to their increased cost. People in small towns and rural areas may also be less in favour as the technical infrastructure may not be in place to fully take advantage of the technology and the congestion and pollution gains will also be less. Although, against this, people in rural areas tend to make more trips, and for longer distances, than people in towns.[3] In addition, women tend to travel for less time in commuting to work in cars (Plaut, 2006) in part because they are, at least in part, home-based (Schwanen et al., 2004). There is also evidence to suggest that even for non-work trips they travel less (Van Acker and Witlox, 2010). Older people also tend to drive less in terms of distance than younger people (Schwanenet al., 2004). Education and personal income are also positively linked with driving distance (Van Acker and Witlox, 2010), the former possibly because educated people may have more specialized employment. There is also evidence that those traveling more often and for longer distances by car tend to prefer any type of car automation (Bansal and Kockelman, 2016). Because of this, women, older and less well educated people may all see less advantage in driverless cars. We would also anticipate people to be more in favour in regions of high current accident incidence. We know that men and young people are more likely to be involved in accidents and hence on this basis alone we would expect them to be more in favour of AVs. This tendency also leads to men and young people paying higher car insurance than others. In the EU it is illegal to differentiate car insurance rates on the basis of gender, but women still tend to pay less because of fewer claims leading to higher no claims discounts. Driverless cars can be expected to reduce these differences based on age and gender, and hence regardless of what happens to overall insurance rates, men and young people will in relative terms gain. With respect to driverless trucks, many of the same factors are relevant. But in addition there is the increased possibility of job loss which would be highest amongst truck drivers and also perhaps farm workers because of their link to tractors. On the benefit side, there is the possibility of cheaper goods for everyone due to a reduction in transport costs.

These are the issues and hypotheses we will be exploring in this paper. They are important, as successful implementation of this technology requires public acceptance (Bansal et al., 2016). This is so for most new technologies, but is particularly the case for driverless cars, given that they are bought by individuals. In doing the analysis we make use of Eurobarometer survey data relating to November/December 2014 of approximately 1000 people in each EU country, giving 27,801 respondents in total. This allows us to analyse attitudes across all the countries of the EU using a much larger number of observations than is usually the case in previous studies. The paper proceeds as follows. In the next section we present the methodological issues and in particular the key problem of proxying underlying attitudes to robots. We then present the survey data and the results. The latter will be based on regression analysis, specifically the technique of ordered probit which is appropriate to analyse attitudinal data of this kind. Finally we conclude the paper.

[3] https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/457752/nts2014-01.pdf.

2. Methodology

The primary contribution of this paper is to analyse the determinants of individual attitudes to AVs, both cars and trucks, across all EU countries. In doing this we differentiate between the impact of socio-economic characteristics on underlying attitudes to robots and their impact on attitudes to AVs, independent of attitudes to robots. Thus we assume that people's acceptance of AVs is linked to both their underlying attitudes to new technology, and robots in particular, as well as socio-economic and demographic variables reflecting self-interest as previously outlined. The latter variables include those which either theory or the literature suggests impact on attitudes to AVs. They include gender, age, education age, i.e. the age the individual left full time education, location and personal prosperity. Apart from individual socio-economic characteristics, we also include country dummy variables. For a particular country these take a value of one when the individual lives in that country and zero for the remaining individuals. The regression coefficient thus reflects how that country differs to others. Dummy variables are frequently used to model discrete differences, in this case between countries (Greene, 2003). These differences may be due, for example, to the regulatory regime or current levels of accidents.

The Eurobarometer data relates to the responses to a series of questions, Including two relating to how comfortable people felt about driverless cars and trucks. These are defined in more detail in the Appendix A. The responses were ordered across ten values ranging from totally uncomfortable (coded 1) to totally comfortable (coded 10). The ordering refers to the fact that the variables have a natural ordering as we move from totally uncomfortable to totally comfortable. The responses to these form the dependent variables in our analysis. We use the technique of ordered probit. This generalises binomial probit, which analyses discrete dependent variables taking two values, to analysing ordered categorical variables when there are more than two choices. As with binomial probit, the equation is estimated using a maximum likelihood technique (Greene, 2003). In the regressions we also correct the standard errors and t statistics for heteroscedasticity using the Huber/White/sandwich estimator. Heteroscedasticity occurs when the variance of the error terms is not constant across the sample. This can cause us to underestimate standard errors and overestimate t statistics. The Huber/White/sandwich estimator is commonly used to correct for this by taking account of this heteroscedasticity in calculating adjusted standard errors.

Underlying attitudes to robots will be found using factor analysis based on variables measuring attitudes to robots on several dimensions. This methodology has similarities to Yap et al. (2016). The analysis was done using the econometrics package program STATA. The data relating to the individual responses were downloaded in STATA readable form. These could then be immediately analysed and used to derive summary data. The appropriate regressions were done restricting the sample to individuals with a full set of responses. The description and the coding of all variables can be found in the Appendix A.

3. Survey data

Table 1 summarises the average responses by different socio-economic characteristics. For the sample as a whole, the average response was 3.65 for driverless cars, i.e. people tended to be more uncomfortable than comfortable. Thus on average people tend to be hostile to AVs, although more so to driverless cars than trucks, and the differences between the two are significant at the 1% level in all cases. This is in slight contrast to much of the literature we looked at earlier, where attitudes were sometimes more favourable. This caution is a characteristic of all types of people, but more so for women, the old and the less prosperous. Hostility to AVs also declines with the education age and is lowest for those who live in large towns or cities. The most favourable group by occupation are professionals and senior managers. The latter in running firms have potentially much to gain. These socio-economic differences are significant in almost every case as indicated in the Table. The least favourable to AVs are the unskilled who may feel particularly vulnerable to robots and automation in terms of their own employment. However people whose work involves driving, e.g. truck and taxi drivers, but also travelling salesmen tend to be slightly more favourable than most. But most drivers are men and if we compare drivers with non-drivers of the same sex, then drivers are consistently and substantially more hostile than non-drivers.

The views are not normally distributed as can be seen in Fig. 1. There is a very large peak at the first, and most negative response, and smaller peaks at the mid-point answer and the last, and most, positive answer. Indeed of those who have a view, 45% are totally

Table 1
Attitudes to AVs.

	Cars	Trucks		Cars	Trucks
All	3.65**	4.32**	Skilled manual	3.70	4.32
Young	4.12**	4.77**	Unskilled manual	3.19**	3.67**
Old	3.42**	4.10**	Unemployed	3.46**	4.04**
High education	4.49**	5.25**	Retired	3.11**	3.78**
Medium education	3.74**	4.45**	Student	4.57**	5.19**
Low education	3.01**	3.56**	House person	2.98**	3.49**
Prosperous	3.79**	4.46**	Male	4.17**	4.83**
Village	3.46**	4.09**	Female	3.21**	3.89**
Town	3.56**	4.19**	Driver	3.96**	4.53*
City	3.98**	4.77**	Professional/manager	4.79	5.60

Notes: These are the average responses from a scale of 1 (totally uncomfortable) to 10 (totally comfortable), **/* denotes that the figure is significantly different to the rest of the sample at the 1%/5% levels of significance respectively. In all cases the figure for cars was significantly different to that for trucks at the 1% level of significance. Source calculated from Eurobarometer survey 82.4.

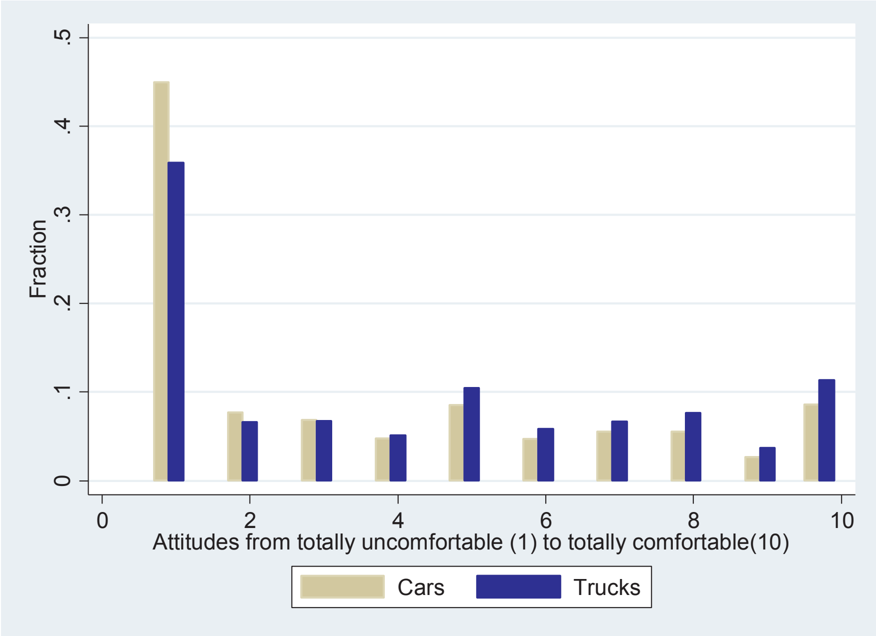

Fig. 1. Histogram of attitudes to AVs.

uncomfortable with driverless cars and just 8.6% totally comfortable. The bar of the histogram for cars is substantially above that for trucks at the first peak and slightly above it for the following responses. But by response 4, the bar for cars is consistently below that for trucks. Clearly people are consistently more negative in their attitudes to cars than trucks, although even for cars a substantial minority have a favourable view. This pattern of attitudes is similar to those on robotic care for the elderly (Hudson et al., 2017).

Fig. 2 illustrates the impact of education on attitudes to driverless cars. There are far fewer highly educated people, i.e. those who finished formal education after they were 22 years old, who are totally uncomfortable with the technology and substantially more who are to, varying degrees, comfortable. Although even with the highly educated, the first peak is dominant. We get similar distributions if we differentiate by age, gender and locality, with older people, women and those in rural areas less favourable to AVs. Fig. 3 further illustrates the relationship between age and attitudes to driverless cars. It plots the average response for each age

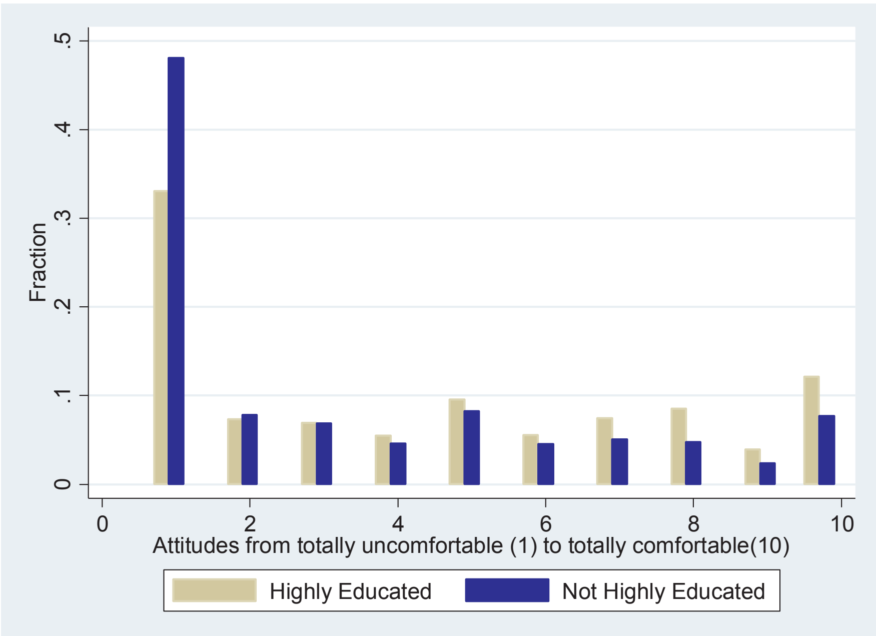

Fig. 2. Histogram of attitudes to driverless cars.

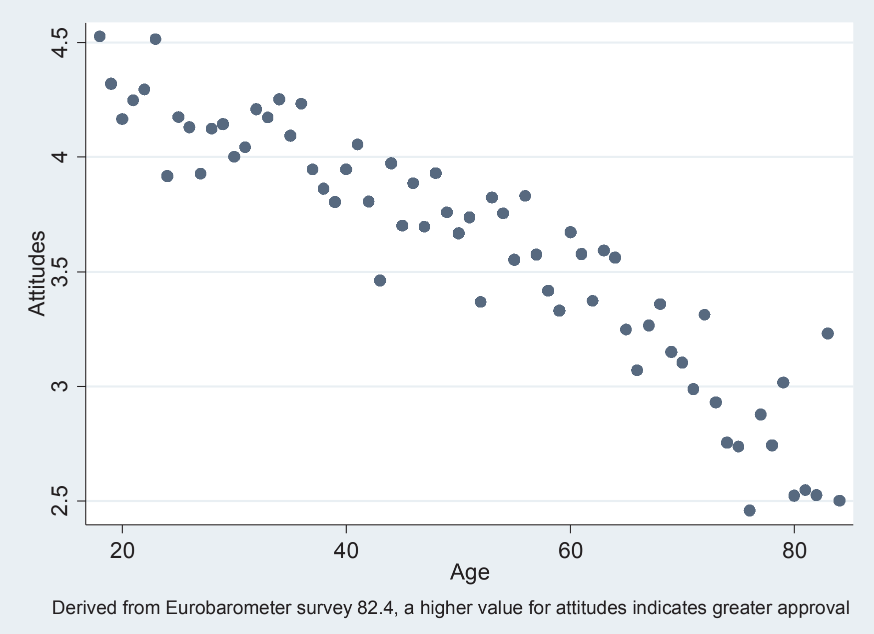

Fig. 3. Age and average attitudes to driverless cars.

against age. Clearly, and slightly unusually for this type of relationship, the relationship looks to be largely linear, with older people steadily becoming more hostile to AVs. Indeed there is the possibility that they become increasingly hostile.

Apart from socio-economic and demographic differences, there are also substantial differences between countries as Table 2 shows. The most hostile to driverless cars were respondents in Cyprus, Malta and Greece. The most favourable were those in Poland, Netherlands and Sweden. To a substantial extent these rankings carry over to trucks, but there are differences, with, e.g., Spain replacing Greece as one of the four most hostile countries. Of course, these differences between countries could reflect either different basic attitudes, possibly linked to institutional factors such as the current state of road safety, or they could reflect differences between countries with respect to their socio-economic characteristics. In order to differentiate between these possibilities we turn in the next section to multiple regression analysis.

4. Regression results on individual responses

4.1. Extracting latent attitudes to robot approval

In this section we construct, using factor analysis, a variable which reflects underlying attitudes to robots. We will then use this

Table 2
Attitudes to AVs by country.

	Car	Truck		Car	Truck
Poland	5.36	6.03	Germany	3.44	4.28
Netherlands	4.75	5.48	UK	3.43	3.76
Sweden	4.60	5.69	Italy	3.40	3.77
Denmark	4.58	4.70	Estonia	3.31	4.17
Lithuania	4.41	5.13	France	3.3	3.37
Bulgaria	4.17	5.31	Slovenia	3.29	3.78
Austria	4.14	4.85	Portugal	3.23	3.83
Czech	3.90	4.88	Latvia	3.23	4.34
Hungary	3.87	4.68	Slovakia	3.20	4.37
All	3.65	4.32	Croatia	3.17	3.75
Ireland	3.55	3.91	Spain	3.06	3.39
Belgium	3.50	3.87	Greece	2.84	3.94
Romania	3.47	3.97	Malta	2.78	3.31
Finland	3.45	4.41	Cyprus	2.43	3.22
Luxembourg	3.45	3.84			

Notes: These are the average responses from a scale of 1 (totally uncomfortable) to 10 (totally comfortable), Source calculated from Eurobarometer survey 82.4. Data ordered from most to least favourable attitudes to cars.

variable as an independent variable in the regressions explaining attitudes to AVs. There are several methods of using factor analysis to construct this underlying approval variable. We will use two, and then use the one which is best in the analysis for AVs. Attitudes to robots per se, i.e. robot approval, underlie several of the responses to questions in the questionnaire. These relate to acceptance of robots for (i) looking after elderly people, (ii) in education, and (iii) performing a medical operation on the respondent, which were all scaled 1–10. A fourth variable which related to people's attitudes to robots doing dangerous jobs was scaled 1–4. The variables are more fully defined in the data Appendix A. We extract from these four variables a common factor using the factor command in Stata. The first eigenvalue is 1.22 and the second −0.04. Stata follows the Kaiser (1960) rule in equating the number of factors to the number of eigenvalues greater than one, which therefore strongly suggests in our case just one factor. The resultant factor loadings are primarily positive for factor 1 and, apart from dangerous jobs are of similar size. Whereas, the second factor loadings are much more variable with a similar number of positive and negative signs. We assume this first factor, which accounts for a proportion of 0.3919, represents underlying 'robot approval', which is how we refer to it from now on. It is defined in such a way that approval increases as the factor increases. The loadings are: elderly care (0.6316), education (0.6938), surgery (0.5739) and dangerous jobs (0.390).

However, the data is categorical, although with 10 different values which is quite a lot for this type of analysis, and the use of standard, or Pearson, correlations can lead to biased estimates in factor analysis. These variables imply ordinal scales, whereas Pearson correlations assume interval measurement scales and their use with ordinal scales may attenuate the relationship between categorical variables, thus biasing factor analysis. A polychoric correlation assumes that the observed categories serve as proxies for bivariate normal continuous variables and have been shown to produce improved parameter estimates in factor analysis (Holgado-Tello et al., 2010). Thus despite the large number of categories, we also generated a matrix of polychoric correlations using the user written program[4] relating to the Stata command polychoric. Having obtained this matrix we then used the factormat command to perform factor analysis using the matrix as input rather than the raw variables. The resulting eigenvalues were similar to previously and the factor loadings were also similar at: elderly care (0.590), education (0.635), surgery (0.566) and dangerous jobs (0.476). In the analysis which follows, the explanatory power of the regressions tended to be higher with the factor extracted with the first approach, with little difference in terms of the significance of the other variables. Hence it is these we report, but where there are differences we also note these.

4.2. Regression results

The regressions were estimated by ordered probit and are shown in Table 3. In the first column we show the basic results relating to driverless cars. Care needs to be taken in interpreting these as in the case of ordered probit the coefficients do not directly relate to the impact of the variable on the probability of feeling uncomfortable, for that we need the marginal effects which we turn to later. The interpretation is also based on the assumption that nothing else changes, e.g. we look at the differences between a man and a woman, but with all other characteristics the same. With these qualifications in mind, we can see that support significantly, at the 1% level, declined linearly with age, with a squared age term being insignificant and thus excluded from these regression results. Support was lower for those who live in villages and to a lesser extent small towns, compared to city dwellers. The coefficients on these two variables were not significantly different at even the 10% level, and we have replaced the two locational ones with just one relating to whether the individual lived in a city or not. The positive coefficient indicates that people in large towns or cities are significantly, at the 1% level, more favourable than others. People's degree of comfort with driverless cars also increased with their level of education and prosperity. This is complementary to previous results on attitudes towards robots (Haboucha et al., 2017) as well as with previous findings that educated people, and people with higher income, travel significantly more (Van Acker and Witlox, 2010; Bansal and Kockelman, 2016). The impact of being a skilled and semi-skilled manual workers was also similar and these too have been combined together into a single variable reflecting that the individual was a manual worker, which was negatively significant. Support was also significantly lower for the unemployed, the retired and farmers. The coefficients on these occupational variables are relative to the default case, i.e. the occupations not reported in the Table which together make up 31.3% of the sample. The results on attitudes to driverless trucks, shown in column 2, are similar, although middle managers are now more favourable, at the 1% level of significance, and those whose occupation involves driving less favourable.

We earlier discussed the possibility that socio-economic variables can impact on attitudes directly, in reflecting the different perceived benefits of AVs to different people, and indirectly via their impact on attitudes to robots per se. That is people have a basic attitude of approval or disapproval to all robots and it is this basic attitude which partially informs their opinion on AVs. In addition, we hypothesise that people's attitudes to AVs are influenced by how they view AVs, independently of their views of robots. We know that there is evidence from previous research that women tend to be more hostile to AVs than men, (Payre et al., 2014; Schoettle and Sivak, 2014) and approval tends to decline with age (Bansal et al., 2016). Is this because they have negative views of robots, or something more specific to AVs? Our analysis is seeking to differentiate between these two different impacts, i.e. the direct and indirect effects. Hence in the next two regressions we included the single factor extracted earlier, which we termed robot approval, with approval increasing as the variable increases. Because of potential nonlinearities we also include its square (in the table this is 'robot approval squared'). In the two regressions (regressions 3.3 and 3.4), shown in Table 3, they were highly significant, indicating that general attitudes to robots impact on attitudes to AVs. The positive sign on robot approval and the negative sign on its square

[4] These are programs which are not provided in the Stata program, but are written by users and can be downloaded and once installed function as any other Stata command.

Table 3
Regression results for approval of AVs.

Regression:	Cars 3.1	Trucks 3.2	Cars 3.3	Trucks 3.4	Cars 3.5	Trucks 3.6	Robot approval 3.7
Age	−0.00696**	−0.00564**	−0.00501**	−0.00362	−0.00471**	−0.00301**	−0.00283**
	(11.79)	(9.75)	(7.89)	(5.88)	(4.90)	(3.24)	(6.80)
Gender	0.3460**	0.3192**	0.2229**	0.1958**	0.2208**	0.1919**	0.2102**
	(24.01)	(22.53)	(14.29)	(12.86)	(7.77)	(7.33)	(20.61)
City	0.08665**	0.1112	0.0557**	0.0814**	0.0728**	0.1124**	−0.0707**
	(5.36)	(7.01)	(3.22)	(4.83)	(2.72)	(4.19)	(5.20)
Log of	0.6274**	0.6558**	0.3610**	0.3976**	0.3582**	0.4295**	0.4281**
Education age	(16.34)	(17.44)	(8.71)	(9.85)	(4.75)	(6.53)	(15.93)
Professional/	0.1736**	0.1919**	0.09204**	0.1240**	0.08451**	0.1300**	0.08640**
senior man.	(6.00)	(6.60)	(3.02)	(4.05)	(2.61)	(3.73)	(4.10)
Unemployed	−0.09111**	−0.1065**	−0.07523*	−0.09506**	−0.08108**	−0.09592**	−0.07883**
	(3.26)	(3.90)	(2.48)	(3.21)	(2.60)	(3.45)	(3.99)
Retired	−0.09103**	−0.08544**	−0.09491**	−0.08769**	−0.09775**	−0.09044**	−0.03196
	(3.63)	(3.51)	(3.51)	(3.38)	(3.68)	(3.56)	(1.84)
Middle	0.05824*	0.08040**	−0.00104	0.02523	−0.00219	0.02728	0.05711**
management	(2.06)	(2.86)	(0.03)	(0.85)	(0.07)	(0.87)	(2.82)
Manual	−0.09118**	−0.1109**	−0.04871	−0.08269**	−0.0527	−0.07702**	−0.1002**
	(3.60)	(4.44)	(1.78)	(3.23)	(1.59)	(2.91)	(5.57)
Driver	−0.05554	−0.1080**	−0.02794	−0.08097	−0.01451	−0.05001	−0.04564
	(1.41)	(2.77)	(0.66)	(1.92)	(0.29)	(1.14)	(1.62)
Prosperity	0.05351**	0.04592**	0.001933	−0.00089	−0.00339	−0.02147	0.07997**
	(4.32)	(3.77)	(0.15)	(0.07)	(0.16)	(1.09)	(9.23)
Farmer	−0.2832**	−0.1769*	−0.1063	−0.02414	−0.05464	0.07674	−0.1965**
	(3.32)	(2.10)	(1.21)	(0.29)	(0.85)	(0.87)	(3.11)
Robot			0.8214**	0.8109**	0.8216**	0.8146**	
Approval			(64.32)	(66.99)	(21.38)	(21.49)	
Robot Approval			−0.06629**	−0.08430**	−0.05943**	−0.07826**	
squared			(4.96)	(6.64)	(2.94)	(4.43)	
Log Road					0.02166	0.09523*	
traffic deaths					(0.40)	(1.96)	
Country Dummies	Yes	Yes	Yes	Yes	No	No	Yes
Observations	25,302	25,003	22,556	22,414	22,556	22,414	21,814
Log Likelihood.	−45,618	−49,097	−38,554	−41,674	−38,733	−41,860	−23,894
X^2	2878	3003	6362	6909	801.5	1053	

Notes: Regressions estimated by ordered probit, apart from 3.7 which was estimated by OLS. Standard errors corrected for heteroscedasticity, apart from 3.5 and 3.6 where clustered standard errors were estimated. **/* denotes significance at the 1%/5% level of significance.

indicate that as robot approval increases, support for AVs also increases, but it does so at a declining rate. Thus, the impact of robot approval on approval for AVs is nonlinear. Once more we emphasise that this interpretation of the coefficients is based on the assumption that the other covariates are fixed. In general, the socio-economic variables used in the previous regressions retain their significance. The principal exceptions are prosperity and farmers. In general too, the occupational variables are insignificant in the cars' regression, but significant for trucks. This may reflect a greater perceived impact of the latter on their firms and their jobs.

It was also discussed earlier that attitudes to AVs may be tempered by driving standards in the individual's country. Thus, where there are a significant number of fatalities associated with driving, we might expect support for AVs to be relatively high. If we compare the regression coefficients for countries from the previous two regressions against road deaths per million vehicles, there is a positive correlation between both, with that relating to trucks significant at the 5% level. Given that we only have 28 observations, this is suggestive of a relationship. When we replace the country dummy variables with the log of road traffic deaths, it is not significant in the cars regression, but is significant at the 1% level in the trucks regression. When we replaced the previous correction for standard errors with one based on the clustering of countries, due to the omission of the country fixed effects, this was again significant, although at the 5% level. Hence there is some evidence that attitudes to driverless trucks are more favourable in countries with high number of road deaths.

The final column of Table 3 relates to the constructed robot approval variable. Thus, in this regression we are analysing the underlying determinants of attitudes to robots. As expected, and consistent with other work which has analysed attitudes to new technologies, hostility is greater for women (Schoettle and Sivak, 2014), increases with age (Nomura et al., 2009) and declines with the level of education (Haboucha et al., 2017). It is also less for those who live in cities or large towns and for manual workers, particularly unskilled manual workers although this is not shown in the regression.

Hence older people, for example, are more hostile to AVs both because of their attitudes to AVs as such and because of their attitudes to robots in general.

In Table 4 we first show the probabilities, calculated from the regressions, of responding up to the option 5 cut-off point, i.e. they tended to be uncomfortable with the option, for the default case. The default case here is a representative individual with whom we compare alternatives with. This representative person is a 45 year old woman from Finland in middle management, living in a city,

Table 4
Probabilities of being uncomfortable with AVs.

Scenario	*Cars*	*Trucks*	*Scenario*	*Cars*	*Trucks*
Default	0.788	0.663	Young	0.734	0.610
Professional	0.753	0.622	Old	0.826	0.703
Manual	0.828	0.729	Not city	0.826	0.718
Driver	0.819	0.728	Not city + Manual	0.862	0.779
Highly educated	0.738	0.599	Cyprus	0.898	0.805
Difficulty with bills	0.803	0.680	Denmark	0.690	0.656
Male	0.674	0.540			

Note: The default scenario is a 45 year old woman from Finland in middle management, living in a city, with an education age of 17, with only occasional problems paying bills. The other scenarios replace this with the options shown. Based on regressions 3.1 and 3.2.

with an education age of 17, with only occasional problems paying bills. The probability of such an individual tending to be uncomfortable with cars is 0.788. These probabilities are derived from the regressions in the first two columns of Table 3, i.e. they show the full impact of socio-economic characteristics on attitudes, implicitly including the indirect one on general approval for robots. If we simply change the default case to now make the woman a professional or senior manager[5] then the probability declines slightly to 0.753, and changing her to a manual worker increases it to 0.828. Changing the woman to a man has a very substantial impact on the probability in reducing it to 0.674. There are also substantial differences between a 20 year old and a 65 year old, where the probabilities are 0.734 and 0.826 respectively. The effects are also partially cumulative, as we can see from combining 'not a city dweller' and manual worker together. Finally, for those in Denmark the probability is much lower than someone living in Cyprus. In column 2 we show the same probabilities for driverless trucks. People tend to be much less hostile to this possibility. But in relative terms the impacts of the different characteristics are similar to those for driverless cars.

4.3. Marginal effects

We now combine these 10 categories into just 4 categories on the basis of the interval cut-off points from the ordered probit regressions 3.1 and 3.2. For cars, the nine cut-off points were 1.63, 1.84, 2.03, 2.16, 2.42, 2.58, 2.79, 3.06 and 3.22 respectively. The first category, operative before the first cut-off point, is simply the first category on the ten point scale, which contained over 40% of the responses. It can be seen that there is a large gap of 0.27 between cut-off points 4 and 5, which suggests that the responses up to cut-off point 4 are different to those which come after. Hence the second grouping combines responses 2–4. A similar logic defines the other two categories which equate to grouping responses 5–7 and 8–10 respectively. This recategorization resulted in a similar number of responses in each of the redefined categories, apart from the first. We refer to these four categories as strongly uncomfortable, weakly uncomfortable, weakly comfortable and strongly comfortable. We followed the same procedure for trucks, and the cut-off points suggested the same recategorization as for cars. We based the cut-off points on the regressions in Sections 3.1 and 3.2 because we are interested in the overall relationship between choices and covariates, not the factors.

This recategorization assumes that the gaps between cut-off points 4 and 5 and between cut-off points 7 and 8 are greater than the gaps between the other adjacent cut-off points. However, these are estimates subject to error and it could be that the assumption is not robust, and that it is feasible that some adjacent cut-off points could have greater gaps. In order to clarify this, we first test that the difference between these two sets of cut-off points are significantly greater than the difference between adjacent ones. T tests indicated that this was indeed the case for both cars and trucks, with significance levels well below the 1% significance level. Secondly we engage in a 1000 replication bootstrap, i.e. doing regressions based on repeated sampling, with replacement, of the data. This is often done to find the standard errors of the coefficients (Greene, 2003). It provides 1000 different estimates of the differences between adjacent cut-off points. The standard deviations of these estimates allows us to build 99% confidence intervals for those differences. These are shown in Table 5. These confidence intervals are very similar for cut-off points 4 and 5 and for 7 and 8, and for both, the lower end of the confidence interval is greater than the upper end of the adjoining confidence intervals. The results of the bootstraps themselves are also shown in Table 5. For cars, the smallest difference between cut-off points 4 and 5 in any replication was 0.240. The maximum differences in any replication between cut-off points 3 and 4 and 5 and 6 were 0.147and 0.176 respectively, i.e. much smaller than for the minimum for the difference between cut-off points 4 and 5. Similarly the minimum difference between cut-off points 7 and 8 was 0.243 and the maximum differences in any replication between cut-off points 6 and 7 and 8 and 9 were 0.227 and 0.188 respectively. For trucks the results are even more emphatic. Hence we can conclude that the recategorization of the data is based on robust assumptions regarding the cut-off points.

Table 6 shows the marginal effects for these recategorised variables. The first and fifth columns relate to the impact on the probability of someone being strongly uncomfortable with driverless cars and trucks respectively. For cars, males were more likely to be all of weakly uncomfortable, weakly comfortable and strongly comfortable as can be seen from columns 6.2–6.4. For trucks the result is slightly different, in that males are less likely to be weakly uncomfortable. This difference between cars and trucks with

[5] Hence all the other characteristics of the person remain unchanged, i.e. they are still a 45 year old woman from Finland, living in a city, with an education age of 17, with only occasional problems paying bills. But they are now a professional or senior manage rather than in middle management.

Table 5
Differences between adjacent cut-off points.

Cut-off points	Cars:	Bootstrap Range:		Trucks:	Bootstrap Range:	
	99% C.I.	Minimum	Maximum	99% C.I.	Minimum	Maximum
1–2	0.197–0.223	0.196	0.226	0.173–0.200	0.171	0.205
2–3	0.180–0.198	0.175	0.202	0.171–0.195	0.170	0.198
3–4	0.125–0.142	0.123	0.147	0.127–0.148	0.126	0.149
4–5	0.245–0.273	0.240	0.279	0.280–0.304	0.274	0.310
5–6	0.150–0.170	0.146	0.176	0.164–0.183	0.158	0.186
6–7	0.199–0.227	0.194	0.227	0.209–0.230	0.202	0.242
7–8	0.244–0.281	0.243	0.283	0.284–0.320	0.285	0.321
8–9	0.145–0.180	0.144	0.188	0.170–0.198	0.164	0.203

Notes: The data relate to estimates from two 1000 replication bootstraps. The confidence intervals are centred on the cut-off points in the first two regressions in Table 3, with standard errors obtained from the bootstraps.

Table 6
Marginal effects relating to adjusted dependent variables with four response categories.

	Cars				Trucks			
	Pr(Y = 1)	Pr(Y = 2)	Pr(Y = 3)	Pr(Y = 4)	Pr(Y = 1)	Pr(Y = 2)	Pr(Y = 3)	Pr(Y = 4)
Variable	6.1	6.2	6.3	6.4	6.5	6.6	6.7	6.8
Age	0.002603**	−0.00017**	−0.0008**	−0.00164**	0.002018**	0.000109**	−0.00052**	−0.00161**
	(11.76)	(10.01)	(11.59)	(11.71)	(9.72)	(8.33)	(9.59)	(9.70)
Gender	−0.1306**	0.007755**	0.0401**	0.08278**	−0.1111**	−0.0069**	0.02839**	0.08964**
	(24.09)	(14.60)	(22.76)	(23.25)	(21.96)	(12.97)	(20.79)	(21.39)
City	−0.03333**	0.001896**	0.01008**	0.02136**	−0.0428**	−0.0029**	0.01061**	0.03508**
	(5.48)	(6.03)	(5.52)	(5.37)	(7.55)	(5.98)	(7.76)	(7.34)
Log of	−0.2377**	0.01566**	0.07269**	0.1494**	−0.2386**	−0.01284**	0.06138**	0.1901**
Education age	(16.66)	(12.84)	(16.28)	(16.39)	(17.81)	(11.69)	(17.17)	(17.62)
Professional/	−0.06478**	0.002087**	0.01881**	0.04388**	−0.0634**	−0.00588**	0.01442**	0.05486**
Senior man.	(5.94)	(9.34)	(6.29)	(5.51)	(6.22)	(4.26)	(7.22)	(5.72)
Unemployed	0.03714**	−0.0031**	−0.01165**	−0.02239**	0.04275**	0.001336**	−0.01172**	−0.03236**
	(3.54)	(2.91)	(3.46)	(3.69)	(4.30)	(7.85)	(4.06)	(4.52)
Retired	0.03602**	−0.00265**	−0.01121**	−0.02216**	0.03222**	0.001514**	−0.00853**	−0.02521**
	(3.79)	(3.38)	(3.72)	(3.87)	(3.65)	(4.10)	(3.54)	(3.71)
Middle	−0.02147*	0.001181*	0.006462*	0.01383	−0.02665**	−0.00185*	0.00654**	0.02196*
management	(1.99)	(2.45)	(2.02)	(1.94)	(2.65)	(2.14)	(2.78)	(2.56)
Manual	0.03682**	−0.00302**	−0.01152**	−0.02228**	0.04315**	0.001405**	−0.01178**	−0.03278**
	(3.86)	(3.20)	(3.78)	(4.01)	(4.72)	(7.81)	(4.47)	(4.95)
Driver	0.01879	−0.00143**	−0.00583	−0.01153	0.03358*	0.001128**	−0.00913*	−0.02558*
	(1.25)	(1.11)	(1.24)	(1.28)	(2.30)	(4.90)	(2.18)	(2.40)
Prosperity	−0.02015**	0.001328**	0.006161**	0.01266**	−0.01835**	−0.00099**	0.00472**	0.01461**
	(4.36)	(4.25)	(4.35)	(4.36)	(4.24)	(4.11)	(4.23)	(4.24)
Farmer	0.1061**	−0.01316*	−0.03489**	−0.05803**	0.06045	0.00097	−0.01719	−0.04423*
	(3.33)	(2.29)	(3.15)	(3.85)	(1.91)	(1.44)	(1.76)	(2.08)

**/* denotes significance at the 1%/5% level of significance.

respect to the probability of being weakly uncomfortable tends to carry over to the other covariates. Fig. 4 shows for the two continuous covariates, age and education age, the marginal plots calculated at different points for cars. There were similar results for trucks, except the second probability, of being weakly uncomfortable, now slightly increased with age and declined with education age.

These marginal effects indicate that the most important variables in terms of impact on attitudes relate to age, education age and gender. We focus on the probabilities of being strongly comfortable and then strongly uncomfortable. Thus for cars, the probability of a man with a given set of characteristics being strongly comfortable is 0.083 greater than for a women with the same characteristics, and the probability of the man being strongly uncomfortable is 0.131 lower than for a woman. If we increase age by ten years, the first probability falls by 0.0164 and the second increases by 0.026. Education age is included as a log and hence its interpretation is slightly different. If we increase the education age from 16 to 20, then the first probability increases by 0.033 and the second, i.e. of being strongly uncomfortable, declines by 0.053. The occupation related coefficients need interpreting with caution. Superficially if they were a professional or senior manager then the probability of being strongly comfortable is 0.044 greater than the default occupations, i.e. those not in any of the categories listed in the Table. However, if we compare with being middle management then the net increase in the probability is 0.03, i.e. 0.044–0.014.

Comparison of these impacts with other results is difficult, in part because there has not been that much regression analysis and even when there has been, often that analysis is not directly comparable with what we have done. However, in general terms our

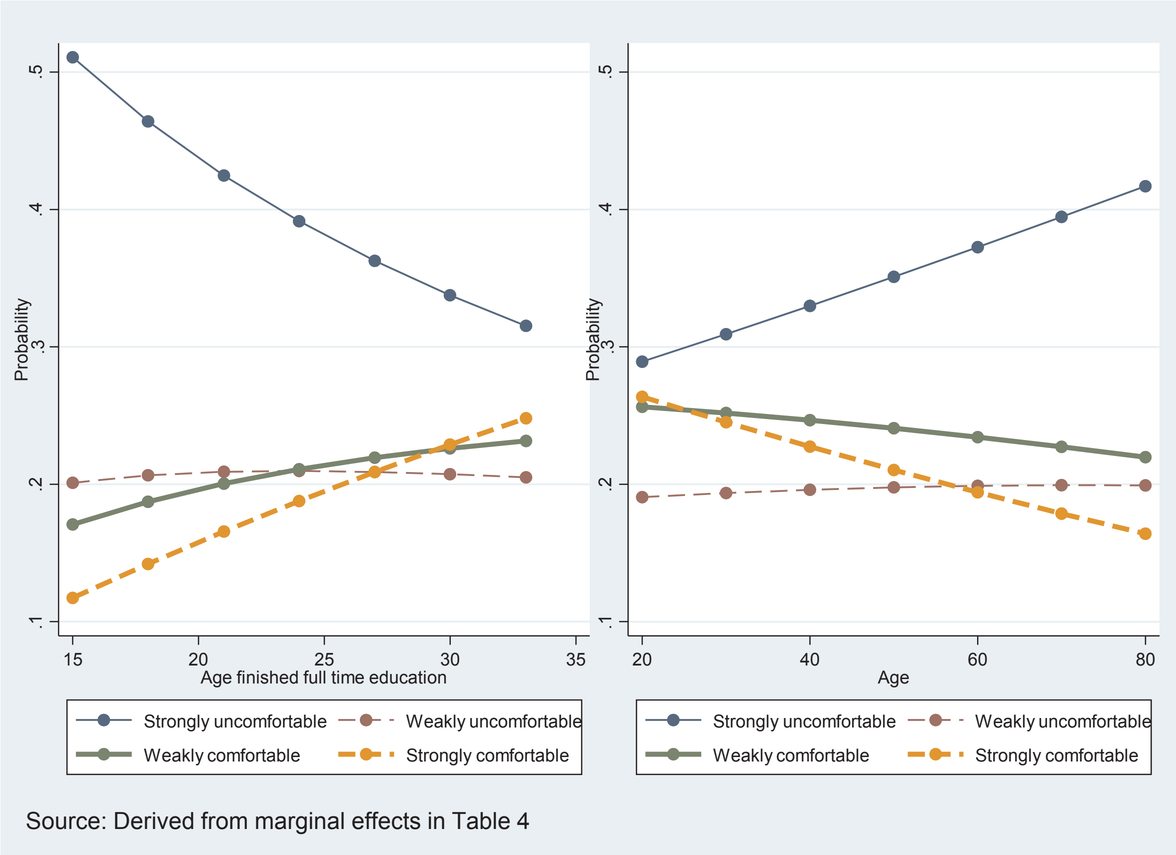

Fig. 4. Marginal effects for attitudes to driverless cars.

results are consistent with those of Schoettle and Sivak (2014), Bansal et al. (2016) and Payre et al. (2014) who found, in different contexts, some evidence for men being more favourable than women to self-driving cars. Similarly, a significant effect of gender was found by Nomura et al. (2007) using correlation analysis based on a Robot Anxiety Scale (RAS). Bansal et al. (2016) also found evidence for older people being less favourable. The results are also consistent with evidence that those traveling more often and for longer distances tend to be less hostile to AVs (Bansal and Kockelman, 2016) together with evidence that women tend to travel for less time by car (Plaut, 2006; Van Acker and Witlox, 2010), as well as older people (Schwanenet al., 2004). Results with respect to education are less common, but several mention that knowledge of technology is an important factor impacting on support for AVs (Daziano et al., 2017). The results are also similar to research which analysed other forms of robot technology, in finding variables such as age, education and gender to be significant (Hudson et al.,2017; Nomura et al. (2009). There is, however, even less research on the impact of occupation on attitudes with which to compare our results.

5. Conclusions

The results show that in the countries of the EU, people are slightly uncomfortable with the concept of driverless trucks and even more uncomfortable with driverless cars. There are wide differences between countries, but even in countries which are relatively favourable, a majority in most cases are still more uncomfortable than comfortable. Being as this is a technology which seems to be inevitably progressing, this should be a cause of concern. Our results also find substantial differences within countries. Thus the old, retired, unemployed, less well educated and women tend to be more hostile to AVs. Whilst professionals and senior management tend to be more in favour. There are also differences based on localities, with those in large towns and cities most in favour. These preferences are likely to be related to the perceived impact on AVs on individuals, such as the possibility of using such a vehicle for those who cannot drive, and for drivers the increased utility from being able to do other things whilst travelling. There is also the potential for pollution to decline and most importantly, perhaps, for fewer traffic accidents. The costs relate to the perceived impact on unemployment, any increase in the price of cars, the potential for pollution to increase if more vehicle journeys are made and any other risks such as hacking and those related to privacy. These costs and benefits differ across different socio-groups as we saw when looking at the literature, with e.g. older people and women tending to drive less. The gains from AVs may be greatest in large urban areas where the infrastructure, such as roadside sensors, is more likely to be developed and, because of greater population density, the potential for vehicle sharing greater. In rural areas, and even small towns, this is less likely. Driverless cars will, initially at least, be more expensive than purely manually driven cars and thus be less attractive for poorer people, as this is again reflected in our results. But they will tend to even out insurance differentials across drivers, and hence be relatively more attractive to the young and men.

However, our results also indicate that such characteristics impact on attitudes on two levels. First, there is the direct impact as discussed above which may be linked specifically to the characteristics of AVs and how they impact on different individuals. But secondly, there is a general concern about robots per se which also impacts on attitudes to AVs. This may well be related even more generally to a concern about technology, and is linked to socioeconomic characteristics with, e.g., women, the old and those living outside large towns being more concerned about robots per se. Hence, if concerns about AVs are to be allayed, this should be part of a general approach linked to concerns with robots and perhaps even more generally with technology. If those trying to promote AVs simply focus on the way AVs impact on people, they will only have limited success. There also needs to be a focus on people's concerns about robots and technology in general. In part such concerns may be reduced by education in general terms, i.e. not just formal education, and particularly scientific education. Although it must also be realised that some of the concerns about the impact of robots on, e.g., jobs, a loss of control and the potential dangers of hacking, are not unfounded and these issues need to be addressed. Good regulation is particularly important in this respect. This regulation must apply to both robots in general and AVs in particular. The latter means addressing the specific issues related to affordability, hacking, insurance and jobs. In addition governments should try to ensure that the technology benefits everyone including those outside large cities by construction of the appropriate infrastructure. However, if attitudes to AVs are conditioned by people's attitudes to robots, then the reverse is likely to be true and as people get used to and accept driverless cars, they may also become more favourable in their attitudes to robots per se.

There are, of course, limitations to the study. Firstly, it is a snapshot in time. It would be of interest to know how individual attitudes evolve over time both as individuals age and as technology evolves. Secondly it would have been useful to have more information on the individuals' educational background, particularly if they had studied science. In terms of variables which might have played a mediating role, trust in science, industry and regulators would all have been valuable, and help us understand on which institutions to focus attention in terms of increasing trust and possibly increasing acceptance of the technology. Finally, more work too is needed in terms of attitudes to using AVs in multiple countries, something particularly pertinent to the EU, with different road signs, speed limits, and even differences relating, e.g., to 'priority to the right'.

Acknowledgements

John Robert Hudson was born in Birmingham in 1947. He moved to the University of Bath in 1978. In 1990 he became Reader in Economics and in 2002 he was promoted to Professor of Economics. He remained a caring teacher, PhD supervisor and prodigious researcher at Bath until his death in July 2018. Prof. Hudson authored over eighty articles in international academic journals, numerous reports and books. The book *Inflation: A Theoretical Survey and Synthesis* (1982) was selected by *Choice*, the American library journal, as one of the outstanding books of the year. His final book, completed shortly before his death, was on the economics of robotics, an area in which he was becoming increasingly interested. His untimely death robbed us of an exceptional researcher and an exceptional personality. We will miss him very much. We gratefully acknowledge the help of the editor and the comments of three anonymous referees which have substantially improved the paper.

Appendix A

Independent variables, Attitudes to:	
Driverless cars	Travelling in autonomous or driverless car. Coded 1 (totally uncomfortable) to 10 (totally comfortable)
Driverless trucks	Transport goods in an autonomous or driverless commercial vehicle or lorry. Coded 1 (totally uncomfortable) to 10 (totally comfortable)
Dependent variables	
Age	The respondent's age in years
Gender	The gender of the respondent: Male = 1; Female = 0
Education age	Age at which the individual finished full time education
Village	Coded 1 if the respondent lives in a rural area or village, otherwise 0
Town	Coded 1 if the respondent lives in a small sized town, otherwise 0
City	Coded 1 if the respondent lives in a large town or city, otherwise 0
Professional/Senior Manager	Respondents current occupation: 1 if employed professional or senior manager, otherwise 0
Middle management	Respondents current occupation: 1 if middle manager, otherwise 0
Skilled manual work	Respondents current occupation: 1 if skilled manual worker, otherwise 0
Unskilled manual work	Respondents current occupation: 1 if unskilled manual worker, otherwise 0
Farmer	Respondents current occupation: 1 if farmer, otherwise 0
Driver	Respondents current occupation: 1 if involves travelling, e.g. driver or salesperson, otherwise 0
House person	Respondents current occupation: 1 if house person, otherwise 0
Unemployed	Respondents current occupation: 1 if unemployed, otherwise 0
Retired	Respondents current occupation: 1 if retired, otherwise 0
Prosperity	Difficulties to pay bills at the end of the month during the last twelve months.
Dependent variables to extract latent attitudes to robots, Attitudes to:	

Robot care	Having a robot to provide services and companionship to elderly or infirm people. Coded 1 (totally uncomfortable) to 10 (totally comfortable)
Robot education	Using a robot in school as a means for education (e.g. learning how to programme one). Coded 1 (totally uncomfortable) to 10 (totally comfortable)
Robot surgery	Having a robot perform an operation on the respondent. Coded 1 (totally uncomfortable) to 10 (totally comfortable)
Robot dangerous jobs	Robots are necessary to do hard or dangerous jobs. Coded 1 (totally disagree) to 4 (totally agree)

Source: Derived from Eurobarometer 82.4, November-December 2014
Road traffic deaths per million vehicle on the road in 2013
Number of registered vehicles: WHO http://apps.who.int/gho/data/node.main.A995?lang=en
Road traffic deaths: WHO http://apps.who.int/gho/data/node.main.A997?lang=en

Appendix B. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.tra.2018.08.018.

References

Bansal, P., Kockelman, K.M., 2016. Are we ready to embrace connected and self-driving vehicles? A case study of Texans. Transportation. https://doi.org/10.1007/s11116-016-9745-z.
Bansal, P., Kockelman, K.M., Singh, A., 2016. Assessing public opinions of and interest in new vehicle technologies: an Austin perspective. Transp. Res. Part C 67, 1–14.
Bhavsar, P., He, Y., Chowdhury, M., Fries, R., Shealy, A., 2014. Energy consumption reduction strategies for plug-in hybrid electric vehicles with connected vehicle technology in urban areas. Transp. Res. Rec. 2424, 29–38.
Burns, L.D., 2013. A vision of our transport future. Nature 497, 181–182.
Daziano, R.A., Sarrias, M., Leard, B., 2017. Are consumers willing to pay to let cars drive for them? Analyzing response to autonomous vehicles. Transp. Res. Part C 78, 150–164.
Fagnant, D.J., Kockelman, K., 2015. Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. Transp. Res. Part A 77, 167–181.
Greene, W.H., 2003. Econometric Analysis, fifth ed. Prentice Hall, New York, NY.
Grunwald, A., 2016. Societal risk constellations for autonomous driving. Analysis, historical context and assessment. In: Maurer, M., Gerdes, J.C., Lenz, B., Winner, H. (Eds.), Autonomous Driving. Springer, Berlin, pp. 641–663.
Haboucha, C.J., Ishaq, R., Shiftan, Y., 2017. User preferences regarding autonomous vehicles. Transp. Res. Part C 78, 37–49.
Holgado-Tello, F.P., Chacón-Moscoso, S., Barbero-García, I., Vila-Abad, E., 2010. Polychoric versus Pearson correlations in exploratory and confirmatory factor analysis of ordinal variables. Qual. Quant. 44, 153–166.
Howard, D., Dai, D., 2014. Public perceptions of self-driving cars: the case of Berkeley, California. Annual Meeting of the Transport Research Board.
Hudson, J., Orviska, M., 2011. European attitudes to gene therapy and pharmacogenetics. Drug Discovery Today 16, 843–847.
Hudson, J., Orviska, M., Hunady, J., 2017. People's attitudes to robots in caring for the elderly. Int. J. Soc. Robot. 9, 199–210.
Le Vine, S., Zolfaghari, A., Polak, J., 2015. Autonomous cars: the tension between occupant experience and intersection capacity. Transp. Res. Part C 52, 1–14.
Kaiser, H., 1960. The application of electronic computers to factor analysis. Educ. Psychol. Measur. 20, 141–151.
Kalra, N., Paddock, S.M., 2016. Driving to safety: How many miles of driving would it take to demonstrate autonomous vehicle reliability? Transp. Res. Part A 94, 182–193.
Katrakazas, C., Quddus, M., Chen, W.H., Deka, L., 2015. Real-time motion planning methods for autonomous on-road driving: state-of-the-art and future research directions. Transp. Res. Part C 60, 416–442.
Krueger, R., Rashidi, T.H., Rose, J.M., 2016. Preferences for shared autonomous vehicles. Transp. Res. Part C 69, 343–355.
Kyriakidis, M., Happee, R., De Winter, J.C.F., 2015. Public opinion on automated driving: results of an international questionnaire among 5000 respondents. Transp. Res. Part F 32, 127–140.
Mersky, A.C., Samaras, C., 2016. Fuel economy testing of autonomous vehicles. Transp. Res. Part C 65, 31–48.
Moon, A., Danielson, P., Van der Loos, H.M., 2012. Survey-based discussions on morally contentious applications of interactive robotics. Int. J. Soc. Robots 4, 77–96.
Nomura, T., Kanda, T., Suzuki, T., Kato, K., 2009. Age differences and images of robots: social survey in Japan. Interact. Stud. 10, 374–391.
Nomura, T., Suzuki, T., Kanda, T., Kato, K., 2007. Measurement of anxiety toward robots. In: RO-MAN'07. Proceedings of the 14th IEEE International Symposium on Robot and Human Interactive Communication. IEEE Press, pp. 372–377.
Payre, W., Cestac, J., Delhomme, P., 2014. Intention to use a fully automated car: attitudes and a priori acceptability. Transp. Res. Part F 27, 252–263.
Pillath, S., 2016. Automated Vehicles in the EU, Briefing document for the European Parliament by the European Parliamentary Research Service. http://www.europarl.europa.eu/RegData/etudes/BRIE/2016/573902/EPRS_BRI(2016)573902_EN.pdf (consulted February 1st, 2018).
Plaut, P.O., 2006. The intra-household choices regarding commuting and housing. Transp. Res. Part A 40, 561–571.
Schoettle, B., Sivak, M., 2014. A survey of public opinion about autonomous and self-driving vehicles in the U.S., the U.K., and Australia, Michigan, USA.
Schwanen, T., Dieleman, F.M., Dijst, M., 2004. The impact of metropolitan structure on commute behavior in the Netherlands: a multilevel approach. Growth Change 35, 304–333.
Thrun, S., 2010. Toward robotic cars. Commun. ACM 53, 99–106.
Van Acker, V., Witlox, F., 2010. Car ownership as a mediating variable in car travel behaviour research using a structural equation modelling approach to identify its dual relationship. J. Transp. Geogr. 18 (1), 65–74.
Wadud, Z., MacKenzie, D., Leiby, P., 2016. Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. Transp. Res. Part A 86, 1–18.
Yap, M.D., Correia, G., van Arem, B., 2016. Preferences of travellers for using automated vehicles as last mile public transport of multimodal train trips. Transp. Res. Part A 94, 1–16.
Yerdon, V.A., Marlowe, T.A., Volante, W.G., Li, S., Hancock, P.A., 2017. Investigating cross-cultural differences in trust levels of automotive automation. Springer, Cham, pp. 183–194.