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Bicycle helmets – A case of risk compensation?

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ABSTRACT

Several studies have shown that bicycle helmets have the potential of reducing injuries from accidents. Yet, no studies have found good evidence of an injury reducing effect in countries that have introduced bicycle helmet legislation. Two of the most promising explanations for why helmet laws do not work as intended are risk compensation and shifts in the cycle population as a response to the law.

The present article investigates whether the lack of effect of helmet wearing laws is due to risk compensation mechanisms or population shifts (i.e. discouraging cyclists with the lowest accident risk, and thereby increasing the overall average risk per cyclist). A random sample of 1504 bicycle owners in Norway responded to a questionnaire on among other things helmet use, bicycle equipment use, accident involvement, cycling behaviour and risk perception. Data were analysed by using structural equation model (SEM). The results show that the cyclist population in Norway can be divided into two sub-populations: one speed-happy group that cycle fast and have lots of cycle equipment including helmets, and one traditional kind of cyclist without much equipment, cycling slowly. With all the limitations that have to be placed on a cross sectional study such as this, the results indicate that at least part of the reason why helmet laws do not appear to be beneficial is that they disproportionately discourage the safest cyclists.

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1. Introduction

Falling of a bicycle can be painful, but it can also be dangerous. In the EU (19 member states) road accidents kill approximately 2000 cyclists each year (ERSO, 2010). A device that has the potential of reducing these numbers drastically is the bicycle helmet. As yet, only a few countries have legislated mandatory bicycle helmet use as a measure, but several countries are considering introducing helmet laws. What would be the effect of such a law? Would fatality rates be reduced?

Most case-control studies show injury reducing effects of bicycle helmets, as has been summarised in several reviews (Attewell, Glase, & McFadden, 2001; Thompson, Rivara, & Thompson, 2000). These results mainly come from cross sectional studies of helmet users vs. non-helmet users. However, the evidence from countries that have introduced helmet laws is mixed. Some studies report that head injuries among cyclists have been reduced following the helmet use law (Carr, Skalava, & Cameron, 1997; Hendrie, Legge, Rosman, & Kirov, 1999). Other population studies show that these reductions are not larger than for other road user groups (i.e., other accident reducing mechanisms than the helmet are at work) and that the reductions over time in other injuries are of similar magnitude to the reductions in head injuries (Rissel, 2012; Robinson, 2006). This has been interpreted as an indication that the main reason for the reductions is reduced cycling and not an effect of the helmet. Furthermore the case-control findings are often criticised for not having sufficient control for other factors, i.e., that there are many other factors that differ between cases and controls in these studies, and that the effects are related to

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these factors and not to helmet wearing (Elvik, 2011). Robinson (2007) shows that lack of effects from helmet laws seem to be the rule rather than the exception.

The explanations given in population studies for why helmet laws do not work as intended are most often risk compensation; i.e., that cyclist wearing a helmet encourages cyclists to ride faster and take more risks (Robinson, 2006). The reasoning is that people perceive risk to be lower when wearing a helmet (than not wearing a helmet), and compensate for this perceived decrease in risk and increase in safety by cycling faster and more aggressively. The issue of risk compensation connected with helmet use has been the focus of a quite heated debate within the research community (e.g. Adams & Hillman, 2001a; Curnow, 2005; Elvik, 2011; Robinson, 2006, 2007; Thompson et al., 2000).

Another explanation why helmet laws do not seem to give the results hoped for could be that helmet laws reduce the number of cyclists and thus put the remaining cyclists more at risk. The more cyclists on the road, the more will car drivers be aware of them. Such a "safety in numbers" effect has been documented by Jacobsen (2003), Turner, Wood, Hughes, and Singh (2011) and others. Furthermore, and an issue we will address in particular in the present paper is that helmet wearing laws may generate shifts in the cyclist population as a response to the law. Helmet laws generally reduce the number of cyclists (Gidske, Grendstad, & Nordtømme, 2007; Robinson, 2006), and if the cyclists remaining after the introduction of a law are the ones behaving most risky it is not surprising that the law does not give the expected result. In particular one may expect a decrease in traditional cyclists, who do not have many accidents anyways. Indeed, it could also be that the helmet law is introduced as a response to increased cycle accidents – which again could be related to changes in the cycle population towards a more training oriented type of cyclists with fast cycles and special equipment, including helmets. If so, a helmet wearing law would only boost such a trend.

Perceived risk is normally not studied in relation to the risk compensation theory, even if it is quite clearly an integral part of the risk compensation mechanism. An underlying assumption of the risk compensation hypothesis is that potential changes in risk perception following the introduction of a safety device are more or less "cancelled out" due to behavioural changes. In other words, when someone starts to use a helmet, they perceive risk to be reduced, and thus allow themselves to cycle faster off-setting some of the safety effect. Given such risk compensation, one would expect the perceived risk to return the previous level after a while. According to Wilde's risk homeostasis model (1994) it would return to the exact same level as before.

By contrast, the population shift hypothesis implies that after a mandatory helmet wearing law is introduced the most risky cyclists remain in the population whilst others are discouraged, so the population average risk-taking increases. The hypothesis also implicates that in a situation where a helmet wearing law is not yet introduced, helmet users perceive risk as being greater than non-users. This is mainly due to the fact that helmet wearing is part of an equipment "package" suitable for training and fast cycling. However, there might also be another subgroup of cyclists that voluntarily wear helmets *because* they are particularly safety oriented, and not because the helmet is part of a larger equipment package.

Fig. 1 is a simplified illustration of the potential implications of using vs. not using a helmet according to the risk compensation theory (left panel) and population shift theory (right panel). The figure is an attempt at operationalising the two theories to fit our cross-sectional research design. We also believe that such a concrete representation can provide a testable conceptual basis for future empirical studies and can contribute to further advancing the scientific debate concerning helmet use among bicyclists. As the figure illustrates, both models indicate that helmet users cycle faster than non-users. However the models differ in their prediction about risk perception. According to risk compensation theory helmet users do not perceive the risk of an accident as higher than non-users, and most likely they would perceive it as lower. According to a population shift explanation, helmet users perceive the risk as higher than non-users.

To our knowledge, no large scale population studies have investigated and tested the risk compensation hypothesis or the population shift hypothesis with respect to bicycle helmets. The risk compensation hypothesis have been mentioned by several researchers as a possible explanation for the lack of effect for helmet wearing laws (Adams & Hillman, 2001b; Robinson, 2007), but generally not confronted with empirical data. One exception is Walker (2007) who reported a tendency for car

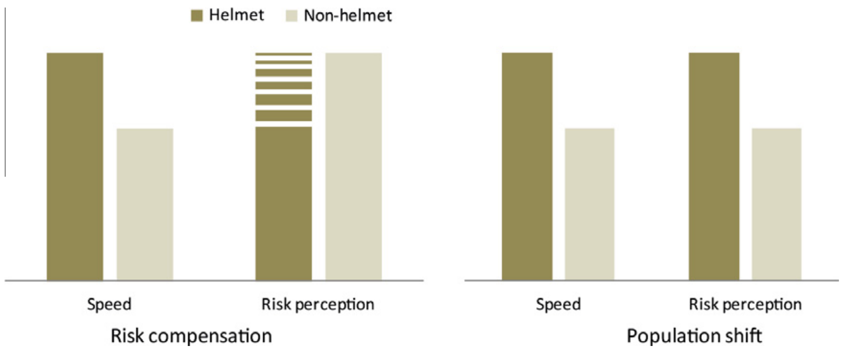

Fig. 1. Theoretical model of the potential implications of using vs. not using a helmet on speed and risk perception according to the risk compensation theory (left panel) and population shift theory (right panel).

drivers to overtake cyclists with less safety margins when the cyclist used a helmet - thus implying risk compensation, not among cyclists but among fellow road users. Also, significant risk compensation was observed when children ran an obstacle course wearing a helmet and wrist guards; tripping, falling and bumping into things increased by 51% compared to running the course without protective equipment (Morrongiello, Walpole, & Lasenby, 2007). A recent field experiment (Phillips, Fyhri, & Sagberg, 2011) showed that when not wearing a helmet, routinized helmet users reported higher experienced risk (explicit measure) and cycled more slowly. No such differences was found when cyclists unaccustomed to helmets were asked to use them.

An important question in the discussion about risk compensation of safety devices is: "why are some devices or measures compensated and others not?" A traditional assumption is that the intervention in question has to be either intrusive or conspicuous in order to be compensated. However, some researchers also claim that there is a distinction between *injury reducing* and *accident reducing* interventions, and that normally only the latter are compensated (Bjørnskau, 1995; Graham, 1982; Lund & O'Neill, 1986; OECD, 1990; Sagberg, Fosser, & Sætermo, 1997). The bicycle helmet is not an accident reducing device and hence should not "fall victim" of risk compensation. However, it can be argued that the accident/injury distinction makes less sense for the bicycle helmet than it does for a typical safety device for cars, such as seat belts. As a cyclist the perceived difference between being in an accident and having an injury is rather small, whereas for a car driver an accident may not necessarily imply being injured due to the protection inherently offered by the mass of the car. It has been argued that if the ratio of personal injury to non-personal injury is large also injury reducing measures will be victim of risk compensation (Bjørnskau, 1995; Fridstrøm, 1999). Thus it might well be that the helmet is potentially the subject of a risk compensation mechanism.

To our knowledge there are no studies that have systematically investigated risk perception as such among different groups of cyclists, and especially not helmet users vs. others. The closest we get to this is a study by McGuire and Smith (2000) who looked at the correlation between helmet use and use of other safety equipment, and a study by Lajunen and Rasanen (2004) who studied correlations between helmet use and positive health behaviour. These studies suggest that helmet users are more safety conscious than other cyclists. However, the results cannot really differentiate between what one would expect according to the risk compensation hypothesis and the population shift hypothesis.

The purpose of the present article is to investigate whether the lack of effect of helmet wearing laws is due to risk compensation mechanisms or population shifts, by looking at risk perception, cycling behaviour, accident involvement, and use of various cycling equipment.

The *population shift hypothesis* that will be focused in the following is the shift that normally follows from the introduction of helmet wearing laws, namely that a large number of cyclists abandon cycling. This self selection changes the cyclist population and possibly in such a fashion that the remaining cyclist population on average is a more equipped and training oriented type of cyclist. An important premise for this hypothesis is that these high equipment users cycle faster and more aggressively and subsequently have more accidents than other cyclists.

The *risk compensation hypothesis* states that the individual cyclist changes his behaviour as a response to wearing a helmet whereas the population shift hypothesis states that it is the group characteristics of helmeted and non-helmeted cyclists – and the changes in the ratio between these groups – that is the central mechanism behind the lacking effects of helmet wearing laws.

In Norway helmet use is not mandatory. The use of bicycle helmets has been annually registered through behaviour observations on counting stations since 1999. In 2008 39% (35% females and 41% males) of passing bicyclists above 17 years of age in eastern Norway used a helmet (Muskaug, Nygaard, Rosland, Johansen, & Sjøvold, 2009).

2. Method

2.1. Sample and procedure

A random sample of 5000 participants was drawn from the Falck National register of bicycle owners in Norway. The Falck register is a cooperation effort between the major insurance companies, and is a voluntary registry of the bicycle's frame number and the owners name and address. Approximately 900,000 of Norway's 2,000,000 bicycles are registered in the register. The respondents were approached via email. Due to non-existent mail addresses, etc., the final sample consisted of 3930 persons who received invitations to fill in a web questionnaire during September 2008.

A total of 1504 respondents participated in the study, i.e., a 38% response rate. Sixty-three percent of respondents were males, 37% were females. The age ranged from 16 to 65 years ($M = 43$, SD = 9.21). The sample is biased compared to the Norwegian population. People between 20 and 49 years and people holding a university degree are overrepresented in the sample (79% of the respondents held a university degree).

2.2. Measures

The questionnaire began by asking about the frequency of bicycle use, ownership and frequency of helmet use, and ownership and frequency of use of other bicycle equipment (cycling jacket, cycle trousers, cycling shoes, cycling computer). Accident involvement was measured by a series of questions. First, respondents were asked if they had ever been involved in a bicycle accident in which they had been injured (none, one, more than one). Those who had been involved in one or more accidents were then asked about how recently the accident had occurred and about how serious the accident had been (on a scale ranging from 1 "not severe at all" to 7 "very serious"). Those who had been involved in more than one accident were then given the same question again for accident number two. The respondents were also asked if they had been involved in any non-injury accidents. These measures where all combined to form a composite measure in the form of a scale of *accident involvement*, with scores ranging from 0 (no accidents) to 9 (several accidents, one serious accident within the last 6 months). The mean score on this index was 1.48, and 52% of the respondents scored 0, indicating that most of the cyclists had been involved in no accidents, and only very few had been involved in any serious accident or more than one accident.

The respondents were also asked to state their degree of agreement (from 1 "totally disagree" to 7 "totally agree") on four items concerning themselves as cyclist types: (1) "I like to cycle fast"; (2) "I can easily get aggressive towards other road users when cycling"; (3) "I often try to cycle faster than other cyclists on the road"; (4) "I do not like it when other cyclists are faster than me". Four other measures aimed at capturing cyclist types via self reported behaviour were used: "How often do you do any of the following..." ("never", "rarely", "sometimes", "often", "every time"): (1) "Step of the bicycle when about to cross at zebra crossing"; (2) "Cycle against red lights when there is no crossing traffic"; (3) "Cycle against the direction in a one-way street when this is the shortest route"; (4) "Reach out the arm before making a right turn when there are cars nearby".

Assessed risk was measured as "How large do you believe the risk is for you to be involved in an accident when you are out cycling?" Feeling unsafe was measured as "To what degree do you feel unsafe when you are out cycling?" Probability was measured as "How probable do you think it is that you will be involved in an accident when you are out cycling?" Consequence was measured as "If you were to be involved in an accident, how serious do you think the consequences would be?" All items were to be scored on 5 point Likert scales (1 = low/weak, 5 = high/strong).

In order to measure personality, we used selected items from a Norwegian version of The Big Five Inventory (Engvik & Føllesdal, 2005). In full, this inventory consists of 44 items measuring five personality traits, and is frequently used in research where space and time limit the use of longer tests, such as the NEO-PI R (240 items) (John, Srivastava, & Pervin, 1999). In the current questionnaire there was not room for asking about all five personality traits. Extraversion (8 items) and emotional stability vs. neuroticism (8 items), were thus measured by means of statements, e.g., "I see myself as someone who is reserved". Respondents were to indicate on 7 point Likert scales to what degree they agreed with the various statements (i.e., items), from 1 *not suitable* to 7 *very suitable*.

2.3. Analyses

Data were analysed by use of ordinary table analyses and analyses of variance (ANOVA). Factor analyses and a more complex multivariate model were formulated using structural equation modelling (SEM) by use of the software package AMOS 16.0. There are two components in a structural equation model, the measurement model and the structural model. The measurement model describes relations between latent variables, and can be compared to what is done in a traditional factor analysis. The structural model concerns the relationship between observed variables. The use of a structural model allows the estimation of both indirect and direct effects. Thus, SEM can perform factor analysis, multiple regression analysis and path analysis simultaneously.

Due to missing values, the sample size for these models is lower ($N = 1339$) than the total sample ($N = 1504$).

2.3.1. Model fit

There are a number of ways to assess model fit for structural models. Using the simple probability level (p) as measure of fit has been much debated especially for models based upon large samples (Jöreskog, 1969). The goodness-of-fit index (GFI) and the adjusted root mean square error of approximation (RMSEA) are often used as alternatives. In cases such as ours with as many as 1339 respondents, the most commonly used approach for model fit is to look at the chi square/degree of freedom ratio, also called the relative chi square (Hu, Bentler, & Hoyle, 1995). A rule of thumb is that the chi square should be less than two times its degrees of freedom.

3. Results

3.1. Cycling frequency and helmet use

On the face of it, the sample seems to be more "eager" cyclists than the average population: 31% reported that they "normally" use their bicycle more than 5 times a week, and as many as 30% report to "normally" cycle even in wintertime. If we look at the number of respondents who reported to have used their bicycle on the day prior to answering the questionnaire we find that 44% of the respondents in the current study had one or more bicycle trips. Data from the national travel survey (Vågane, 2006) show that 11% of the population had at least one cycling trip the previous day in September. This confirms that the respondents of the survey have a cycling frequency that is far higher than for the average population of Norway.

Eighty-nine percent of the participants had a bicycle helmet, and 54% claimed that they use it all the time. In a survey about attitudes and behaviour in traffic in Norway using a random population sample 33% of the cyclists (people who cycle more than once a month) claimed to always use a bicycle helmet (Phillips & Fyhri, 2009).

Table 1 summarises the measured variables to be included in the analysis and their bivariate relationship with use of bicycle helmet (% always using helmet). All the included variables except accident involvement and degree of neuroticism are significantly correlated with helmet use. The relationship between use of other types of cycling equipment and use of bicycle helmet seems to be particularly strong.

If we explore this relationship further (see Fig. 2) it becomes apparent that a large proportion (65%) of those who never or seldom use bicycle helmet do not use any other types of cycling equipment. Among the helmet users there is a quite large proportion (35%) who uses all the other types of relevant equipment (cycling jacket, cycle trousers, cycling glasses and cycling computer).

Table 1
Independent variables included in the structural equation model with coding. Bivariate relationships with bicycle helmet use (% always using helmet). Variables in italics are interval level in the SEM analysis but are recoded into categorical for ease of presentation.

Variable	Values	*N*	% Always using helmet
Gender***	Female	501	48
	Male	838	58
*Age****	16–30	101	47
	31–50	907	56
	51–65	331	51
Region**	City	774	56
	Small town	234	43
	Village	263	58
	Countryside	68	56
Cycling frequency***	Never	6	50
	Seldom	76	34
	At least once/month	137	45
	At least once/week	242	53
	2–4 times/week	467	59
	5 times/week or more	411	55
Accident involvement	None	770	52
	Once	240	57
	More than once	329	57
*Equipment level****	None	343	35
	1–3 other types of eq.	883	56
	4 other types of eq.	113	97
*Likes speed****	Low	196	40
	Medium	698	54
	High	445	60
*Cycles faster than others****	Low	629	47
	Medium	566	59
	High	144	65
*Competitiveness***	Low	619	49
	Medium	529	56
	High	191	65
*Risk perception****	Low	390	39
	Medium	859	58
	High	90	81
*Probability****	Low	383	44
	Medium	875	57
	High	81	67
*Consequence****	Low	112	34
	Medium	968	55
	High	259	59
*Feeling unsafe****	Low	583	42
	Medium	594	63
	High	162	63
*Extraversion**	Low	54	43
	Medium	299	49
	High	986	56
Neuroticism	Low	830	54
	Medium	388	53
	High	121	59

* $p < .05$.
** $p < .01$.
*** $p < .001$.

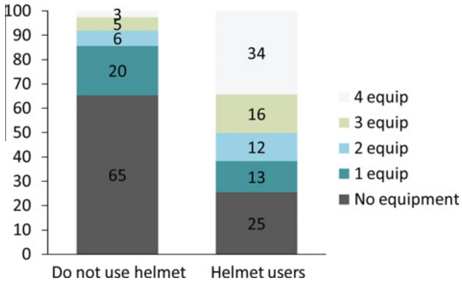

Fig. 2. Use of other types of bicycle equipment for helmet users (sometimes, often or always) and non-users (never or seldom) ($N = 1389$). Percent.

Subjects were divided into two groups according to their use of bicycle helmet (‘Non-users’: never or seldom; ‘Users’: sometimes, often, always), and into three groups according to their use of other bicycle equipment (‘None’: no other equipment; ‘some’: occasionally or often use some other equipment; ‘much’: use more than two other equipment often or always).

A two-way between groups analysis of variance was conducted to explore the impact of helmet use and equipment use on risk perception. Table 2 clearly reveals a much higher level of risk perception among helmet users ($M = 3.6$) than among non-users ($M = 2.7$). Furthermore, there is also a clear tendency that risk perception levels increase with equipment levels among helmet users.

The main effect of helmet use on risk perception [$F(1,1333) = 35.19$, $p < .001$] is statistically significant, with a moderate effect size (partial eta squared = 0.07). There was a statistically significant main effect of equipment use on risk perception. Non-users scored 3.0; some equipment 3.4; much equipment 3.7 [$F(2,1333) = 3.03$, $p < .05$]. However the effect size was close to zero (partial eta squared = 0.003). The interaction effect [$F(2,1333) = 2.08$, $p = .13$] did not reach statistical significance. As we can see from Table 2 there are very few respondents who do not use a helmet, but who use much other equipment, which partially explains the low effect size of equipment use.

A similar analysis of variance, this time using the accident index as dependent variable, was conducted. The mean scores and standard deviations are presented in Table 3. The table indicates a clear effect of equipment use on accidents: Non-users scored 1.23; some equipment 1.39; much equipment 2.28 [$F(2,1333) = 3.6$, $p < .05$], even if the effect size is rather weak (partial eta squared = 0.005). There is a difference between helmet users (1.71) and non-users (1.25) in accident involvement which is significant according to a bivariate analysis (t-test), but which is not significant when controlling for equipment use in the ANOVA. There is no significant interaction effect.

Table 2
Risk perception (score from 1 to 7) according to helmet use, and amount of other equipment. Means, standard deviations (SD) and N.

Other equipment	No helmet[a]			Helmet[b]			Total		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
None	2.6	1.3	123	3.3	1.4	220	3.0	1.4	343
“Some”[c]	2.8	1.4	106	3.6	1.3	473	3.4	1.4	579
“Much”[d]	2.0	0.8	8	3.7	1.4	409	3.7	1.5	417
Total	2.7	1.3	237	3.6	1.4	1102	3.4	1.4	1339

[a] Never or seldom.
[b] Sometimes, often or always.
[c] Use of some other equipment occasionally or often.
[d] More than 2 other types of equipment often or always.

Table 3
Accident involvement (index from 0 to 9) according to helmet use, and amount of other equipment. Means, standard deviations (SD) and N.

Other equipment	No helmet[a]			Helmet[b]			Total		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
None	1.05	1.67	123	1.34	1.95	220	1.23	1.86	343
“Some”[c]	1.41	2.08	106	1.39	2.02	473	1.39	2.03	579
“Much”[d]	2.13	2.80	8	2.28	2.31	409	2.28	2.31	417
Total	1.25	1.91	237	1.71	2.16	1102	1.63	2.13	1339

[a] Never or seldom.
[b] Sometimes, often or always.
[c] Use of some other equipment occasionally or often.
[d] More than 2 other types of equipment often or always.

We calculated three approximations of risk (using number of accidents as numerator and either number of trips per week, number of trips on the day before the interview or kilometres cycled on the day before the interview as denominators (exposure measures)). Only the first risk measure (number of accidents per weekly bicycle trips) was positively related to cycling frequency. None of these "risk" measures were related to helmet use.

These results point to an effect that is in accordance with the population shift hypothesis. However, a more detailed multivariate analysis is required in order to investigate these tendencies further.

3.2. Multivariate analysis, step 1: measurement models

In order to isolate the effects of different independent variables we used structural equation models (SEM). The first step in this analysis is to formulate a measurement model, a task similar to conducting a traditional confirmatory factor analysis. This analysis was performed on 8 items pertaining to different types of bicycling behaviour. The model (N = 1339) is presented in Fig. 3. Circles represent latent variables and rectangles represent measured variables. A two factor model of behaviour was formulated, with one type of behaviour being coined "traffic violations" and one type being coined "fast cycling". The two factors are hypothesised to co-vary with each other.

Traffic violations consist of three manifest variables: "Red lights", "One-way" and "Walk on zebra". "Red lights" and "One-way" measure whether or not cyclists cycle against red traffic lights and against one-way traffic. "Walk on zebra" is a measure of the degree to which cyclists get off their cycle and walk over zebra crossings to cross a road. To cycle over zebra crossings is strictly not a violation in Norway. However crossing cars are not obliged to give way to cyclists at zebra crossings but they are obliged to give way to pedestrians at zebra crossings. So if a cyclist gets off the cycle, he is by definition a pedestrian and entitled the right of way at zebra crossings.

The item "walk on zebra" loads negatively on the latent variable "traffic violations", indicating the violators tend to not go off their bicycle when crossing a street. The path coefficient is not strong (0.29), which makes sense as this is not a violation as such, but rather an expression of a certain type of behavioural disposition.

Bicycle speeding consists of four items: "Aggressive", "Likes speed" "Faster than others" and "Competitive". The latter three variables are all strongly linked to bicycle speeding with path coefficients above 0.7. The item "Aggressive" is a bit different from the other items in the "speeding" factor, indicating that this type of behaviour is rather distinct from speeding, even if there is a strong correlation.

The model does not adhere to assumptions of multivariate normality. Especially the variable "aggressive" is skewed (skewness = 1.02, c.r = 15.3). However, as the sample size is rather large, this is not considered to be a significant problem for the model (Waternaux, 1976). The chi square/degree of freedom ratio test indicated that the model fits the data well, the $\chi 2/df$ ratio is 1.1. The two factor solution, with the same relative contributions from individual items was confirmed by Principal Component (Factor) Analysis.

Another separate confirmatory factor analysis was performed on 4 items measuring risk perception. The model is presented in Fig. 4. The chi square/degree of freedom ratio test indicated that the model almost perfectly fits the data, the $\chi 2/df$ ratio is 0.2. The model suggests a one-factor solution where the item "unsafe" has the smallest path estimate

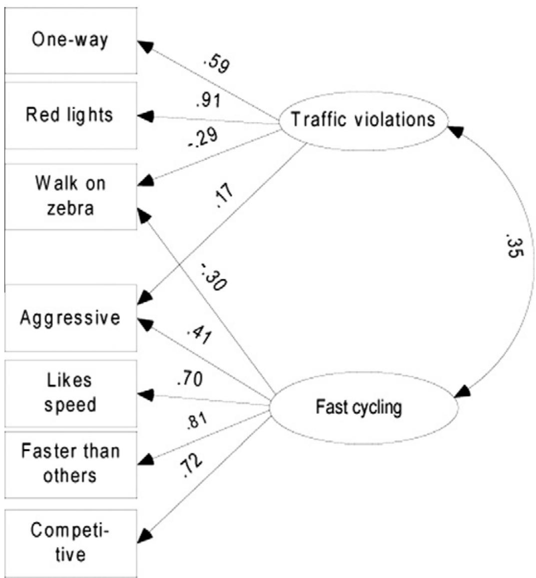

Fig. 3. Results of factor analysis of the relationship between traffic violations, bicycle speeding and independent variables (items). Standardised path estimates. Error terms and covariance paths are not displayed.

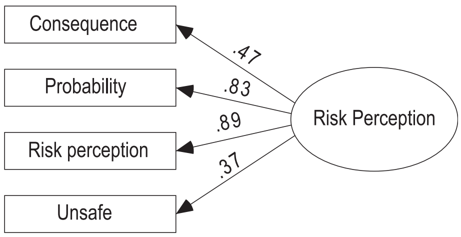

Fig. 4. Results of factor analysis of the latent variable risk perception. Standardised path estimates.

(0.37) indicating that the factor risk perception has less to do with emotional aspects of risk perception than with more cognitive evaluations. The one-factor solution, with the same relative contributions from individual items was confirmed by Principal Component (Factor) Analysis.

3.3. Multivariate analysis, step 2: structural models

In our final structural equation model we tested how the three factors *risk perception, traffic violations* and *bicycle speeding* influence level of helmet use and accident involvement (the accident index).

We have used accident involvement as a dependent variable in the model, and not some measure of risk, i.e. accidents per trip or kilometre cycled. However, when exposure variables are included as independent variables in the model, the notion of risk is implicitly taken care of.

The item "aggressive" (cf. Fig. 3) has been left out of the model, as this item did not give any substantial contribution to the model, most likely because of low variance (rather few of the respondents admitted to being aggressive).

For the presented model the $\chi 2/df$ ratio is 1.43, which is well within acceptable levels. The model is presented in Fig. 5. For ease of presentation the model is illustrated after the removal of paths that are either non-significant or have small standardised path estimates between the explanatory variables. Covariance paths and error estimates for the outcome variables are also omitted in the displayed model. All estimates are presented in Appendix A.

Fig. 2 showed a very clear bivariate relationship between the use of bicycle helmets and the use of other types of equipment. This relationship is confirmed in the SEM model as the covariance between the error terms of these two variables was 0.28 (see Appendix B). There is a strong relationship between fast cycling and use of equipment (standardised path estimate = 0.57). Cycling frequency is also positively related to use of equipment (standardised path estimate = 0.11). Traffic violations on the other hand is negatively related to equipment use (standardised path estimate = −0.22) and helmet use (standardised path estimate = −0.20). Being a fast cyclist is positively related to helmet use (standardised path estimate = 0.24).

The only variable that has any substantial relationship with accident involvement is cycling fast; cyclists who like to cycle fast have had more accidents (standardised path estimate = 0.16). There are also positive links between Frequency and Accidents (which is quite natural, as more frequent cycling leads to more exposure) and between Equipment and Accidents, but these are rather weak.

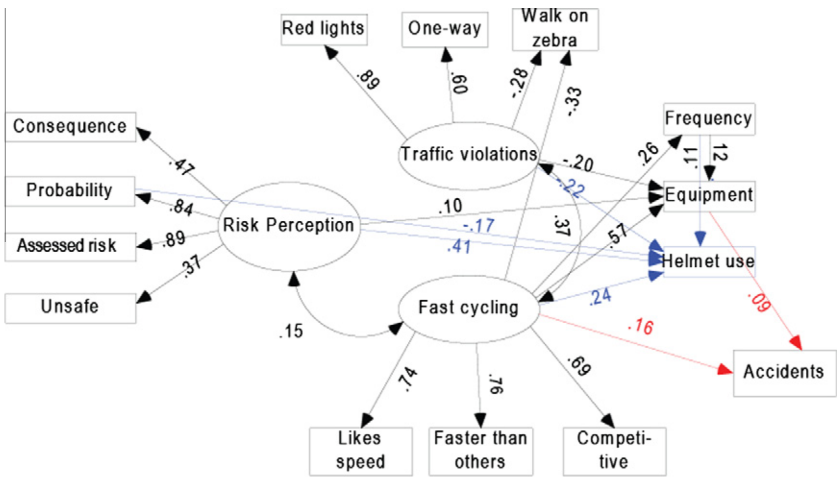

Fig. 5. SEM model with standardised path estimates. Error terms, covariance paths, non-significant paths and paths with estimates <0.10 have been removed from the model.

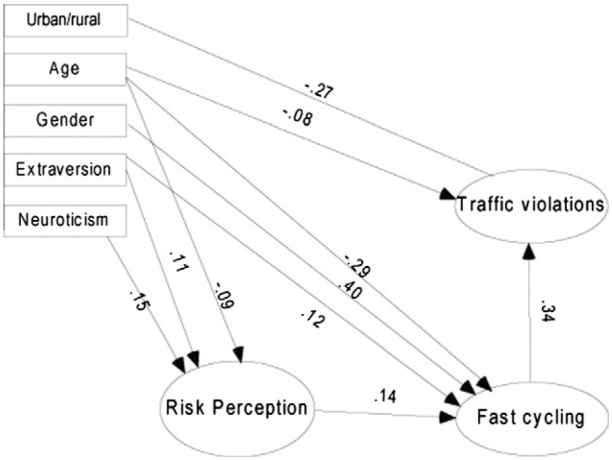

Fig. 6. Simplified SEM model with standardised path estimates. Error terms, covariance paths, non-significant paths and paths with estimates <0.10 have been removed from the model, as well as indicator variables.

Perceived risk is positively related to using a helmet (standardised path estimate = 0.41) and using equipment (standardised path estimate = 0.10), thus confirming the results of the ANOVA analysis. There is a separate path from "probability" to helmet use (standardised path estimate = −0.17). There is also week path between "feeling unsafe" (standardised path estimate = 0.07) and helmet use (not displayed in the figure).

3.4. Model with background variables

The final model looks at the relationship between the background variables gender, age, neuroticism, and extraversion and the latent variables in the model. For the sake of simplicity the variables cycling frequency, equipment use, helmet use and accidents are excluded. Further, the latent variables now have directional paths, rather than covariance paths.

The model fit is lower than for the previous model ($\chi 2/df$ ratio = 2.07). For ease of presentation error terms and covariance paths, as well as indicator variables are left out of the model presented in Fig. 6. The most important finding is that the fast cyclists are young (standardised path estimate = −0.29), male (standardised path estimate = 0.40) and high on extraversion (standardised path estimate = 0.12). Traffic violations are related to degree of urbanisation, with urban residents most often reporting to violate the rules (standardised path estimate = −0.27). Risk perception is positively related to both extraversion and neuroticism.

4. Discussion

4.1. Risk compensation or population shift?

The main objective of this article was to investigate if lacking effect of helmet legislation could be due to population shifts or to risk compensation effects. The analysis of responses from 1339 cyclists by use of a SEM model showed that the variable that had the strongest correlation with accident involvement was "fast cycling". Speed happy cyclists seem to be involved in more cycling accidents. At the same level of equipment use, use of bicycle helmet is not related to accidents.

On the other hand, the strong positive relationships between equipment/helmet use and fast cycling indicate an *indirect effect* of the helmet on accidents. In other words, by using helmet and other equipment some cyclists race even faster than they would have done without, and thus get involved in more accidents.

The topic of causal directions deserves some discussion at this stage. The proposed model suggests that "being a fast cycler" leads to a higher level of equipment use. The data utilised in this analysis are cross-sectional so we can never be certain that the causal paths follow the directions that we have proposed. However, alternative models, with different causal directions were tested and gave substantially worse model fit than the presented model. Even if this is no definitive proof of causality, it is a strong indication of causal direction, given that the relationships between other variables in the model are correctly specified (Pearl, 2009). In other words, the structural model suggests that fast cycling precedes helmet and equipment use rather than vice versa. In order to provide compelling evidence for causality, experimental studies such as that presented by Phillips et al. (2011) are needed.

The differentiated effects of helmets and cycling equipment also lend support to such a conclusion. Being a fast cycler is much more related to using non-safety equipment (shoes, jacket and computer) than safety equipment (a helmet). Thus, the fast cycling behaviour is less likely to be the result of compensating for a safety device, but more likely to be the result of having a desire to cycle fast and as a consequence of this having bought speed-improving equipment.

Thus, the results support the hypothesis that a lacking effect of helmet legislation is most likely a result of a population shift effect, and give less support to the risk compensation theory.

4.2. Risk perception among different types of cyclists

The relationship between risk perception and the other variables in the model is rather complex, and a bit difficult to interpret. The general finding is that risk perception is positively related to helmet use, both directly and indirectly via fast cycling. The path estimate from the latent variable "risk perception" to equipment use is far lower than the path from risk perception to helmet use. In other words cyclists who perceive the risk of an accident as high are somewhat more likely to use other equipment, but the likelihood that they will use a helmet is much larger.

The positive path between risk perception and fast cycling indicates that some cyclists rightly perceive the danger of being involved in an accident as higher than others, because of their own cycling behaviour.

The negative path (−0.17) between probability and helmet use together with a weak positive link between "feeling unsafe" and helmet use (not shown in Fig. 4, but given in Appendix A) indicate that cyclists who use helmet but no other equipment are of a more timid type than the others but that they also consider their own risk of being involved in an accident as quite low. This proposition is supported by a simple analysis showing that cyclists using helmet, and none, or only one other type of equipment had a lower score on the accident index than cyclists using more than one other equipment, and the same score as cyclists not wearing a helmet.

In sum these results may indicate that several mechanisms are at play. Some people cycle fast and acknowledge that this leads to an increased risk. To alleviate the risk and also to be able to cycle faster they use cycling equipment, including helmet. Another group of cyclists, approximately 25% of our sample, put on a helmet because they are afraid of being involved in an accident. For this group their fear is unrelated to the speed with which they cycle, and their likelihood of being involved in an accident is no larger than for the average cyclist.

4.3. Differentiated effect of violations and fast cycling

The results of the factor analysis and the measurement model indicated a distinction between "fast cycling" and "traffic violations". The distinction between these two types of behaviour is more clear-cut for bicyclists than for car drivers, as cycling fast on a bicycle is not a violation (i.e., bicycles can rarely achieve speeds above the speed limit).

The results of the SEM analysis indicated a differentiated effect of these two latent variables in the model. Whereas fast cycling is positively related to helmet/equipment use, violations show a negative relationship with these two variables. Further, violations are not related to risk perception and not to accidents. It could be argued that the lacking relationship between violations and accidents may have to do with cycling environments. Traffic violations for cyclists typically occur in urban environments where amenities such as red lights and one-way streets, exists. In the current dataset, cyclists who live in typical urban environments reported to do more traffic violations than cyclists from more rural environments. However, the inclusion of the "rural/urban" variable into the model does not increase the correlation between violations and accidents.

4.4. Who are the fast cyclists?

The results indicated that the speed happy type of cyclist is typically a young male. The latent variable "traffic violations" is also related to being young, but has a rather low correlation with gender. This confirms the distinction between the violating type of behaviour and the speeding type of behaviour. The results support previous research that has shown a positive relationship between personality (neuroticism and extraversion) and risk perception (Backer-Grondahl, Fyhri, Ulleberg, & Amundsen, 2009; Chauvin, Hermand, & Mullet, 2007; Sjöberg, 2003; Sjöberg & af Wåhlberg, 2002), even if we had to make do with a reduced version of the original Big Five battery of questions. The analysis of background variables presented in Fig. 5, did not include the dependent variables accidents and helmet use. However, a model where all dependent and independent variables included in these two analyses was tested. The model did not reveal any significant paths between the background variables and either helmet use or accident involvement.

The analysis is based on the cyclists' self-reported involvement in accidents with a bicycle. Previous research has found that the correlation between self-report data and hospital register data for motor vehicle injuries is actually quite high (Begg, Langley, & Williams, 1999). However, there might still be some systematic variation in people's tendency to report accidents, and this systematic variation may influence the results obtained in the SEM analysis. A study conducted by Langley, Dow, Stephenson, and Kypri (2003) found that the tendency for under-reporting of *hospital data* of accidents varied systematically with age (children's accidents are less under-reported), ethnicity, injury severity, and length of hospitalisation. There are to our knowledge no studies that have looked at systematic under-reporting in self reported accident data. The results should be treated with this as a potential source of error.

The data does not provide any information on what part of the body was injured. In a study bicycle injuries based on a similar but larger sample from the Falck register, Bjørnskau (2005) found no significant differences in the injury distribution between helmeted and non-helmeted bicyclists, albeit a tendency for a larger portion of neck/shoulder injuries among helmeted cyclists. One of the intriguing effects of helmet laws is that they do not change the ratio of head injuries over other types of injuries. It can be surmised that risk of head injury increases with accident severity. Hence, future studies should aim at having more precise information on type of injury in order to check if speed-happy helmeted cyclists are more likely to suffer from head injury, due to more severe accidents.

The portrayal of different groups of cyclists are of course somewhat caricatured. There are also other subgroups and variations of the existing groups, e.g., urban cyclists without helmets and cycle equipment that typically ride against red lights and one-way traffic – and thus commit violations but without any accidents due to low speed. It should also be noted that the sample in this survey is rather biased as it has a disproportionately high number of the "eager" cyclists and helmet users compared to the average population. Thus, it is likely that the first group is overrepresented on behalf of other types of cyclists. Future research should aim at investigating these relationships further in a more representative sample of cyclists.

5. Conclusion

The results show that the cyclist population in Norway broadly consists of two sub-populations: one training-oriented speed-happy group that cycle fast and have lots of cycle equipment including helmets, and one traditional, old-fashioned kind of cyclists without much equipment, cycling slowly. In the latter group it seems like the most careful and those who feel unsafe wear helmets.

The results of this study indicate that the lacking effect of helmet legislation most likely has to do with a population shift effect, in which the introduction of mandatory bicycle helmet wearing will lead to a decrease of traditional cyclists in the cycling population, who do not have much accidents anyway, whereas the speed-happy helmet- and equipment using cyclists will remain. Reduced cycling will quite clearly have negative social health consequences (Cooper et al., 2008; Gidske et al., 2007; Hendriksen, Simons, Garre, & Hildebrandt, 2010). Reduced cycling may also lead to a reduction in what is called *safety in numbers*, i.e. the fact that the fewer pedestrians or bicyclists there are, the higher is the accident risk for these road users (Jacobsen, 2003).

The results give less support to a risk-compensation explanation, in particular because the speeding behaviour of the speed-happy group is more connected to other types of equipment than to bicycle helmets. The helmet is more or less just one element in the total equipment package. So it is not because of the helmet that these cyclists ride fast; they use all the equipment (including helmets) because they want to ride fast.

However, as these results are based on cross-sectional data, further studies using longitudinal data on cycling behaviour, equipment use and risk perception is needed in order to resolve some of the issues concerning causal directions between the variables.

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Appendix A. Estimated relationships (unstandardised regression weights) with standard errors, and significance levels between all variables in the structural equation model (Model C)

			Estimate	S.E.	p
Cycling frequency	←	Fast cycling	0.238	0.029	***
Equipment	←	Fast cycling	0.719	0.051	***
Equipment	←	Traffic violations	−0.328	0.054	***
Feeling unsafe	←	Risk perception	1.000		
Probability accident	←	Risk perception	1.758	0.160	***
Equipment	←	Risk perception	0.251	0.070	***
Probability accident	←	Fast cycling	−0.074	0.026	.004
Probability accident	←	Traffic violations	0.101	0.030	***
Equipment	←	Cycling frequency	0.166	0.035	***
Competitive	←	Fast cycling	1.000		
Cycle against red traffic lights	←	Traffic violations	1.000		
Cycle against one-way traffic	←	Traffic violations	0.625	0.048	***
Walk on zebra	←	Traffic violations	−0.294	0.037	***
Accident index	←	Fast cycling	0.258	0.064	***
Helmet use frequency	←	Fast cycling	0.298	0.046	***
Helmet use frequency	←	Traffic violations	−0.354	0.057	***
Accident index	←	Equipment	0.111	0.043	.011
Likes speed	←	Fast cycling	0.992	0.053	***

Estimated relationships (unstandardised regression weights) with standard errors, and significance levels between all variables in the structural equation model (Model C) (*continued*)

			Estimate	S.E.	*p*
Walk on zebra	←	Fast cycling	−0.270	0.028	***
Faster than others	←	Fast cycling	1.029	0.033	***
Assessed risk for accidents	←	Risk perception	1.972	0.165	***
Consequence of accident	←	Risk perception	1.004	0.100	***
Helmet use frequency	←	Risk perception	1.036	0.212	***
Helmet use frequency	←	Feeling unsafe	0.064	0.025	.011
Helmet use frequency	←	Probability accident	−0.207	0.081	.011
Accident index	←	Cycling frequency	0.134	0.050	.008
Helmet use frequency	←	Cycling frequency	0.146	0.036	***

*** $p < .0001$.

Appendix B. Correlations and significance levels between variables in the structural equation model (Model C)

			Estimate	*p*
Fast cycling	↔	Traffic violations	0.368	***
Fast cycling	↔	Risk perception	0.154	***
Err. Term Competitive	↔	Err. term faster than others	0.516	***
Err. Term Helmet use frequency	↔	Err. term equipment	0.284	***
Err. Term Risk perception	↔	Err. term feeling unsafe	−0.159	.002

*** $p < 0.0001$.

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