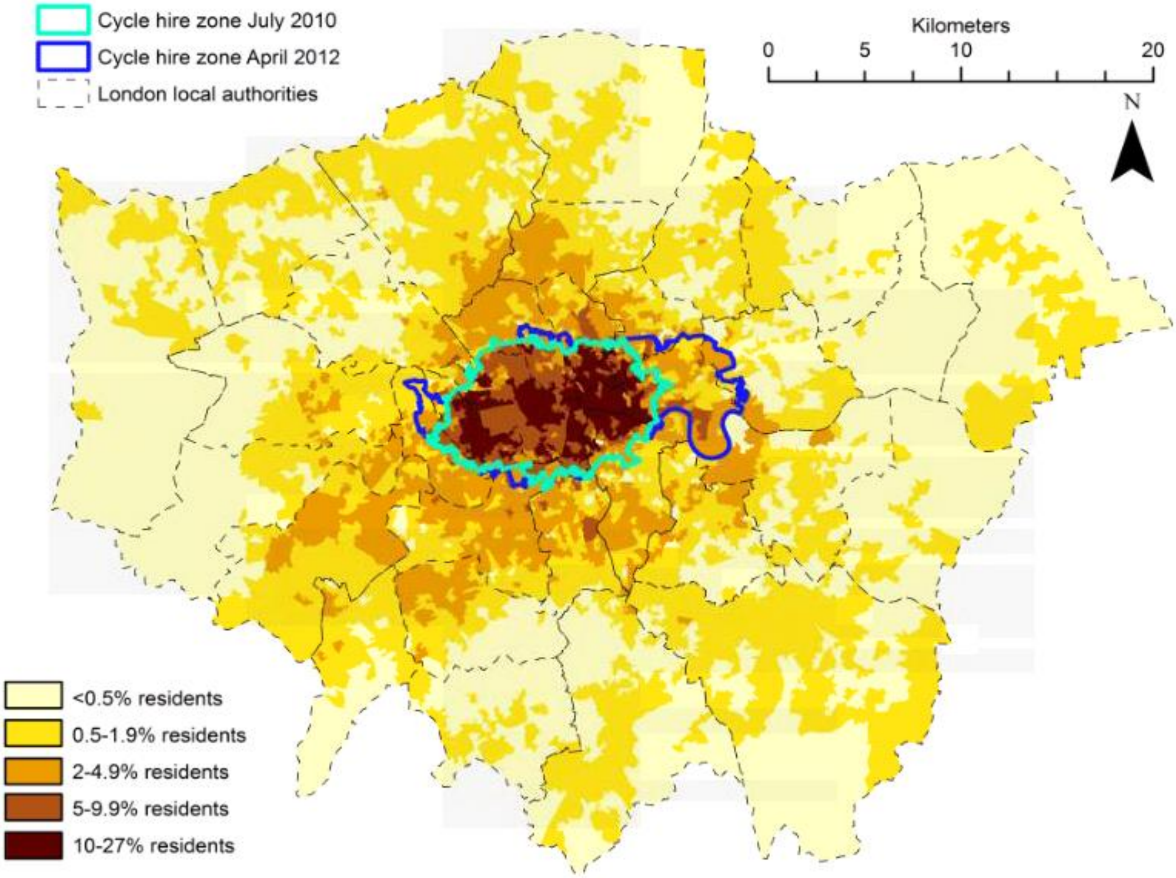
Online Appendices

Appendix 1: London 'cycle hire', the London bicycle sharing system

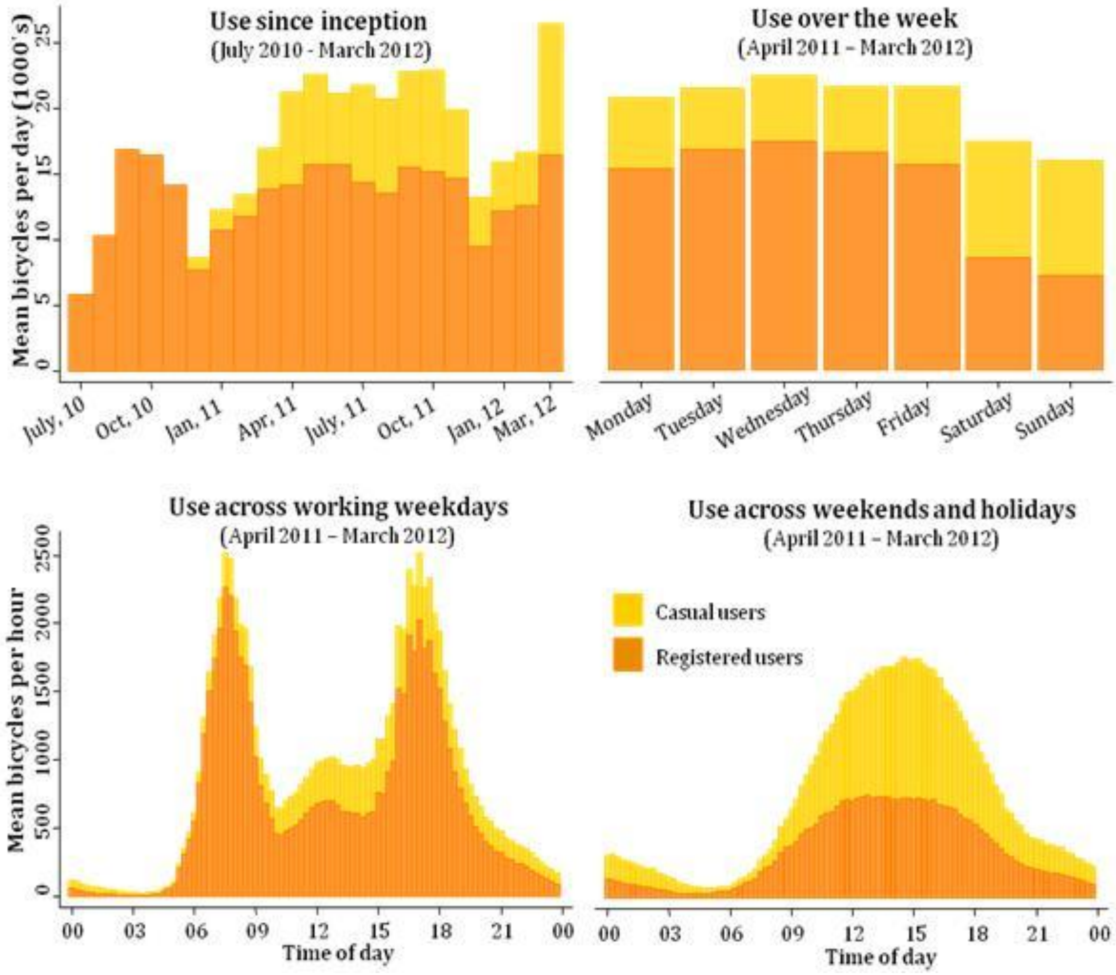
The London bicycle sharing system is known locally as the London 'cycle hire' scheme, and was launched by the public body Transport for London on 30th July 2010. The scheme initially comprised 5000 bicycles located across 315 docking stations, spread at approximately 300m intervals across 45km^2 of central London. In March 2012 the scheme extended East and now incorporates 8000 bicycles at 571 docking stations across 65km^2 (see Figure 1). These bicycles can be taken from any docking station and returned to any other docking station, with the scheme operating 24 hours a day, 365 days a year. To hire a bicycle, users can either register online for an access key ('registered use'), or else pay by credit/debit card at docking stations ('casual use', available since 3rd December 2010). Users initially pay for access to hire bicycles (prices 1-day access £1, 7-day access £5 or annual access £45 in 2010-2011). After paying the access fee, trips of under 30 minutes are free but longer trips incur additional usage charges at a progressively faster rate. Users must be 18 years old or over to register and 14 years old or over to use the bicycles.

Figure 1: Map of the London cycle hire scheme's coverage and registration rate among adult residents of Greater London, as of 31st March 2012



Registration rate calculated at the Lower Super Output Area level (average population 1500), with the denominator defined as London residents aged 16 or over in mid 2010[1]. Cycle hire zones encircle Lower Super Output Areas of which any part is within 500m of a docking station.

Figure 2: Average number of cycle trips across the day and over the months since the London cycle hire scheme was launched



By March 2012 the overall adult registration rate was 1.9% for Greater London as a whole (118,356 / 6,295,195) and 10.2% in the area where the cycle hire was first launched (49,904 / 487,175: Figure 1). As shown in Figure 2, cycle hire trip rates showed substantial seasonal variation but also a general upward trend, reflecting the continuation of high levels of use by registered users plus a growing proportion of use by casual users. There were notable differences between the usage profiles of registered and casual users, with casual users making fewer, longer trips on average (Table 2 in main text); making a greater proportion of those trips in the summer and on weekends (Figure 2); starting or ending more trips in one of London's large parks (16% trips [365,709/2,292,640], vs. 4% of registered-user trips [195,564/5,099,425]); and not showing the marked rush hour peaks seen among registered users (Figure 2). In total, casual users made 75% of weekend trips which started or ended in a London park (187,098/250,552) as opposed to 31% of all cycle hire trips (2,292,640/ 7,392,065). Taken together, this suggests that casual cycle hire use was much more likely to involve cycling for recreation, perhaps often by short-term visitors in London, while registered cycle hire use was dominated by cycling for transport, particularly commuting. This substantiates the finding in Transport for London's surveys that a far higher proportion of 'leisure' trips among casual than registered users (62% [636/1028] vs. 15% [390/2652]).

Appendix 2: Further details on model implementation in Analytica

In this study a new version of the Integrated Transport and Health Model (ITHIM) was implemented in Analytica (Lumina). This model is available from Dr James Woodcock on email request: see Figure 3 for a screen shot of the main user interface for this model. This model differed from the model implemented previously in Excel (Microsoft)[2 3] in a number of important ways.

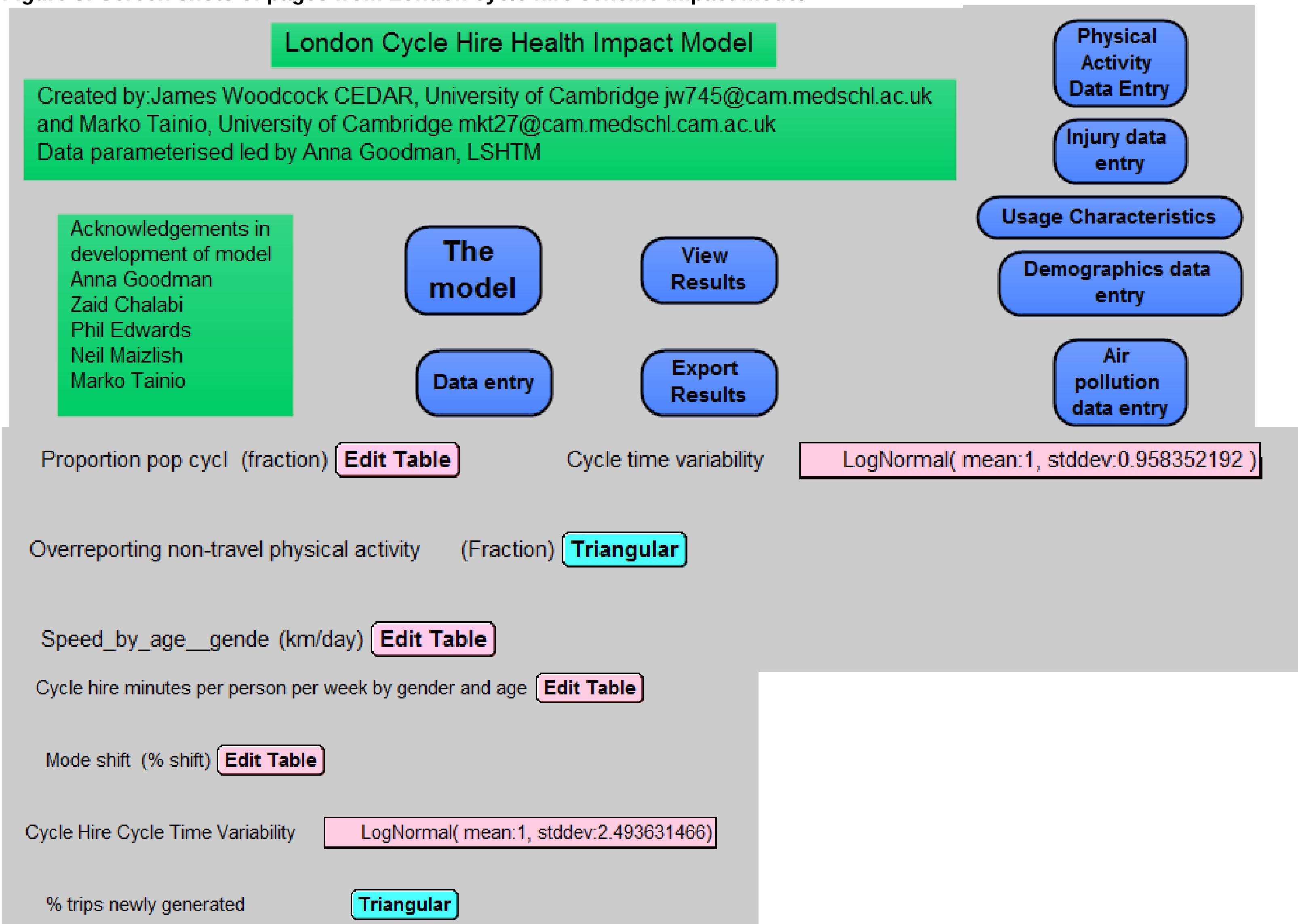
Firstly the new model was implemented with stochastic simulation. The method used was median Latin Hypercube sampling (50,000 runs). For the majority of results we present credible intervals based on 95% of the model runs. The same approach was used to represent both uncertainty and variability. The uncertainty around key parameters is presented in Table 1. This new approach allowed stochastic uncertainty simulation analyses.

Secondly, a modified approach was used for modelling physical activity exposure. Previously, each age and sex group was modelled as having one log normal distribution of active travel time with a certain proportion of this being from walking and a certain proportion being from cycling. To the median of each quintile of these distributions were added estimates of non-travel physical activity. In the new model, each domain of physical activity was modelled as a separate distribution. The four domains of physical activity modelled were: cycle hire cycling, own-bicycle cycling, walking and 'other' physical activity, with the last category incorporating house and garden work, sport and work. These different activity domains were modelled as log normal distributions amongst a percentage of the population who were specified as participating in these activities. Those not participating had a zero value. For each distribution, time in activity was then converted into an equivalent distribution of MET hours per week, and these distributions were then stochastically combined. No correlation between time spent in activity in each domain was assumed. In previous versions of ITHIM the median MET hours for each fifth of the distributions were compared under the different scenarios, in the new version the median MET hours for each tenth of the distributions were compared.

Thirdly, a different approach for modelling injuries and air pollution was used from in earlier papers with ITHIM. Because the changes in motor vehicle use were small, we did not model how reductions in vehicle use affected the air pollution emissions and injury rates faced by other road users. However, we did model mode-specific exposure and ventilation rates for air pollution and mode-specific age variation in injury rates.

Calculations to parameterise the model were performed in Stata 12, except for geocoding which used ArcMap 10 and route-mapping which used Routino (www.routino.org).

Figure 3: Screen shots of pages from London cycle hire scheme impact model



Appendix 3: Methods and data sources

Summary of input to uncertainty analyses

Table 1: Summary uncertainty analyses (See also appendix text)

	Input	**Description of uncertainty analysis**	**Rationale for uncertainty analysis**
Cycle hire usage	% cycle hire travel time by age group and sex	Input distribution from survey multiplied by second distribution (mean 1, sd 0.1)	The age distribution of the population was taken from a small survey and hence comes with considerable uncertainty.
	Proportion of trips newly generated by cycle hire	9% mode (3.5% to 20%, triangular distribution)	3.5% trips by registered users not made prior to cycle hire [D1]; midpoint estimate 20% among casual users giving 9% value overall
PA model	Baseline levels of PA	Users' baseline PA modelled as intermediate between general London population and cyclists (triangular distributions)	Assumed that the baseline walking and 'other' physical activity of cycle hire users were intermediate between the general London population and cyclists. The physical activity values for the general population and for cyclists were calculated separately by age and sex. The distribution was modelled as triangular, with the midpoint between these values as the mode.
	PA health impacts, via specific diseases	Power transformation of MET exposure: 0.5 mode (0.25 to 1, triangular)	Assumed a non-linear association between physical activity and health outcomes, specifically assuming that changes in disease risk log-linearly associated with a power transformation of the MET exposure.
	PA health impacts, directly to all-cause mortality	Power transformation of MET exposure: 0.5 mode (0.25 to 1, triangular)	Assumed a non-linear association between physical activity and health outcomes, as for specific diseases (see previous point)
		Benefit scaled down by - 0.5 (0.33 to 0.67 triangular) for ages 15-29 years; - 0.667 (0.5 to 0.8, triangular) for ages 30-44 years - 0.75 (0.7 to 0.8, triangular) for ages 45-59 years.	Assumed RR reductions ('benefit') from physical activity on all-cause mortality are smaller at younger ages due to the different composition of deaths.[4]
Air pollution model	PM2.5 concentration along cycle hire & counterfactual routes	PM2.5 concentration in London underground 200 mgm^{-3} (280 mode, 130 to 480 triangular)	Assumed PM2.5 concentration of 200 mgm-3 in the London underground, following reports of concentrations of 270–480 mgm-3 in the drivers cab and 130–200 mgm-3 on the platform in 2003.[5]
	Pollution exposure factor in different modes	MET uncertainty modelled as for physical activity, for ventilation rate scaling factor	In calculating the pollution exposure factors, ventilation rates for walking and cycling equivalent to MET values.[6]
		Underground uniform 0.1 to 1, for pollution composition scaling factor	The composition of PM2.5 pollution in the underground is different to that on the surface and could be less harmful to health.[7,8]
Injuries model	Modelled injury rates for counterfactual modes	E.g. 22 fatalities for male cyclists from 100.08 hours of travel, Poisson distribution (see Table 14)	For each mode, the recorded number of injuries used as the number of events [D3,[9]], estimated time at risk as the exposure time [D4, [10]].

	Input	Description of uncertainty analysis	Rationale for uncertainty analysis
	Under-reporting of injuries in routine data	Injuries scaling factors: • Walk: Triangular, 0.7 (0.67 to 0.78) • Cycling: Triangular, 0.69 (0.66 to 0. 96) • Bus, car, taxi, train, underground: Triangular, 0.72 (0.68 to 0 .90) • Motorbike: Triangular, 0.78 (0.73, to 0.85) Fatalities scaling factor: • All modes: Uniform, 0.9 to 1	These scaling factors drew on London-specific comparisons of police data vs. hospitalisation rates.[11] A midpoint of 10% of fatalities not reported is suggested by both a report for London[11] and by Netherlands data.[12] Underreporting in central London is unlikely to be higher than this, given the high density of people and 10% was therefore set as the upper limit for fatalities.
	Percentage of serious injuries that are lifelong [13]	Triangular scaling factor 1 (0.5 to 1.5)	Uncertainty range for these scaling factors not based on data but to cover range of plausible values.
	YLD weights for injuries	Triangular scaling factor 1 (0.5 to 1.5)	Uncertainty range for these scaling factors not based on data but to cover range of plausible values.

D1: Online survey of 2652 registered cycle hire users July 2011, provided by Transport for London
D2: Health Survey for England, 15,054 adult England residents 2008[14]
D3: Stats19, 2005-2009[15]: routinely collected police information on all road traffic crashes
D4: London Travel Demand Survey, 56,671 adult London residents 2005-2009.[16]

Further details on data sources and calculations relating to input data

In modelling health impacts, we used disease burden data from the World Health Organization (WHO) for the UK for 2010 that were not age weighted or discounted. The data were reweighted for the size and demographic structure of the population of people using cycle hire. It was assumed that the same disease-specific dose-response relationships applied to YLDs (years of health life lost due to disability), YLLs (years of life lost), and premature deaths.

For modelling all-cause mortality, mortality rates were taken from London-specific lifetables, provided by the Office for National Statistics. YLLs were estimated assuming that, in each demographic group, the same ratio of YLLs: deaths as in the WHO data.

London cycle hire scheme: operational data supplemented by survey data

Total-population operational data on cycle hire registration and usage

Transport for London provided operational usage data for all trips made between 30/07/2010 and 31/03/2012, including trip-level data for the final 12 months. This trip-level data included the start and end time (in seconds) and location of each trip, and a unique ID number linking trips made on the same credit/debit card (for casual users) and/or on the same cycle hire key (for registered users). For registered users, this unique ID was also linked to anonymised operational registration data for the period up to 31/03/2012. In this registration data, individuals' titles and/or first names were used to assign sex (available for 99.4%) and home postcodes were used to assign Lower Super Output Area of residence (mean population 1500; available for 99.9%).

When analysing trip duration, we assumed that 30 seconds was spent getting the cycle out of the docking station or putting it back. We capped trip duration at 2 hours (1.0% trips, assumed likely to include some non-cycling time) and excluded trips where the start and the end station were the same and the hire bike was hired for under 2 minutes (0.8% trips, assumed likely to involve no actual travel). For trips with missing end time (2.7%) we imputed duration as equal to the mean trip duration from that docking station; data on start times were complete.

Survey data on age structure and modal shift

We estimated the age structure of cycle hire users and the modal shift attributable to cycle hire using the best data available to us, namely two surveys conducted during July 2011 by Transport for London. For registered members, an online survey was emailed to a representative sample of the 25% of individuals who had agreed to receive such surveys. Of these 2652 took part (9% of those emailed, 2.5% overall response rate). For casual members, a brief intercept survey was conducted with 1034 casual users on a mixture of week and weekend days at a sample of cycle hire docking stations (response rate not available). Both surveys recorded age and sex, and the online survey also asked respondents to report a) the duration of their most recent cycle hire trip and b) what alternative mode they would typically have used for that trip before cycle hire was introduced. Despite their low/unknown response rates, these survey data generated fairly accurate estimates of values that could be cross-checked against the total-population operational data. For example, in the surveys 77% of registered users were male (2031/2652) vs. 76% in the operational data (69893/92100); and 71% of registered users were London residents (1873/2633) vs. 76% in the operational data (70723/92664).

Proportion of total cycle hire travel time accounted for by men and women of different ages

Table 2 presents the age distribution of male and female respondents to the online and intercept surveys. Table 3 presents these same age distributions after re-grouping the age categories to correspond to those used in the World Health Organisation burden of disease data. Note that this involved the assumptions that 1) the proportion of users aged 25-34 who were aged 25-29 was 30% for registered users and 60% for casual uses (estimated based on the shape of the age distribution in each group) and 2) 60% of those aged ≥65 years were aged 65-69, 35% were aged 70-79 and 5% were aged over 80.

Table 2: Age and sex distributions of registered in the online survey and casual users in the intercept survey

		Registered users,		Casual users	
		Male, N (column %)	Female, N (column %)	Male, N (column %)	Female, N (column %)
Age (years)	≤15	0 (0%)	0 (0%)	0 (0%)	0 (0%)
	16-18	7 (0.3%)	1 (0.2%)	46 (7.3%)	39 (10.3%)
	19-24	65 (3.2%)	30 (4.8%)	167 (26.6%)	122 (32.3%)
	25-34	609 (30.0%)	261 (42.0%)	218 (34.7%)	136 (36.0%)
	35-44	676 (33.3%)	156 (25.1%)	119 (18.9%)	48 (12.7%)
	45-54	482 (23.7%)	113 (18.2%)	55 (8.7%)	28 (7.4%)
	55-59	121 (6.0%)	36 (5.8%)	12 (1.9%)	3 (0.8%)
	60-64	51 (2.5%)	20 (3.2%)	10 (1.6%)	0 (0%)
	≥65	20 (1.0%)	4 (0.6%)	2 (0.3%)	2 (0.5%)
	All ages	2031 (100%)	621 (100%)	629 (100%)	378 (100%)

Note age and/or sex information missing on 27 of the 1034 casual users.

Table 3: Estimated age distributions of registered and casual users, grouped according to WHO burden of disease age categories

		Registered users,		Casual users	
		Male, column %	Female, column %	Male, column %	Female, column %
Age (years)	≤14	0%	0%	0%	0%
	15-29	12.5%	17.6%	54.7%	64.2%
	30-44	54.3%	54.5%	32.8%	27.1%
	45-59	29.7%	24.0%	10.7%	8.2%
	60-69	3.1%	3.6%	1.8%	0.3%
	70-79	0.3%	0.2%	0.1%	0.2%
	≥80	0.05%	0.03%	0.02%	0.03%
	All ages	100%	100%	100%	100%

The next step was to weight these distributions by the average annual duration of cycle hire travel by male and female registered and casual users. Table 4 shows how these values were estimated from a mixture of total-population operational data and intercept survey data, and the left-hand three columns of Table 5 show the age and sex distribution obtained by applying the values in Table 4 to those shown in Table 3. Note this assumes that mean trip duration is the same between male and female casual users, and also that users of different ages have the same average duration of cycle hire use. Some justification for this latter assumption is provided by the fact that, although the online survey of registered users correctly picked up the sex difference in the frequency of use ($p<0.001$ for chi-squared association) it found no evidence of an age difference in either the duration of the last trip ($p=0.14$ for association) or the frequency of use ($p=0.10$ for association). In order to model uncertainty around these estimated age distributions we then approximated them in Analytica by parameterising normal distributions, truncated at age 15 years, generating the approximations shown on the right-hand side (‘version 2’) of Table 5. We used truncated normal distributions, with a mean of 36, standard deviation of 12.3 for men and with a mean 30.5, standard deviation 14.5 for women.

Table 4: Calculation of the total duration of cycle hire use in the past year by men and women

	Registered	Casual	Data source
No. cycle hire trips in past year	5,099,425	2,292,640	Operational data
Proportion of trips by men	81.6%	62.5%	Operational for registered users, intercept for casual users
Average trip duration (minutes)	12.5	26.7	Operational data
Average trip duration (minutes) for men	12.2	26.7	Operational data (estimated for casual users)
Average trip duration (minutes) for women	14.2	26.7	
Total duration cycle hire use in past year by men (minutes)	50,765,796 [40.5% total time]	38,258,430 [30.5% total time]	Total no. cycle hire trips & % each sex
Total duration cycle hire use in past year by women (minutes)	13,323,778 [10.6% total time]	22,955,058 [18.3% total time]	Average duration each sex

Table 5: Estimated distribution of total cycle hire travel time by age and sex, applying the percentage time for each sex in Table 4 to the distributions presented in Table 3

		Version 1: original estimated distribution †			Version 2: approximated distribution implemented in Analytica		
		Male, cell %	**Female, cell %**	**Both sexes**	**Male, cell %**	**Female, cell %**	**Both sexes**
Age (years)	**≤14**	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	15-29	21.7%	13.6%	35.4%	21.4%	13.7%	35.1%
	30-44	32.0%	10.7%	42.7%	32.5%	10.5%	43.0%
	45-59	15.3%	4.0%	19.3%	15.2%	4.2%	19.4%
	60-69	1.8%	0.4%	2.2%	1.7%	0.5%	2.2%
	70-79	0.17%	0.06%	0.23%	0.2%	0.1%	0.3%
	≥80	0.02%	0.01%	0.03%	0.01%	0.01%	0.01%
	All ages	71.0%	29.0%	100%	71.0%	29.0%	100%

† generated by applying the weights highlighted yellow in Table 4 to the distributions presented in Table 3

To reflect the methodological limitations of low/unknown response rates, we modelled these age distributions stochastic sensitivity analyses assuming that the mean age was multiplied by another normal distribution (mean 1, SD 0.1). Note that we maintained 15 years as the lower age limit, since this is close to the lower limit of 14 years permitted for cycle hire use. This gave the range (2.5 percentile to 97.5 percentile) shown in Table 6 below.

Table 6: Age distribution sensitivity analysis

		Low estimate (2.5 percentile)			High estimate (97.5 percentile)		
		Male, cell %	**Female, cell %**	**Both sexes**	**Male, cell %**	**Female, cell %**	**Both sexes**
Age (years)	**≤14**	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	15-29	34.5%	17.5%	52.0%	9.6%	9.2%	18.8%
	30-44	28.2%	8.7%	36.9%	29.4%	11.5%	40.9%
	45-59	7.8%	2.5%	10.3%	25.9%	6.8%	32.6%
	60-69	0.5%	0.2%	0.7%	5.1%	1.2%	6.3%
	70-79	0.04%	0.03%	0.1%	1.0%	0.3%	1.2%
	≥80	0.001%	0.002%	0.003%	0.1%	0.04%	0.1%
	All ages	71.0%	29.0%	100%	71.0%	29.0%	100%

Modal shift: Duration of time spent in alternative modes if cycle hire were not available

In the Transport for London online surveys, registered users were asked for the main mode that would typically have used to make their most recent cycle hire trip before the scheme was available, with main mode being defined as that covering the longest distance in the trip. Table 7 presents the distribution of these alternative modes among the 96.5% of respondents who said they would still have made the trip before the introduction of cycle hire, stratified by the travel time of the most recent trip which registered users also reported in the online survey. Table 8 shows the number of trips made in the past year by cycle hire in each of these duration band, and the mean duration of travel within each band. Note that Table 10 assumes 9% of these trips would not otherwise have been made, based on the observed frequency of 3.5% in the online survey and an assumed frequency of 20% among casual users.

Table 7: Modal shift by trip duration reported by registered users in the online survey, among the 96.5% of respondents who would still have made the trip in the absence of cycle hire

		Cycle hire trip duration, column % (N)					
		<10 minutes	10-19 minutes	20-29 minutes	30-44 minutes	≥45 minutes	Total
Alternative main mode	Own bicycle	7.7% (N=34)	7.5% (N=69)	9.1% (N=56)	6.1% (N=5)	4.9% (N=2)	7.9% (N=166)
	Walking	55.1% (N=242)	26.7% (N=246)	11.4% (N=70)	7.3% (N=6)	17.1% (N=7)	27.2% (N=571)
	Bus	18.2% (N=80)	22.3% (N=205)	19.8% (N=122)	17.1% (N=14)	17.1% (N=7)	20.4% (N=428)
	Underground	13.2% (N=58)	33.9% (N=312)	49.0% (N=302)	54.9% (N=45)	43.9% (N=18)	35.0% (N=735)
	Train or light railway	0.7% (N=3)	3.0% (N=28)	3.4% (N=21)	6.1% (N=5)	2.4% (N=1)	2.8% (N=58)
	Taxi or minicab	2.5% (N=11)	3.7% (N=34)	4.1% (N=25)	4.9% (N=4)	4.9% (N=2)	3.6% (N=76)
	Car or van	1.1% (N=5)	1.7% (N=16)	2.1% (N=13)	3.7% (N=3)	7.3% (N=3)	1.9% (N=40)
	Motorcycle/ moped/ scooter	0.9% (N=4)	0.5% (N=5)	0.8% (N=5)	0.0% (N=0)	0.0% (N=0)	0.7% (N=14)
	Other	0.5% (N=2)	0.7% (N=6)	0.5% (N=3)	0.0% (N=0)	2.4% (N=1)	0.6% (N=12)
	Total	100.0% (N=439)	100.0% (N=921)	100.0% (N=617)	100.0% (N=82)	100.0% (N=41)	100.0% (N=2100)

Note mode and/or duration information missing on 475 of the 2652 registered users.

Table 8: Number and mean duration of trips of different duration categories in the operational usage data (combining registered and casual users).

	Cycle hire trip duration					
	<10 minutes	10-19 minutes	20-29 minutes	30-44 minutes	≥45 minutes	Total
No. trips by cycle hire	2,754,341	2,805,403	1,052,427	378,718	401,176	7,392,065
No. trips that would otherwise have been made by alternative modes (here assumed 91%)	2,506,450	2,552,917	957,709	344,633	365,070	2,506,450
Mean trip duration (minutes)	6.1	14.2	23.7	35.7	75.6	16.9

The first column of Table 9 presents the ratio of ‘speed by an alternative mode’ / ‘speed by hire bicycle’ for journeys with a given start and end point. These ratios are estimated from the London Travel Demand Surveys 2005-2009, which are an ongoing set of surveys of around 14,000 London residents per year (12,000 adults) and which include detailed one-day travel diaries.[16] Mean cycle speed on a hire bicycle was assumed to be 10% slower than for cycling in general, reflecting the fact that the bicycles are fairly heavy. This gives the ratio of 1/0.9=1.1 for ‘own bicycle cycling’ in Table 9. For other modes, the ratios were calculated by calculating the speed for all trips by adults (aged 16 or over) starting and ending in central London by each mode of travel. Note that these ratios are calculated in terms of Euclidean (‘crow-flies’) distances rather than actual distances along a route, because we assumed that all cycle hire and counterfactual mode trips are ultimately aiming to travel between a specific origin and a specific destination. This recognises the fact that pedestrians and cyclists can often take more direct routes than other modes, and so may arrive at a given destination quicker than would be expected based solely upon a comparison of velocities of travel.

The subsequent columns of Table 9 then go on to apply these speed ratios to the mean duration of cycle hire travel in each duration band (estimated in Table 8), to estimate how long that trip would have taken if conducted by the alternative mode in question. For example, on average the (Euclidean) speed of walking trips made by adults in inner or central London between two points is 0.43 of the speed of cycling trips between those same points. As such, a trip taking 6.1 minutes by cycle hire (the mean duration of the shortest category of cycle hire trips) would be estimated to take 6.1/0.43=14.3 minutes by walking.

Note that these calculations also involve assuming that the pattern of mode shift in casual users was the same as in registered users, except that the proportion of new trips among casual users was higher. Some justification for this was provided by the fact that, although casual users were more likely to report using hire bicycles less than once a month and making their most recent trip ‘for leisure’, these factors showed similar associations with mode displacement among registered users (e.g. 34% would otherwise use their own bicycle or walk for leisure trips vs. 32% for non-leisure trips).

Table 9: Ratio of trip speed for different modes in central and inner London, and consequent estimated duration of cycle hire trips if made by alternative modes, estimated from the London Travel Demand Survey

		Ratio of 'Euclidean' speed for alternative mode versus cycle hire†	Mean trip duration by alternative modes for each trip duration category by hire bicycle (hire bicycle mean duration * ratio of travel speed)				
			<10 minutes by cycle hire	10-19 minutes by cycle hire	20-29 minutes by cycle hire	30-44 minutes by cycle hire	≥45 minutes by cycle hire
	Cycle hire	1	6.1	14.2	23.7	35.7	75.6
Trip main mode	Own bicycle	1.11	5.5	12.8	21.4	32.2	68.1
	Walking	0.43	14.3	33.3	48.8	67.8	75.6
	Bus	0.70	8.8	20.4	34.1	51.4	108.8
	Underground	1.13	5.4	12.5	20.9	31.5	66.7
	Train or light railway	1.22	5.0	11.6	19.4	29.3	62.0
	Taxi or minicab	1.28	4.8	11.1	18.5	27.9	59.0
	Car or van	1.21	5.1	11.8	19.6	29.6	62.6
	Motorcycle/ moped	1.77	3.4	8.0	13.4	20.2	42.8
	Other	0.98	6.3	14.6	24.3	36.6	77.5
	Trip not made	n/a	0	0	0	0	0

† based on Euclidean ('crow-files') distances, i.e. the time it takes one to travel between point A and point B, using different modes for a journey with a given start and end point.

Table 10: Estimated numbers of hours of alternative travel modes displaced by cycle hire trips over the past year

		Estimated number of trips by different modes displaced by cycle hire trips of different durations (millions of trips)						Estimated number of hours of travel by different modes displaced by cycle hire trips of different durations (millions of hours)					
		<10 min	**10-19 min**	**20-29 min**	**30-44 min**	**≥45 min**	**Total**	**<10 min**	**10-19 min**	**20-29 min**	**30-44 min**	**≥45 min**	**Total**
Trip main mode	Own bicycle	0.19	0.19	0.09	0.02	0.02	0.51	0.02	0.04	0.03	0.01	0.02	0.12
	Walking	1.38	0.68	0.11	0.03	0.06	2.26	0.33	0.38	0.09	0.03	0.08	0.90
	Bus	0.46	0.57	0.19	0.06	0.06	1.34	0.07	0.19	0.11	0.05	0.11	0.53
	Underground	0.33	0.86	0.47	0.19	0.16	2.01	0.03	0.18	0.16	0.10	0.18	0.65
	Train or light railway	0.02	0.08	0.03	0.02	0.01	0.16	<0.005	0.02	0.01	0.01	0.01	0.05
	Taxi or minicab	0.06	0.09	0.04	0.02	0.02	0.23	<0.005	0.02	0.01	0.01	0.02	0.06
	Car or van	0.03	0.04	0.02	0.01	0.03	0.13	<0.005	0.01	0.01	0.01	0.03	0.05
	Motorcycle/ moped	0.02	0.01	0.01	<0.005	<0.005	0.04	<0.005	<0.005	<0.005	<0.005	<0.005	<0.005
	Other	0.01	0.02	<0.005	<0.005	0.01	0.04	<0.005	<0.005	<0.005	<0.005	0.01	0.02
	Trip not made	0.25	0.25	0.09	0.03	0.04	0.67	<0.005	<0.005	<0.005	<0.005	<0.005	<0.005

Modelling health impacts via physical activity

We modelled four different domains of physical activity, each calculated separately by sex and age group. Three were assumed to change as a result of cycle hire: cycle hire cycling was assumed to increase (from zero) by the amount observed in the operational data, while own-bicycle cycling and walking decreased by the estimated duration displaced by cycle hire trips. Other physical activity was assumed to be unchanged.

Cycle hire cycling distribution

The distribution of cycle hire cycling was modelled as a series of log-normal distributions with mean 4.6 minutes per week (standard deviation 11.5) for men and mean 3.4 for women (standard deviation 8.5).

Own-bicycle cycling distribution

The counterfactual distribution of own-bicycle cycling comprised i) a proportion of people doing no cycling in the past year plus ii) a log normal distribution reflecting the average minutes per week of cycling among the remainder of the population (Table 11). The one-day diaries of the London Travel Demand Surveys 2005-2009[16] were used to estimate the mean among those doing any cycling, while coefficients of variation were estimated from the weekly travel diaries of the London sample of the National Travel Survey 2002-2009.[17] The National Travel Survey was also used to estimate the proportion of London residents doing no cycling trips in the past year. Cycle hire users were assumed to be more likely to do any own-bicycle cycling in the past year than the general population, in line with their average rate of bicycle ownership in the cycle hire online survey (74% vs. 26% in the general London population). We assumed the same association between bicycle ownership and past-year cycling applied among cycle hire users as in the general population, and used this to estimate the proportion of past year cyclists at each age group. For example, among 15-29 year old males in the general population, 14% with no bicycle had cycled in the past year as opposed to 81% with a bicycle. Among cycle hire users in the online survey, 64% of this age group had a bicycle, indicating a (0.64*0.80 + 0.36*0.14) = 56% rate of past year cycling.

Table 11: Parameters defining the distribution of counterfactual ('baseline') cycling among cycle hire users, and the associated MET values

Age group	% doing any activity in the past month		Cycling min/ month if any activity in past month mode	
	Male	Female	Male	Female
15-29	56%	45%	27.4	17.1
30-44	55%	48%	42.3	23.7
45-59	62%	46%	39.7	33.9
60-69	41%	30%	25.3	19.1
70-79	36%	24%	37.8	23.8
80+	42%	24%	13.5	29.0
CV: 0.958352192 LogNormal(median:5.8, gsdev:1.3)				

London Travel Demand Survey, 56,671 adult London residents 2005-2009 [16] and National Travel Survey 10,949 adult London residents 2005-2009.[17]

When modelling the cycle hire own-bicycle cycling distribution we reduced the mean by 0.26 minutes per week amongst men and 0.19 minutes per week amongst women, to reflect the transfer of own cycling to cycle hire trips.

Walking distribution

The counterfactual distribution of walking time comprised i) a proportion of people doing no walking trips longer than 20 minutes in the past year plus ii) a log normal distribution reflecting the average minutes per week of walking among the remainder of the population (see Table 12 for parameters). We used 'any past-year walking trip of at least 20 minutes' not 'any past-year walking trip of any duration' as our definition of 'no walking' because this aligns more closely with the way in which 'sedentary behaviour' is defined in the epidemiological studies from which we derived our relative risks for physical activity. It is not known if the cycle hire users have walking levels similar to the general population of adult London residents or whether they might have the somewhat higher levels observed among existing cyclists. Therefore, we modelled uncertainty around the counterfactual distribution using triangular distributions with the minima based on the general population of adult residents in London and the maxima based on the equivalent population of existing cyclists. This was done for each age group and by sex. The one-day diaries of the London Travel Demand Surveys 2005-2009[16] were used to estimate the mean among those doing any walking, while coefficients of variation were estimated from the weekly travel diaries of the London sample of the National Travel Survey 2002-2009 (excluding short walks, as these were only measured on one day).[17] The National Travel Survey was also used to estimate the proportion of individuals doing no walking trips of more than 20 minutes.

Table 12: Parameters defining the distribution of counterfactual ('baseline') walking among cycle hire users, and the associated MET values

Age group	% doing any activity in the past month mode (minimum, maximum)		Walking min/ month if any activity in past month mode		Speed (kmph)	
	Male	Female	Male	Female	Male	Female
15-29	84 (80 to 88)	86 (81 to 92)	190	215	4.90	5.18
30-44	85 (80 to 90)	88 (83 to 93)	176	204	4.74	5.05
45-59	83 (76 to 89)	86 (80 to 91)	161	171	4.66	4.93
60-69	82 (74 to 91)	83 (71 to 96)	163	185	4.51	4.67
70-79	76 (67 to 85)	73 (62 to 83)	171	186	4.17	4.5
80+	73 (54 to 92)	72 (44 to 100)	178	156	4.16	4.43
CV: 0.970893; Formula for METs: Marginal METs=1.45*exp(0.19*Speed)-1 with minimum of 1.5						

London Travel Demand Survey, 56,671 adult London residents 2005-2009 [16] and National Travel Survey 10,949 adult London residents 2005-2009.

For the cycle hire users we modelled a reduction in walking physical activity (based on walking trips displaced by cycle hire) as a new distribution with a mean of 1.94 minutes per week for men and 1.44 minutes for women and a coefficient of variation of 0.97. This distribution was subtracted from the existing walking distribution.

Non-travel physical activity

Non-travel physical activity was estimated based on data from the Health Survey for England 2008,[14] combining the domains of work, sport (excluding cycling) and house/garden tasks. Non-travel physical activity was only used with relative risks taken from studies that included these domains of activity (see Health Impacts below). It was assumed that non-travel physical activity remained unchanged. Analyses were done separately for each age group and by sex. We took the percentage that had positive values in the past month, and then from amongst those we took the mean and the standard deviation. This was modelled as a singular log normal distribution plus an inactive percentage of the population for each demographic group.

Our data analysis found that in general cyclists are on average more active in other domains than non-cyclists. We do not know if the cycle hire users are more like the general population of non-cyclists or cyclists. Therefore we modelled an uncertainty range using a triangular distribution with the bottom being the whole population average (for London), the top being the average amongst cyclists (whole of England due to small London sample size), and the mode being the mean of these values. This was done separately for percentage active, mean and coefficient of variation of the mean. For the oldest age groups (70 years plus) we grouped together cyclists male and female due to high uncertainty with small numbers.

MET values

MET values for each domain of travel and non-travel activity were taken from the Physical Activity Compendium.[6] For walking, we used an algorithm to convert mean walking speed for each demographic group to MET values,[3] assuming a minimum intensity of 2.5 METs (slow walking). Distributions of estimated METs from active travel and non-travel physical activity were stochastically combined. MET values of under 2.5 did not count towards total physical activity, meaning that we did not include MET contributions from time spent travelling by motorised travel modes. The short walks involved in getting to a bus or underground stop in central London were assumed to be balanced out by the short walks involved in getting to a cycle hire docking station.

Table 13: Parameters defining the log normal distribution of counterfactual ('baseline') non-travel physical activity cycle hire users, and the associated MET values

		% doing any activity in the past month mode (minimum, maximum)		MET min/ month if any activity in past month mode (minimum, maximum)		Coefficient of Variation if any activity in past month mode (minimum, maximum)	
		Male	Female	Male	Female	Male	Female
Age group	15-29	85 (75 to 95)	76 (61 to 92)	58 (48 to 68)	51 (50 to 53)	1.0 (0.9 to 1.1)	0.9 (.8 to 0.9)
	30-44	87 (82 to 93)	79 (69 to 88)	65 (60 to 70)	42 (36 to 47)	1.0 (1 to 1.1)	1.0 (0.9 to 1)
	45-59	85 (78 to 92)	80 (71 to 89)	55 (53 to 58)	50 (47 to 52)	1.0 (0.9 to 1.1)	1.0 (0.9 to 1.1)
	60-69	63 (47 to 78)	58 (41 to 75)	45 (39 to 50)	26 (19 to 34)	0.9 (0.8 to 1.1)	0.9 (0,7 to 1.1)
	70-79	53 (41 to 65)	55 (45 to 65)	17 (16 to 17)	15 (12 to 17)	0.8 (0.8 to 0.8)	0.8 (0.8 to 0.8)
	80+	46 (26 to 65)	42 (18 to 65)	13 (9 to 17)	15 (13 to 17)	0.8 (0.8 to 0.8)	0.8 (0.8 to 0.8)
Work METs walking 3.3, climbing 8, lifting 4; sport METs 7, house and garden work METs 4							

Data source: Health Survey for England, 2669 adult London residents 2008 [14]

Health impacts

The health impacts were modelled with Comparative Risk Assessment approach using an updated version of the Integrated Health Impact Modelling tool (ITHIM).[2 3] In the model the median MET exposures for each tenth of the combined age and gender specific distributions were compared with and without the changes attributed to the implementation of the cycle hire.

The relationship between physical activity and health outcomes was taken from the systematic overview in Woodcock et al 2009,[18] see Table 14. A non-linear relationship between MET hours per week and health outcome is supported by the literature (e.g. [19 20]) and in the absence of evidence on the exact nature of the relationship for specific disease outcomes it was assumed for the main analyses that changes in disease risk were log-linearly associated with a transformation of the exposure (mean power 0.5, min 0.25, max 1). Relative risks for breast cancer, colon cancer, dementia, depression relative risks were taken from studies using broad measures of physical activity. By contrast, relative risks for diabetes and cardiovascular disease were taken from meta-analyses of walking alone, and therefore active travel exposure distributions alone were used for these two diseases, excluding non-travel physical activity.

Time spent in more vigorous physical activity may accrue additional benefits beyond the greater number of MET hours.[e.g. 4] To represent this we applied stochastic scaling factors to the MET values for walking and cycling, increasing larger values by to 10% and decreasing smaller values by up to 10%.

Table 14: Marginal METs and relative risks from Woodcock *et al.*

	Exposure: Marginal METs*	**Relative risk**
Breast Cancer	3.5	0.94
Colon cancer: male	31.0	0.80
Colon cancer: female	30.0	0.86
Ischemic heart disease & cerebrovascular disease	5.4	0.84
Dementia	24.5	0.72
Depression	0.8	0.96
Diabetes	5.6	0.83
All-cause mortality Woodcock	8.6	0.81

*These marginal METs were recalculated from Woodcock et al 2009, Table 5

Sensitivity analysis: all-cause mortality

In the main analysis we modelled the impact of changes in physical activity on individual diseases. In sensitivity analysis we modelled the impact on all-cause mortality, combining deaths and YLLs from each cause. We did this using two main approaches. The first main sensitivity analysis used the estimated exposure response function from a recent systematic review [19], stochastically applying the same distribution of power transformations as we used for individual diseases (see above).

The second main sensitivity analysis took relative risks for four levels of physical activity from a recent cohort study of over 400,000 adults.[4] This approach therefore did not assume a transformation of the physical activity exposure, but rather fitted a series of different linear relationships to connect different categories of MET hours per week (Table 15). Wen et al. produced relative risks corresponding to leisure time physical activity therefore a new distribution of non-work physical activity was generated from HSE (not shown, available on request).

Table 15: Marginal METs and relative risks from Wen *et al.*

Group	Minutes per week of activity	Marginal MET intensity	Marginal MET hours per week	Relative risk (95%CI)	RR for 1 marginal MET hour	Range of MET hours per week to which RR is applied
1	91.9	2.0	3.1	0.86 (0.81, 0.91)	0.9520	0 to 6.5
2	222.1	2.7	10.0	0.80 (0.75, 0.85)	0.9896	6.6 to 14.3
3	361.6	3.1	18.7	0.71 (0.65, 0.77)	0.9864	14.4 to 29.8
4	523.5	4.7	41.0	0.65 (0.60, 0.70)	0.9961	29.8 to 54.8*

RR=relative risk. *Wen *et al.* [4] reported there were no additional benefits beyond 100 minutes per day of activity, this equates to 54.8 MET hours per week. We therefore capped MET hours per week at 54.8 in these calculations. Data recalculated from Table 3 in Wen *et al.* 2011

Relative risk reductions from physical activity on all-cause mortality are likely to be smaller at younger ages, due to the different composition of deaths. For example, the cohort of 400,000 adults which provided the parameters for our second modelling approach[4] found an overall relative risk of 0.74 in the whole population and 0.83 in adults 20-59, i.e. the benefit in the younger age group was approximately 0.66 as large as in the whole population. To represent this we applied stochastic scaling factors to the benefits from changes in physical activity to all age groups younger than 60 years. These scaling factors were 0.5 (0.333 to 0.6667 triangular) for age group 15-29 years; 0.667 (0.5 to 0.8, triangular) for ages 30-44 years; and 0.75 (0.7 to 0.8, triangular) for ages 45-59 years.

PM2.5 air pollution

Average PM2.5 concentration along routes

Among the urban air pollutants, PM2.5 has by far the largest health impact in Europe.[21] We estimated changes in the PM2.5 exposure rate associated with using cycle hire versus each alternative counterfactual mode as:

Exposure rate = Average PM2.5 concentration along route * ventilation rate * road position scaling factor * pollution composition factor

To calculate average PM2.5 concentration along each route, we modelled the 'most likely' route for each observed cycle hire trip. We then repeated this for four different counterfactual modes (own bicycle [assumed the same as cycle hire routes], walking, car/motorbike/taxi, bus). To do this we used Routino (www.routino.org) software algorithms, calibrated to each transport mode. For example, we assumed cyclists will have a preference for cycle lanes and quieter roads and we built this probabilistically into the algorithm when calculating the most likely route along the road network. Hard constraints, such as cars avoiding cycle tracks were also included as required for other modes.

Each trip route was decomposed into a series of links (road/path sections), each comprising a path between two adjacent junctions (nodes). The distance of individual links was generally small as London streets contain many junctions. For example, the hire bicycles were modelled as making trips on around 22,000 separate links in the past year. We then took the start and end point of each junction (node) and placed them over the 20m^2 grid of estimated 24-hour average PM2.5 concentrations in 2008 for central London [22]. We estimated the pollution concentration for each link as the average between these two values. Each pollution value was then multiplied by both the number of trips passing along it and the distance of the link. These values for individual links were then summed across all links and divided by the total number of trips and by the mean travel distance to give an average exposure concentration along each metre of the route.

Three scaling factors for pollution exposure

We multiplied the PM2.5 concentrations described above by three sets of scaling factors:

1. **Ventilation rate**: On any given route, cyclists and pedestrians will tend to inhale higher concentrations of pollutants because of their greater ventilation rates.[23] We therefore multiplied their average route concentration by a pollution exposure factor equal to their MET values.
2. **Vehicle type and Road position**: We drew on a recent review [24] of the relative exposure faced by different modes using the same route, due to differences in the vehicle characteristics and their position on the road. As there was no meta-analysis we used visual inspection of a graph of the results (Figure 11, p. 67, in 24).
3. **Pollution composition**: Much higher concentrations of PM2.5 have been reported on the London Underground than on the surface (270–480 mgm^{-3} in the drivers cab in 2005 and 130–200 mgm^{-3} on the platform [5]), but it is possible the health effects may differ because of differences in the composition of the particles[7 8]. We modelled both this uncertainty in the route concentration (modal estimate 200 mgm^{-3}) and in its health impact (modal pollution exposure factor, range 0.1 to 1, uniform).

Table 16: Summary of scaling factors applied to route concentrations

	Ventilation rate scaling factor (equal to MET value)	Vehicle/ road position type exposure factor	Pollution composition scaling factor	Total scaling factor (reported in Table 4 in main text)
Cycle hire	median 6.8	1	1	6.8
Own bicycle	median 6.8	1	1	6.8
Walking	3.3 average across age & gender	0.8	1	2.64
Bus	1.5	1	1	1.5
Underground	1.5	1	0.1 to 1 (uniform)	0.825
Train or light railway	1.5	1	1	1.5
Taxi or minicab	1	1.3	1	1.3
Car or van	1.5	1.3	1	1.95
Motorcycle/ moped	2.5	1	1	2.5
Other	1	1	1	1

Change in exposure and health impacts

Time spent travelling in each mode was multiplied by that mode's pollution exposure rate. Pollution exposure during the rest of the day was assumed to be at the background level of 14.91 (the 2008 inner London average), with the assumption that one third of time was spent resting (1 MET) and the rest in low intensity activity (1.5 METs). Together these were used to estimate a change in daily total exposure to PM2.5. To calculate health impacts from changes to PM2.5 exposure associated we used the values recommended by the WHO [25] for an effect on cardiovascular disease, respiratory disease, and lung cancer. Because we translated exposure into a change in average daily exposure we used the recommended relative risks for this range of PM2.5 values rather than using different relative risks for time spent in differentially polluted environments.

Road traffic and other transport injuries

Only modelled results are available for the health impacts of physical activity and air pollution exposure. For injuries, however, we were able to represent health impacts from transport injuries in two ways, first using observed injury rates (Approach A, based on recorded injuries involving a hire bicycle) and then using modelled injury rates (Approach B, assuming cycle hire injury rates were the same as for cycling in general in the cycle hire zone).

Approach A, observed injury rates

In collecting STATS19 data, the police were requested to note if a hire bicycle was involved, and these incidents were collated by Transport for London. Transport for London additionally identified any STATS19 incidents which were not initially noted as involving a hire bicycle but where the person involved had called the cycle hire customer service number and where the police could subsequently confirm that a hire bicycle was involved. In 76% (59/78) of incidents identified between these two methods, the cycle hire involvement was noted in the original STATS19 report, suggesting a reasonably good level of cycle hire recording by the police. For the denominator of these observed rates, we used the total cycle hire travel time recorded in the operational usage data. These estimates used cycle hire data from the first 21 months (end July 2010 to end April 2012), over which time we estimated 2.07 million hours cycle hire travel time by males, and 0.78 million hours by females. Table 17 presents the number of injuries reported in this way, and the resulting estimates for injury rates per million hours of cycle hire travel time. Results are reported by sex for consistency with our modelling approach elsewhere, however there were no significant differences in the injury rates between men and women. Rates of road traffic injuries do often vary between men and women (as appears to be the case for background cycling in the cycle hire zone) but do not yet have sufficient evidence as to whether the rates vary for cycle hire users.

Table 17: Number of injuries and risk of transport injuries per million hours on cycle hire (observed)

	Male			Female		
	Fatal injury	**Serious injury**	**Slight injury**	**Fatal injury**	**Serious injury**	**Slight injury**
N traffic injuries in first 21 months	0	9	44	0	5	9
Rate per million hours over first 21 months (95%CI)	0 (0, 1.78)	4.35 (2.00, 8.25)	21.26 (15.44, 28.54)	0 (0, 4.72)	6.40 (2.08, 14.96)	11.52 (5.28, 21.90)

We used the period up to end March 2013 to calculate injury rates as it was across this period that Transport for London could provide validated data on cycle hire injury risks. As a sensitivity analysis, however, we also estimated the expected number of fatalities up to end November 2013. We did this because in mid July 2013 the first fatality occurred on a cycle hire bicycle, involving a female cyclist hit by a heavy goods vehicle. Our denominator data on cycle hire time duration was calculated using observed durations for the period up to 25 May 2013, the most recent date for which operational data were available; after 2013. From 26 May 2013 to 30 November 2013, we estimated the duration by using trip rates and average trip duration figures published by the Greater London Authority (http://data.london.gov.uk/datastore/package/number-bicycle-hires). Increasing or decreasing this estimated duration by +/-20% did not change our overall findings

Across the period up to end November 2013 there was an estimated total duration of 7.47 million hours of cycle hire cycling (estimated to correspond to 5.34 million hours for males and 2.13 million for females). Applying the sex-specific background rates for cycling in general, one would have expected this duration of cycling to have generated 2.13 fatalities (1.01 among males, 1.11 among females). The 1 observed fatality therefore does not change the pattern across the first 21 months of cycle hire fatality rates being non-significantly different from the expected rate ($p>0.7$), but with a trend towards rates on the cycle hire scheme being lower than expected. We have not included the one observed fatality elsewhere in our analyses of observed cycle hire injuries because (a) to extend follow-up period *post hoc* in order to capture one rare event would tend to bias our estimates of fatality risk upwards[26] and (b) serious and slight injury data is not available beyond April 2012, meaning we would not be able to extend follow-up time consistently.

Approach B, modelled injury rates

The modelled injury rates used routinely collected data from 2005 to 2011. For the numerators, we used routinely collected STATS19 police data[15] to identify the number of men and women aged 16-60 who were killed, seriously injured or slightly injured in road collisions in the cycle hire zone (original 2010 boundary).

To estimate the denominator for injury rates per million hours by different modes in central London, we multiplied the estimated total number of trip stages for each mode between 2005-2011 (estimated by Transport for London [10]) by the average duration of each trip stage and then by the proportion of total travel time accounted for by a) men and b) women aged 16-60 and travelling within the cycle hire zone (estimated from one-day travel diary data from of the London Travel Demand Surveys from 2005-2011). In consultation with Transport for London, we inflated these estimates of travel time within the cycle hire zone by 10% (i.e. multiplied by 1.1) for cycling and motorised modes, and by 25% for walking. This was done in order to take account of trips by non-Londoners, most of which occur in central London. For example, between 2005-2011 an estimated 1263 million trips stages were made by bicycle in London, with an average duration of 22.2 minutes, and with an estimated 17.5% of all cycling time by London residents being accounted for by men aged 16-60 cycling within the cycle hire zone (see next paragraph). The estimated cycling time exposed for men between 2005-2011 was therefore 1263* (22.2/60) *0.175 * 1.1 = 90.0 million hours (see Table 18).

To estimate the proportion of total travel time accounted for by a) men and b) women aged 16-60 and travelling within the cycle hire zone, we used ArcMap 10 to geocode the start and end point of all trips in the London Travel Demand Surveys starting or ending in central London and made by adults age 16-60. For each mode separately, we then calculated the travel time spent within the cycle hire zone by assuming i) the trip took the shortest network distance between the start and end point, and ii) the trip was made at a constant speed, i.e. the percentage distance in the cycle hire zone was the same as the percentage duration. Dividing the estimated travel duration in the cycle hire zone for a) men and b) women by the total travel time reported for each mode gave the percentage of travel by that mode made by each sex within central London. For example, the total duration of all cycling in London reported in the one-day travel diaries of the London Travel Demand Surveys between 2005 and 2011 was 20.3 million hours, whereas the duration of cycling my men aged 16-60 within the cycle hire zone was 3.56 million hours. This therefore gave the figure of 3.56/20.3 = 17.5% as the proportion of all cycling time in London accounted for men aged 16-60 in the cycle hire zone, as used in the example in the previous paragraph.

To estimate the numerator for injury rates by different modes, we used the number of incidents recorded in STATS19 for individuals aged 16-60. To these we added scaling factors to take account of the fact that age, mode or sex was only present for 98.1% of fatalities, 92.6% of serious injuries and 90.8% of slight injuries in the cycle hire zone. We assumed these data was missing at random, and scaled up all fatal, serious and slight injuries by these proportions. For example, there were 17 fatalities in male cyclists ages 16-60 observed over the period 2005-2011 (Table 18). This gave an estimated rate of (17/0.981)//90.03= 0.19 per million hours (Table 19)

Table 18: Time at risk and number of traffic injuries for different modes in the cycle hire zone of central London, 2005-2011

	Total time at risk for adults 16-60, millions of hours		Number of traffic injuries for adults aged 16-60					
	Male	Female	Male			Female		
			Fatal injury	Serious injury	Slight injury	Fatal injury	Serious injury	Slight injury
Cycle	90.03	39.22	17	657	4311	20	226	1549
Walk	409.32	417.82	36	726	2637	27	498	2368
Car	251.91	140.45	5	215	3178	2	107	1670
Motorcycle/ moped	50.24	4.84	36	859	5252	2	80	712
Taxi	72.65	52.12	0	36	625	0	21	208
Bus	381.88	453.32	0	47	434	0	62	737

We assumed the injury rate for each mode was constant over time and was not changed by the introduction of cycle hire. Visual inspection did not provide any clear indication of a decrease in the cycling fatality rate over time within the cycle hire zone, despite the increases in cycling over this period, and we therefore did not model any ‘safety in numbers’ effects in our model.

To these injuries from road traffic crashes, we added the rate of additional non-intentional fatalities and serious injuries on London’s public transport (e.g. falling while getting on a train).[27] These additional non-intentional injuries were only available from 2006-2010 and were only available at a Greater-London level. The same rates per million hours were assumed to apply in the cycle hire zone as across London as a whole, to both males and females. The numbers of injuries observed were therefore scaled down in proportion to the percentage of total travel time conducted within central London for each mode (calculated from the London Travel Demand Survey using the same method described above). The point estimates of the modelled injury rates for these two sources on injuries are presented in Table 19.

Table 19: Modelled rate of transport injuries per million hours in different modes in the cycle hire zone of central London, among adults aged 16-60

Mode	Type(s)	Male				Female			
		Fatal injury	Serious injury	Major injury	Slight injury	Fatal injury	Serious injury	Major injury	Slight injury
Cycle	Traffic collision	0.192	7.881		52.756	0.520	6.224		43.519
Walk	Traffic collision	0.090	1.916		7.098	0.066	1.287		6.244
Car	Traffic collision	[0.020]	0.922		13.899	[0.015]	0.823		13.100
Motorcycle/ moped	Traffic collision	0.730	18.464		115.167	[0.421]*	17.868*		162.225*
Taxi	Traffic collision	[0.000]	0.535		9.478	[0.000]	0.435		4.397
Bus	Traffic collision	[0.000]	0.133		1.252	[0.000]	0.148		1.791
Bus	Other non-intentional	0.004		1.241		0.004		1.241	
Train	Other non-intentional	0		0.034		0		0.034	
Underground	Other non-intentional	0.002		0.342		0.002		0.342	

Injury rates in square brackets should be treated with some caution as they are based on fewer than five fatalities or injuries. * The rates for female motorcyclists are particularly uncertain as the estimated denominator of time is more than ten time smaller than for any other mode.

Approaches A and B: Scaling for under-reporting

We applied London-specific, stochastic scaling factors to account for the fact that not all road traffic injuries are recorded by the police. For serious and slight injuries, our scaling factors drew on London-specific comparisons of police data vs. hospitalisation rates [11], and were as follows

- Walking: Triangular scaling factor, with distribution 0.70 (0.67 to 0.78)
- Cycling: Triangular scaling factor, with distribution 0.69 (0.66 to 0.96)
- Bus, car, taxi, train, underground: Triangular scaling factor, with distribution 0.72 (0.68 to 0 .90)
- Motorbike: Triangular scaling factor, with distribution 0.78 (0.73, to 0.85)

For fatalities, midpoint of 10% of fatalities not reported is suggested by both this report [11] and by Netherlands data.[12] Underreporting in central London is unlikely to be greater than this, given the high density of people and 10% was therefore set as the upper limit for fatalities. We therefore used a uniform scaling factor for fatalities on all modes, with distribution 0.9 to 1.

Applying these scaling factors to the point estimates presented in Table 19, an assuming that ‘major’ non-intentional injuries could be treated as equivalent to ‘serious’ traffic injuries, resulted in the estimates reported in Table 20 and in the main text.

Table 20: Rate of transport injuries, per million hours in different modes, among adults aged 16-60, including scaling for under-reporting

	Male			Female		
	Fatal injury	**Serious injury**	**Slight injury**	**Fatal injury**	**Serious injury**	**Slight injury**
hire bicycle	[0]	[6.30]	30.80	[0]	[9.28]	[16.70]
Own bicycle	0.20	11.42	76.46	0.55	9.02	63.07
Walking	0.09	2.74	10.14	0.07	1.84	8.92
Bus	0.004	1.91	1.74	0.004	1.93	0.29
Underground	[0.002]	0.47	not used$	[0.002]	0.47	not used$
Train	[0]	0.05	not used$	[0]	0.05	not used$
Taxi	[0]	0.74	13.16	[0]	0.60	6.11
Car or van	0.02	1.28	19.30	[0.02]	1.14	18.19
Motorcycle/ moped	0.77	23.67	147.65	[0.44]	22.91	207.98
Other	0	0	0	0	0	0

Injury rates in square brackets should be treated with some caution as they are based on fewer than five fatalities or injuries. $ not used (i.e. treated as zero), as no reliable data.

Approaches A and B: estimating relative risks of injury by age

Road collision injury rates vary by age differently across modes, but the numerators in the cycle hire zone or even London as a whole were too small to produce reliable estimates, particularly at older ages. We therefore used data from the Netherlands[28] to calculate the relative risks of fatality and injury at different ages by different modes. To do this we calculated relative risks in the Netherlands for each age group in each mode, relative to an arbitrary reference age group. This was initially done across 15 narrow age categories: 15-17 years, 18-19 years, 20-24 years, 25-29 years, 30-34 years, 35-39 years, 40-44 years, 45-49 years, 50-54 years, 55-59 years, 60-64 years, 65-69 years, 70-74 years, 75-79 years and 80+ years. We then pooled these relative risks for each narrow age group into the broader WHO age groups, weighting these relative risks by the relative duration of cycling accounted for by each narrow age category within the broad category (for example, around half the cycling in the cycle hire zone by those aged 15-29 was estimated to be done by those aged 25-29). The shape of these age associations were similar to those reported for London[29] or the UK.[30]

In applying these relative risks to our cycle hire data, we assumed that the same pattern of variation by age applied in London as in the Netherlands from 2005-2009[28],calculating this for each mode separately. For example fatality rates per million hours cycling were 2.75 times larger for those aged 60-69 in the Netherlands compared to those aged 15-29, and we assumed this same relative difference of 2.75 applied to the rates in London (even though in absolute terms the London rates were substantially higher than in the Netherlands). This was done for pedestrian, cyclist, car, and motorbike/moped injuries separately. Due to lack of data on buses, trains and the underground, we assumed that these showed the same pattern of relative rates as were seen for pedestrian injuries, as most of these injuries involve falls. We assumed no variation by age for taxis, and that the same pattern of age variation applied to males and females.

Table 21 and Table 22 show the resulting injury scaling factors, and reveal that mode-specific relative rates of fatality and serious injury increased substantially for older ages (≥60 years for cyclists and ≥70 years for pedestrians and car drivers). Relative rates for car drivers were also elevated in the younger age group (15-29). We multiplied these by the rates shown in Table 20 when calculating the expected number of injuries for men and women of different ages. As an example, the age-specific relative rates and confidence intervals for fatal and serious walking and cycling injuries are presented in Table 23.

Table 21: Netherlands age adjustment factor for fatal injury rate

		Cycle hire & own-bicycle cycle	Walk	Car	Motor-cycle/ moped	Taxi	Bus, train & underground
Age group	**15-29**	0.91	1.17	2.47	1.63	1.00	1.17
	30-44	0.83	0.84	0.72	0.77	1.00	0.84
	45-59	1.36	1.05	0.54	0.91	1.00	1.05
	60-69	2.50	0.98	0.74	3.56	1.00	0.98
	70-79	12.49	2.96	2.27	15.29	1.00	2.96
	80+	49.30	13.70	8.33	114.25	1.00	13.70

Table 22: Netherlands age adjustment factor for serious injury rate

		Cycle hire & own-bicycle cycle	Walk	Car	Motor-cycle/ moped	Taxi	Bus, train & underground
Age group	**15-29**	0.78	1.25	2.31	1.32	1.00	1.25
	30-44	0.91	0.83	0.74	0.91	1.00	0.83
	45-59	1.38	0.90	0.60	0.89	1.00	0.90
	60-69	1.91	1.12	0.75	1.50	1.00	1.12
	70-79	5.76	2.49	1.79	2.22	1.00	2.49
	80+	13.97	6.54	4.05	5.79	1.00	6.54

Table 23: Estimated background rates of walking and cycling transport injuries per million hours travel in central London, by age and sex

		Fatality rate (95%CI)		Serious injury rate (95%CI)	
		Walking	**Cycling**	**Walking**	**Cycling**
Male	**15-29**	0.11 (0.08, 0.15)	0.18 (0.10, 0.28)	3.3 (3.0, 3.7)	8.1 (6.7, 9.4)
	30-44	0.08 (0.05, 0.11)	0.17 (0.09, 0.26)	2.2 (2.0, 2.4)	9.4 (7.7, 10.9)
	45-59	0.10 (0.07, 0.13)	0.27 (0.15, 0.42)	2.4 (2.2, 2.6)	14.3 (11.7, 16.6)
	60-69	0.09 (0.06, 0.12)	0.50 (0.28, 0.77)	3.0 (2.7, 3.3)	19.8 (16.2, 23.0)
	70-79	0.28 (0.19, 0.38)	2.50 (1.41, 3.84)	6.7 (6.0, 7.3)	59.7 (49.0, 69.4)
	80+	1.28 (0.89, 1.74)	9.87 (5.55, 15.17)	17.5 (15.8, 19.2)	144.7 (118.6, 168.0)
Female	**15-29**	0.08 (0.05, 0.11)	0.49 (0.29, 0.73)	2.2 (2.0, 2.5)	6.4 (5.1, 7.7)
	30-44	0.06 (0.04, 0.08)	0.45 (0.26, 0.67)	1.5 (1.3, 1.7)	7.4 (5.9, 8.9)
	45-59	0.07 (0.05, 0.10)	0.74 (0.43, 1.09)	1.6 (1.4, 1.8)	11.3 (9.0, 13.5)
	60-69	0.07 (0.04, 0.10)	1.36 (0.79, 2.01)	2.0 (1.8, 2.2)	15.6 (12.4, 18.7)
	70-79	0.20 (0.13, 0.29)	6.78 (3.96, 10.02)	4.5 (4.0, 5.0)	46.9 (37.4, 56.5)
	80+	0.95 (0.61, 1.33)	26.76 (15.64, 39.53)	11.8 (10.5, 13.0)	113.7 (90.7, 136.8)

Estimating health effects of injuries

We then estimated the number of additional deaths, serious and slight injuries experienced by cycle hire users in the past year, based on the past-year duration of cycle hire travel, and also the number of injuries by other modes averted, based on the estimated duration of alternative travel modes displaced. To estimate the health burden from changes to fatal and serious injuries (both observed and modelled) we converted these into DALYs.

For fatalities we took the age and sex specific ratio of deaths to YLLs from the UK Burden of Disease 2010 figure provided by the World Health Organisation [31], and used these as weights to be applied to the changes in deaths. These are presented in Table 24.

Table 24: YLLs per road traffic fatality

		Women YLLs per death	**Men YLLs per death**
Age group	**15-29**	60.0	57.3
	30-44	44.6	42.3
	45-59	30.5	27.4
	60-69	20.1	17.2
	70-79	12.0	10.1
	80+	4.6	4.9

Values from the UK Burden of Disease 2010, provided by the World Health Organisation [31]

For non-fatal injuries we did not follow previous ITHIM studies[2 3] in using adjusted data from the WHO. Instead we used newly-available data from Dhondt *et al*.[13] on the proportion of serious injuries that were lifelong versus temporary, and on the YLDs associated with each injury type. Dhondt provided data on age group and mode (‘slow modes’, driving, and passenger), for example estimating that a 14.7% of serious injuries among 18-34 year old drivers were lifelong while 85.3% were temporary. We assumed that bus, taxi, motorbike, train and tube all had the same proportion of lifelong injuries as car passengers. For cars we assumed that car time was accounted for by drivers and one third by passengers. We assumed cycling and walking corresponded to ‘slow modes’. We applied a scaling factor to these estimated percentages to model uncertainty in the proportion that were lifelong (triangular 1, 0.5 to 1.5), and then additionally modelled uncertainty on the YLDs associated with temporary and lifelong serious injuries (triangular 1, 0.5 to 1.5). This resulted in the estimated YLDs per serious injury presented in Table 25.

Table 25: YLDs (95%credible intervals) per serious injury

		Walking & cycling	Car (driver & passenger average)	Bus, taxi, motorbike, train and tube
Age group	**15-29**	2.53 (1.37, 4.14)	1.79 (0.97, 2.93)	1.66 (0.90, 2.71)
	30-44	1.72 (0.95, 2.78)	1.14 (0.62, 1.85)	0.97 (0.53, 1.57)
	45-59	1.72 (0.95, 2.78)	1.09 (0.59, 1.79)	0.93 (0.51, 1.53)
	60-69	1.20 (0.67, 1.91)	0.58 (0.32, 0.94)	0.35 (0.19, 0.54)
	70-79	0.72 (0.41, 1.10)	0.30 (0.18, 0.46)	0.24 (0.14, 0.37)
	80+	0.72 (0.41, 1.10)	0.30 (0.18, 0.46)	0.24 (0.14, 0.37)

Values from Dhondt *et al*. [13], with further modelling for uncertainty as described in the text

Finally, we assumed a minor injury resulted in one tenth of the point estimate of the YLDs of temporary serious injury, and again modelled the resulting YLD values with uncertainty (triangular 1, 0.5 to 1.5).

Appendix 4: Results

Table 26: Comparison of health impacts with and without air pollution

		Point estimate of model including physical activity alone	Point estimate of model including physical activity + air pollution
Men	**YLLs**	-59.02	-58.67
	YLDs	-30.73	-30.54
	DALYs	-89.7	-89.21
Women	**YLLs**	-7.08	-7.05
	YLDs	-10.95	-10.90
	DALYs	-18.02	-17.95

DALYs=disability adjusted life years, YLLs=years of life lost, YLDs=years of life lost to disability

Table 27: Benefits versus harms in terms of deaths and YLLs, using background injury cycling injury rates to estimate cycle hire risks (95% credible intervals in brackets)

		Non-injury deaths	Deaths from injury	Net deaths	Non-injury YLLs	YLLs from injuries	Net YLLs
Non-injury deaths/ YLLs modelled via specific diseases	Male	-2.26 (-3.23 to -1.44)	0.25 (0.10 to 0.44)	-2.00 (-2.98 to -1.16)	-57.5 (-81.6 to -36.9)	9.7 (3.6 to 16.8)	-47.7 (-72.7 to -26.0)
	Female	-0.26 (-0.36 to -0.18)	0.25 (0.13 to 0.38)	-0.02 (-0.17 to 0.14)	-7.0 (-9.6 to -4.8)	11.0 (5.8 to 17.1)	4.0 (-1.8 to 10.5)
	Both sexes	-2.53 (-3.59 to -1.63)	0.51 (0.31 to 0.74)	-2.02 (-3.10 to -1.10)	-64.5 (-91.0 to -41.9)	20.8 (12.6 to 30.0)	-43.6 (-71.3 to -19.3)
Non-injury deaths/ YLLs modelled via all-cause mortality from Woodcock *et al.* 2010 ('sensitivity 1')	Male	-3.14 (-5.16 to -2.00)	0.25 (0.10 to 0.44)	-2.88 (-4.90 to -1.71)	-79.3 (-140.6 to -44.4)	9.7 (3.6 to 16.8)	-69.6 (-130.8 to -33.8)
	Female	-0.52 (-0.79 to -0.36)	0.25 (0.13 to 0.38)	-0.28 (-0.56 to -0.06)	-13.9 (-22.8 to -8.5)	11.0 (5.8 to 17.1)	-3.1 (-13.1 to 5.3)
	Both sexes	-3.66 (-5.94 to -2.36)	0.51 (0.31 to 0.74)	-3.16 (-5.44 to -1.82)	-93.2 (-163.5 to -53.0)	20.8 (12.6 to 30.0)	-72.5 (-142.7 to -30.7)
Non-injury deaths/ YLLs modelled via all-cause mortality from Wen *et al.* 2011 ('sensitivity 2')	Male	-5.92 (-6.14 to -5.69)	0.25 (0.10 to 0.44)	-5.66 (-5.93 to -5.37)	-153.1 (-161.6 to -144.0)	9.7 (3.6 to 16.8)	-143.3 (-154.0 to -131.9)
	Female	-0.95 (-0.98 to -0.91)	0.25 (0.13 to 0.38)	-0.70 (-0.82 to -0.56)	-26.8 (-28.5 to -25.1)	11.0 (5.8 to 17.1)	-15.8 (-21.3 to -9.5)
	Both sexes	-6.87 (-7.12 to -6.60)	0.51 (0.31 to 0.74)	-6.36 (-6.68 to -6.01)	-179.9 (-190.1 to -169.1)	20.8 (12.6 to 30.0)	-159.1 (-172.3 to -144.9)

YLLs=years of life lost

Table 28: Trade-off of benefits to harms for cycling in central London: effects by age and sex, per million population

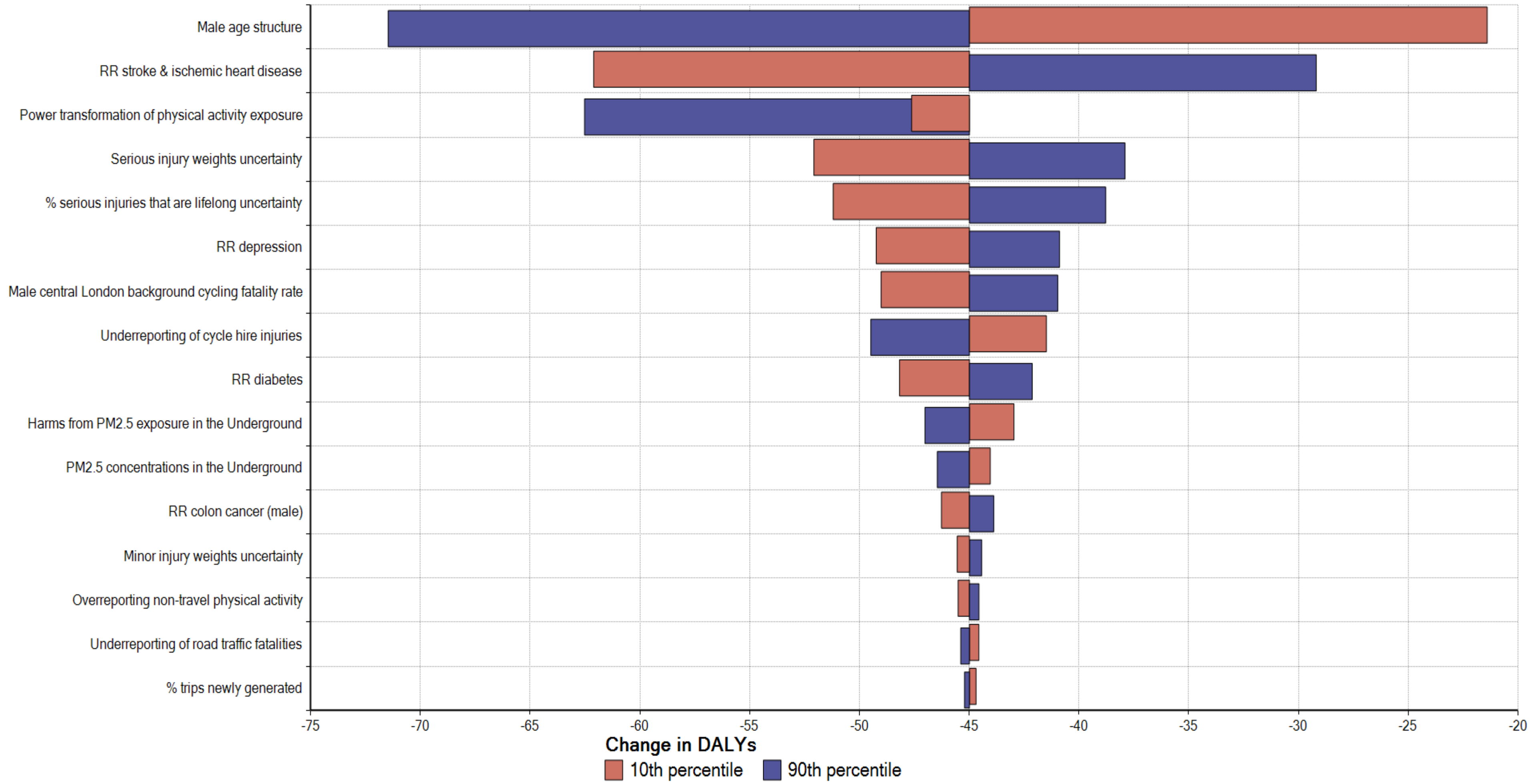
		Males			Females		
		Benefits via impacts on diseases	**Harms via road injuries**	**Net benefits**	**Benefits via impacts on diseases**	**Harms via road injuries**	**Net benefits**
Age group	**15-29**	-22 (-65, -13)	50 (30, 77)	25 (-20, 55)	-25 (-95, -9)	64 (40, 92)	40 (-22, 74)
	30-44	-86 (-137, -57)	44 (27, 66)	-44 (-104, -8)	-60 (-137, -38)	50 (32, 70)	-11 (-88, 20)
	45-59	-276 (-385, -183)	65 (40, 99)	-199 (-307, -105)	-132 (-219, -92)	65 (43, 92)	-60 (-144, -13)
	60-69	-486 (-670, -327)	69 (45, 102)	-461 (-667, -286)	-301 (-408, -220)	74 (50, 103)	-205 (-296, -129)
	70-79	-1425 (-2220, -922)	154 (105, 216)	-1262 (-2042, -761)	-753 (-1241, -513)	191 (126, 264)	-602 (-1056, -350)
	80+	-1839 (-2906, -1199)	344 (233, 487)	-1486 (-2562, -834)	-1434 (-2259, -975)	343 (234, 468)	-1063 (-1839, -603)

Note that these results are presented as per million population, even though in practice very few older people used the cycle hire. Note also that these results use background injury rates for cycling and so should be interpreted as the trade-off for cycling in general in the cycle hire zone and not for specifically using hire bicycles (which may carry lower injury risks)

Stochastic uncertainty analyses

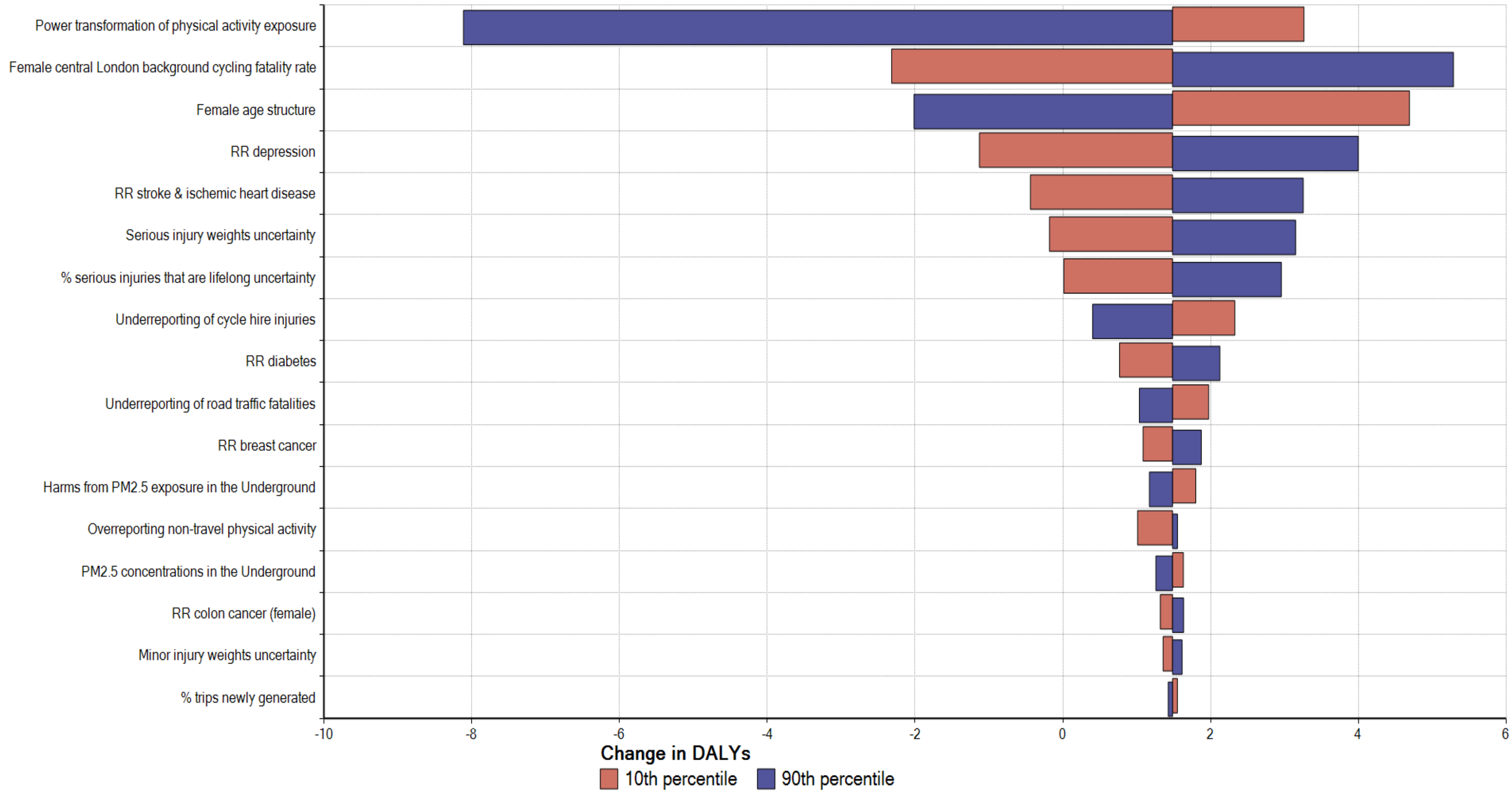
Figure 4 and Figure 5 show the contribution of uncertainty in different parameters to uncertainty in the final estimates of DALYs gained among male and female cycle hire users. The mid-point is the mid estimate of the model. The 2.5th and 97.5th percentiles refer to the corresponding percentile of the sampling distribution for that variable. The order of the variables is the order of difference in DALYs between the two percentiles. Uncertainty in a variable may make a large contribution to final uncertainty either because the variable's value is very uncertain or because the final results are particularly sensitive to that parameter.

Figure 4: Contribution of parametric uncertainty to uncertainty in health impacts (DALYs) among men



RR=relative risk, Central estimate is different from main results as these results are based on simulation with mid-estimates for each distribution rather than the mid-estimate of the 50,000 median Latin Hypercube runs.

Figure 5: Contribution of parametric uncertainty to uncertainty in health impacts (DALYs) among women



RR=relative risk, Central estimate is different from main results as these results are based on simulation with mid-estimates for each distribution rather than the mid-estimate of the 50,000 median Latin Hypercube runs.

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