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Does active transport lead to improved mood and performance? A panel study of travel changes during the Covid-19 lockdown in Norway

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Highlights

- During the lockdown almost all of the participants started working from home and reported to be satisfied with this.
- Lockdown changed participants' travel behaviour: They avoided public transport on behalf of private car and cycling.
- Travel satisfaction is lowest for public transport and highest for active modes.
- Those who walked and cycled to work reported better mood and work performance than passive transport users.

Abstract

Everyday commuting is seen as a burden and an unwanted necessity for people. Recent studies have challenged this notion and have found that certain aspects of commuting can be positive. In particular, research has shown that active commuting can be an important source of everyday physical activity and a pause between arenas for daily routine. The current study uses the Covid-19 lockdown situation in Norway, and the associated travel restrictions, as a backdrop to study the relationship between active travel and self-reported mood and work performance. In a situation where people are strongly encouraged to take up active mobility forms in place of more passive forms, the often-encountered challenge of self-selection is reduced. A convenience sample was recruited via social media (N=1319) in May 2020 and completed a total of six follow-up surveys over a period of four months, thus allowing for a panel design as well as a within-subjects comparison. The survey covered topics related to commute mode, experience of travel, current mood, and work performance. Background variables related to personality, general wellbeing as well as sociodemographic measures were also captured. Multivariate models show that those who during this period commute with active modes (walking and cycling) report a higher degree of travel satisfaction than users of passive modes (driving and public transport). Further, active modes are associated with being in a better mood, and with reporting higher work performance. Finally, looking at individuals who over time change travel mode (N=151), we find that they report improved mood and work performance when travelling with active vs passive modes. The results have implications for policy makers and for employers looking for justification to spend company money on measures to increase active travel.

Keywords

Active commuting; Work performance; Wellbeing; Random-effect GLS panel; Regression; Norway

1. Introduction

Lack of daily physical activity can have a serious negative effect on health and increase the risk of diseases in the long run (Bauman, 2004, Warburton and Bredin, 2017). It is therefore seen as one of the crucial challenges facing the world population today (OECD, 2020). Active commuting can be an effective way to meet this health challenge, besides its obvious positive environmental impacts, and thereby improve wellbeing (Humphreys et al., 2013, Oja et al., 2011). Given that commuting tends to happen with a workplace as the destination, employers might play a role here, but they need to justify spent resources. Thus, it is important to provide empirical evidence about the benefits of active mobility, e.g. in the form of improved mood and enhanced work performance as a result. Using the rise of teleworking and avoidance of public transport in the Covid-19 era as an experimental setting, we investigate interactions between active vs passive mobility patterns and resulting moods and subjective work performance in Norway. This research intends to encourage further policy initiatives prompting the uptake of active commuting, such as the Norwegian national goal to double the number of bicycle trips (Norwegian Ministry of Transport and Communications, 2016), through formalising its benefits for the general population.

1.1. Travel satisfaction determinants

Recorded travel satisfaction has consensually been found more positive for pedestrians and cyclists than for car or public transport (PT) users, especially for commuting (Smith, 2017, Ye and Titheridge, 2017). This can be explained by the possibility to engage in interpersonal conversations during the trip, and by the exposure to varying built and natural environments (Glasgow, Le, Scott Geller, Fan, & Hankey, 2019). Travel duration – and especially reduced congestion and good access and egress trip conditions – predicts higher levels of commuting satisfaction for active modes overall, followed by safety and convenience (Lades et al., 2020, Susilo and Cats, 2014). Typically there is a dissonance between the actual travel duration and a predefined 'ideal commute time' or travel duration affecting commuting satisfaction in general, but Ye, De Vos, and Ma (2019) find that the gap remains the smallest for walking and cycling commutes compared to transit and car journeys, all else being equal. Mokhtarian, Papon, Goulard, and Diana (2015) also show that even if/when walking and cycling gets more physically tiring than passive modes, these were both less mentally tiring than driving a car or taking public transit; and that multimodal trips were more physically and mentally tiring than unimodal trips.

Long-distance and PT commutes are found to make people unhappiest (Lancée, Veenhoven, & Burger, 2017). Research specifically testing the direction of influence from life satisfaction to commuting satisfaction (Eriksson et al., 2013, Gao et al., 2017) finds this proposed link to be more robust than the reverse.

1.2. Wider benefits of active travel

The typical travel patterns of most people imply that shifting from passive to active transport alone can be enough to reach an adequate level of daily physical activity according to suggested health guidelines (Ainsworth et al., 2011, de Geus et al., 2007), accentuated by the fact that active travel is for most people, the "easiest and most acceptable forms of physical activity" (Saunders, Green, Petticrew, Steinbach, & Roberts, 2013). Benefits of active commuting on physical health are quite well-documented (Celis-Morales et al., 2017, Götschi et al., 2016), the greatest health gains from active travel being seen among the least active travellers (Oja et al., 2011).

The benefits from active transport may reach beyond improving physical health. Previous studies find that cycling to work elicit more positive affect and enjoyment compared to other modes of travel (Gatersleben and Uzzell, 2007, Rissel et al., 2016). A review of walking and mental health benefits found that there is evidence, albeit mixed, concerning positive effects on a range of mental health outcomes (Kelly et al., 2018). In the longer term, cycling is also associated with individuals' self-realization, in physical, psychological, and social terms (Kaplan, Wrzesinska, & Prato, 2019).

The transport experience itself, e.g., a combination of time spent and mode used, may leave commuters with a temporary mood (Morris & Guerra, 2015), which can also impact wider and longer-term aspects of wellbeing, such as life satisfaction (De Vos, Mokhtarian, Schwanen, Van Acker, & Witlox, 2016). Still, further evidence, disentangling the effects of background variables such as stable personality traits and general wellbeing from more transient mood changes, is called for.

1.3. Linking travel experiences and perceived work performance

The terms of work productivity and work performance are sometimes used interchangeably in the literature. However, Koopmans et al. (2011) argue that work performance is a wider concept and can be defined as "behaviors or actions that are relevant to the goals of the organization", while work productivity can be defined as input divided by output.

Self-evaluation of work performance has been related to the sentiment of self-efficacy-one may experience when achieving their professional objectives and undertaking "the subsequent activities from the perspective of innovation, action, and cooperation" (Misu, Triculescu, & Petre, 2021). The body of literature linking commuting modes to perceived work performance is fairly recent and rather focused on the terms 'perceived workload' (Stapel, Mullakkal-Babu, & Happee, 2019) and 'perceived mental workload' (Reagan & Bliss, 2013).

Reviewing other 'cousin' notions of perceived work performance, the work of Ma and Ye (2019) connects low perceived mood, tiredness from long car commute, job absenteeism and poor work productivity on the one hand; and positive feelings, physical health of employees, perceived job performance, satisfaction and productivity derived from active commuting on the other hand. A longitudinal study (Dinh, 2019) also identifies a reciprocal causal relationship between job satisfaction, and active commuting. Wener, Evans, and Boately (2005) measured less stress at work among employees who experienced a major improvement in the rail infrastructure in their commute.

Employees who shifted to active commuting reported more positive organizational behaviour, such as going out of their way to be a good employee (Page & Nilsson, 2017). Loong, van Lierop, and El-Geneidy (2017) found an association between commuting mode and energy levels at work and school, as well as punctuality. Their interest was in the current and immediate outcome, not in a general or overall appraisal. Their results show that cyclists had the highest odds of feeling energized at work, as well as being punctual, while car drivers had the lowest odds of feeling energized and highest odds of being late. Results might be due to people with an active lifestyle both choosing to cycle and feeling more energized, but research has shown that physical activity leads to increased wellbeing and mood (Fox, 1999).

1.4. Research gaps and objectives

In the light of such findings, the following research gaps remain:

1. The link between active travel and travel satisfaction has been previously shown, but more evidence is needed as it is context dependent and highly correlated to participants' socio-demographics
2. Travel experience has been analysed in conjunction to job absenteeism and related work productivity notions, but the link between travel mode choice and reported work mood and subjective productivity is barely existent in the literature
3. Whether the aforementioned effects hold when commuters change from passive to active modes has not been investigated.

Therefore, the overall aim of this paper is to investigate whether active commuting leads to higher reported travel satisfaction, mood and work performance compared to passive travel modes, while controlling for influential background variables such as personality traits and general wellbeing.

To address this research question, the following hypotheses are tested:

1. Active travel leads to higher travel satisfaction than passive travel
2. Commuting using active travel modes lead to better mood at the workplace than when using passive modes
3. Using active travel modes for the commute leads to higher perceived work performance than passive modes
4. People changing from a passive to an active mode will report improved mood and performance at the workplace

1.5. The Covid-19 pandemic situation in Norway

Norway had a rapid rise of Covid-19 cases, resulting in the government declaring a national crisis on March 12th, 2020. Schools and kindergartens were shut down, and home office was strongly encouraged, followed by gradually reopening from April and a "new normal" being established after summer, until the second wave struck in late September, and restrictions were reintroduced.

The various phases of the lockdown resulted in quite substantial changes in everyday mobility. In the city of Oslo, there was a 51 percent increase in cycling activity from 2019 to 2020 (April to December). At the same time, there was a reduction in public transport of 40 percent from 2019 to 2020, and a 20 percent reduction in car traffic compared with 2019, whereas for the remained of the lockdown period in 2020, the reduction was smaller (8–9 percent) (Ellis, Elvik, & Nordbakke, 2022).

2. Method

2.1. General approach

The data used in this article were collected through a large survey in Norway during spring, summer and fall 2020 (Table 1). Participants were recruited through a Facebook post which was shared on the institute's website the 6th of May 2020 and advertised for five days, targeting adults in Norway. The survey was also mentioned in the national news on the 18th of May, which resulted in a surge of respondents. This first survey period (T0) ended on the 25th of May. A total of 2,348 people answered this questionnaire. After data cleaning (mostly people who did not want to or were not able to participate in the follow-up surveys) we are left with usable responses from 2,031 people.

Table 1. Overview of the timing of the baseline survey and each follow-up, number of respondents (in our sample of people who commuted at least once) and how many travelled to work at that time.

Period	Date	Number of respondents	Travelling to work
T0	6–25 May	1319	327
T1	13 May-3 June	1228	382
T2	26 May-18 June	1146	518
T3	9–25 June	1060	546
T4	25 August-7 September	1121	712
T5	8–17 September	1086	715
T6	22–28 September	1050	611

Respondents who completed the baseline survey could win a universal gift card of NOK1500 and respondents who completed the follow-up questionnaires could win an additional gift card of NOK1500, and their chances improved with the number of follow-up surveys they completed.

We sent three follow-up surveys during May and June 2020, and another three during August and September that year. Before the first follow-up in May, and the first after the summer holidays, a preparatory e-mail was sent to all respondents with some instructions, and to remind them to check their spam folder if they did not receive the invitation. The instructions informed them that they would receive an invitation to the survey at 9am the following morning and that we wanted them to answer at least one hour after starting work, but before lunch. This instruction was repeated in all survey invitations and reminders, and most respondents complied. From T1 on, more than 90 percent report taking the survey when they had "worked a bit" or they were "about half-way" (Fig. 1). Fig. 1 also shows that this is not true for the recruitment stage T0 when there were no such instructions.

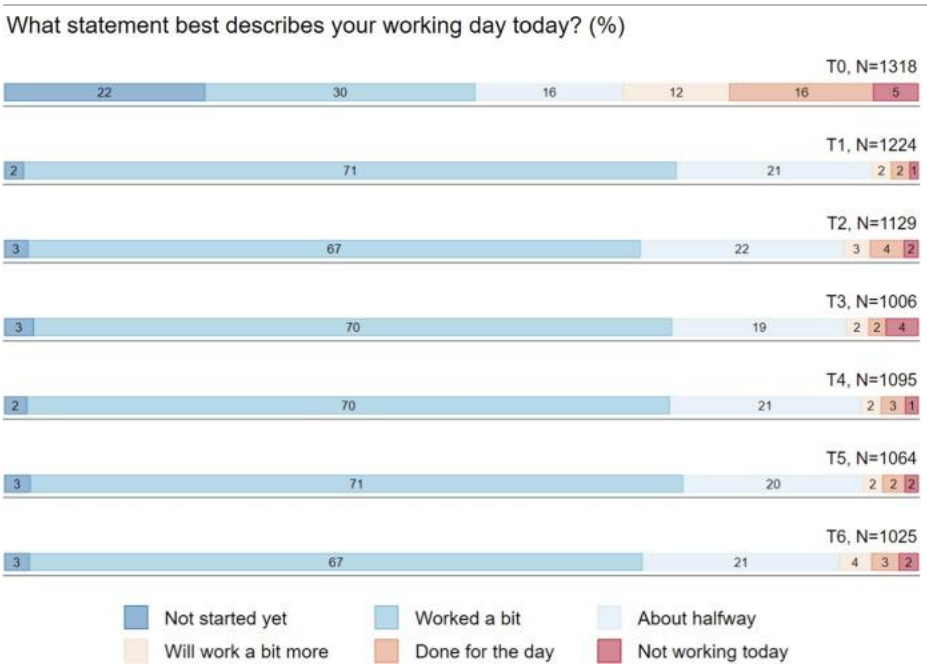

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Fig. 1. Compliance with instructions: when respondents answered the survey at every time period.

In this article we consider only participants who travelled to work in at least one of the survey periods.[1] We have a total of 1319 people who completed the baseline survey. More than 60% of respondent have answered all follow ups, while only 7% of the sample completed<3 follow-ups. On average, respondents took the surveys 6.4 times. The table below shows an overview of the timing of the baseline survey and each follow-up, number of respondents (in our sample of people who commuted at least once) and how many travelled to work at that time.

2.2. Background characteristics of sampled participants

Table 2 shows the summary statistics for the main characteristics of the sample.

Table 2. Summary statistics of demographics and other main sample characteristics (N=1319).

	Percentage/Mean
Female (%)	70
Age (mean)	43
Residence (%)	
East Norway (including the capital)	57
West Norway	18
South Norway	8
Mid and North Norway	18
Higher Education (master's degree) (%)	60
Employed (%)	98
Annual income above 67 000 EUR (%)	34
Access to car (%)	82
Access to (e-)bike (%)	(25) 84

Most of our responders are women, living in Eastern Norway, where the capital, Oslo (33%), is and are on average 43 years old (min 19, max 73). About 65% of respondents have kids. Of those, 25% have one child, 39% have two and 12% have more than two children living in the household. The remaining 24% have children older than 18 years old or not living in the same household.

All respondents are either working or students as this was a selection criterion (2% are students). 40% report working in an office, 35% in academia, 11% are leaders and only 2% works in sales/ service or as health workers. About 34% report earning more than 67 thousand EUR[2] annually (where the average annual income in Norway is around 54 thousand EUR[3]) and around 60% have 5 or more years of university education.

The majority (56%) of respondents work within 10 km of their home and about 60% report a maximum 30 min journey to reach their workplace. About 50% of people express having flexible travel/arrival times. As a part of their commute, 25% of respondents bring children to school/kindergarten, 22% chain their trip with grocery shopping and 6% with performing activities such as exercise.

2.3. Survey measures

The baseline survey (T0) took approximately ten minutes to complete and included sociodemographic questions, specific questions related to work situation at the time (a month and a half after Covid-19 lockdown) and their usual commute before Covid-19. In addition, we included questions regarding current commute, general wellbeing, current mood and subjective work performance, physical activity, and personality.

The short follow-up took 2–3 min to complete and included questions regarding current work situation, work commute that day (if they did not work from home), daily mood and perceived performance, and physical activity over the last 7 days.

2.3.1. Travel mode today

People who travelled to work were asked to choose which travel mode they used that day, from a predefined list of nine travel modes. If they used more than one mode to work (e.g., walked for more than 10 min to public transportation) they were asked to choose all modes used during the trip. They also had the option to write an open comment for “other” modes if no alternative was suitable.

2.3.2. Wellbeing, mood, and personality

Wellbeing in general was measured using five measures to capture the five pillars from Seligman's (2011) PERMA model: positive emotion; engagement; relationships; meaning; accomplishment. Those were found by scanning *the Workplace Well-being Question Bank* (WhatWorksWellbeing, 2020). Only one measure from each pillar was used to reduce respondent burden. Inspired by the measures identified in the question bank, we created the following five statements: "In general, I am satisfied with my life", "my social relationships (family, friends, etc.) are supportive and rewarding", "I lead a purposeful and meaningful life", "I am optimistic about my future" and "I have mostly felt positive and satisfied over the last two weeks". Each statement was measured on 7-point Likert scales anchored with 'completely disagree' to 'completely agree'. They were then combined into a general wellbeing scale with a Cronbach's alpha of 0.84.

We also included four measures related to Covid-19 anxiety. Those were the following: "Regarding the coronavirus, how worried are you that …" (1) "you will be infected", (2) "that your children will be infected" (if they had any), (3) "that someone in your family will be infected" and (4) "that you will infect others". The statements were rated on a 7-point Likert scale anchored with "very little worried" to "very worried". When combined into a scale the alpha was 0.79.

To measure personality, we used a short form of the Big Five Inventory, a 20-item version developed from a Norwegian version of the BFI-44 (Engvik & Clausen, 2011). Each personality factor was represented by four statements. When combined into scales, Extraversion had a Cronbach's alpha of 0.83, Emotional stability of 0.78, Openness of 0.70, Conscientiousness of 0.65, and Agreeableness an alpha of 0.59. These were rated on a 7-point Likert scale anchored with "does not fit" and "fits perfectly".

Wellbeing, Covid-19 related worry and personality were measured only at the first survey, while mood was measured at each time point. We used four of the six statements in the three dimensions of mood scale (Wilhelm & Schoebi, 2007): "tired-awake", "content-discontent", "full of energy-without energy" and "relaxed-tense". The scale had seven steps and their endpoints (1 and 7) included the modifier "very". Statements were prefaced with the introductory clause "Today, I feel …". The combined mood scale had an alpha of 0.78.

2.3.3. Travel satisfaction

Travel satisfaction was measured using items from the satisfaction with travel scale (Ettema et al., 2011) and repeated at all time points. This scale originally had 9 items, but several of those were very similar to the mood ones (e.g., "tired-alert"). Due to the importance of short and non-redundant scales, particularly in repeated surveys, we excluded items that were considered too alike the mood measurement.

Our measure of travel satisfaction consisted of the following statements:: "On my commute today, I was …" (1) "time pressed", (2) "confident I would be in time" and "My commute today …" (1) "worked well", (2) "was the worst I can think of", (3) "was uncomfortable", (4) "was fun", and (5) "was a good separation between work/school and leisure".

We adjusted one statement to better fit with the context (was "uncomfortable" rather than "low standard") and added two additional relevant ones ("fun" and "good separation between work/school and leisure"). We used 7-point Likert scales (completely disagree – completely agree), rather than semantic differential scales.

When the travel satisfaction measures were combined into a scale, it had a Cronbach's alpha of 0.74.

2.3.4. Subjective performance

To examine the association between travel mode and subjective work performance, we developed three measures that were inspired by previous research (see section 1.4), suited to our need for few, time-limited and not industry-specific statements. They were "So far today, I think I am …" (1) "working efficiently", (2) "easily distracted", (3) "concentrating well on my tasks", rated from completely disagree to completely agree. The Cronbach's alpha for the subjective performance scale was 0.87.

2.4. Analysis procedure

When dealing with observational data of multiple individuals over time, it's best to use panel data analysis. In particular, we use Generalized Least Squares (GLS) estimator for panel data using the dedicated environment in the program STATA.[4] The GLS estimator is a generalization of the ordinary least squares (OLS) estimator which estimates the coefficients of a linear regression. GLS is used to deal with situations in which the OLS estimator may be affected by heteroskedasticity or serial correlation.[5] We also choose to use GLS as it allows for the inclusion of both random and fixed effects.

Consider the following linear regression model

$$y_{it} = \alpha + \beta x_{it} + c_i + u_{it}$$

where:

y_{it} is the dependent variable varying over individuals *i* and time *t*.

x_{it} is a vector of independent variables.

c_i is an individual-specific effect.

u_{it} is the error term.

α is the intercept and.

β is a vector of parameters.

We estimate such a model with individual random effects for the following three dependent variables: travel satisfaction, mood, and performance. Our main predictor is transport mode, but we also include a wide range of independent variables, which are described in detail in the result section. All regression results are reported in stepwise regression tables to show how our estimates are reliant on the choice of regressors and to illustrate the robustness of our findings.

Individual random effects are used when we are interested in the effects of various individual characteristics and other regressors on the dependent variable. We assume the variation across individuals is random and uncorrelated with the predictor or other independent variables in the model (c_i is uncorrelated with the independent variables x_{it}).

In addition, we include additional *fixed* effects to remove the possibility of unobserved heterogeneity *between* different time periods, place of residences and types of job. This is important as different Covid-19 related measures were introduced in different areas at different time and could impact some result. Fixed effects (including a dummy variable for each level) hold constant average effects and are used to explore the relationship between a predictor and the outcome variable within an entity.

Even when controlling for a large set of characteristics, it is hard to exclude the possibility of omitted variable bias. Each individual has a set of (observable and unobservable) characteristics that may influence the predictors or the outcome variable. For instance, certain individual characteristics may affect whether or not people travel to work or how they report their daily mood or performance. Individual FE relaxes the assumption that variation across individuals is random. These regressions are run in addition to our main analysis to remove the effect of possible time-invariant characteristics that are unique of each individual and cannot be measured. However, individual FE regression does not allow to analyse the impact of individual characteristics, such as gender, income, education etc which are the focus of our study. This analysis is therefore reported only in the Appendix as robustness check.

Finally, we further exploit the panel structure of our data to study changes *within* individuals who use both active and passive modes over time. Sensitivity power analysis using G*Power (Faul, Erdfelder, Lang, & Buchner, 2007) indicated that we had 80% power to detect effects as small as r^2=0.01 in a linear regression with 22 predictors (N=1300). Our secondary analysis, the delta scores for those who changed between active and passive modes of transport (N=151), indicated that we had 80% power to detect effects as small as d=0.2.

3. Results

3.1. Descriptive statistics results

Fig. 2 shows the percentage distribution for each transport mode used for the trip to work at each survey period (May-September 2020). Note that at every T0, …, T6 time intervals the number of people travelling may vary, so the percentage refers to different totals at every period. The most used modes are bike or e-bike and car (around 30–35% each). Public transport is the third most used mode with about a 15% share, while walking is chosen about 10% of the time. Train, other modes (such as e-scooter, motorbikes etc.) and people using more than one mode in combination account for less than 10%.

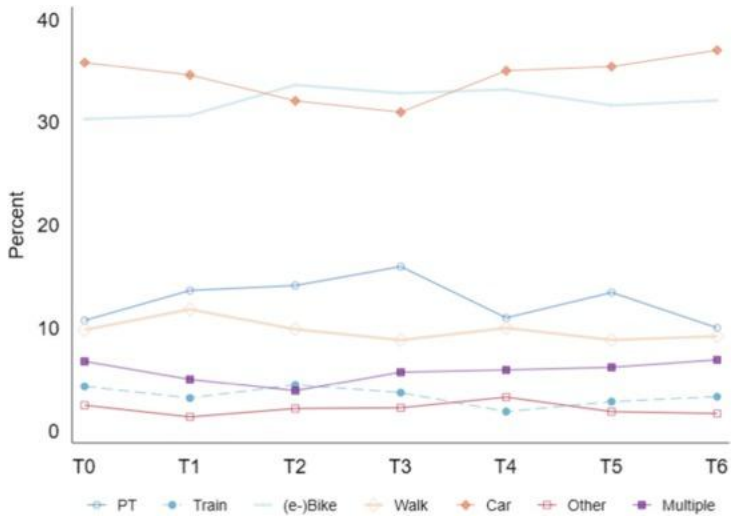

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Fig. 2. Travel mode use for commute travel on day of survey. Share who used each mode to work. Percent.

Reported travel satisfaction has an overall mean of 5.5, with a between-individual standard deviation of 0.86 and a within standard deviation of 0.49. Travel satisfaction for each mode is shown in Fig. 3. People walking and cycling to work report the highest travel satisfaction.

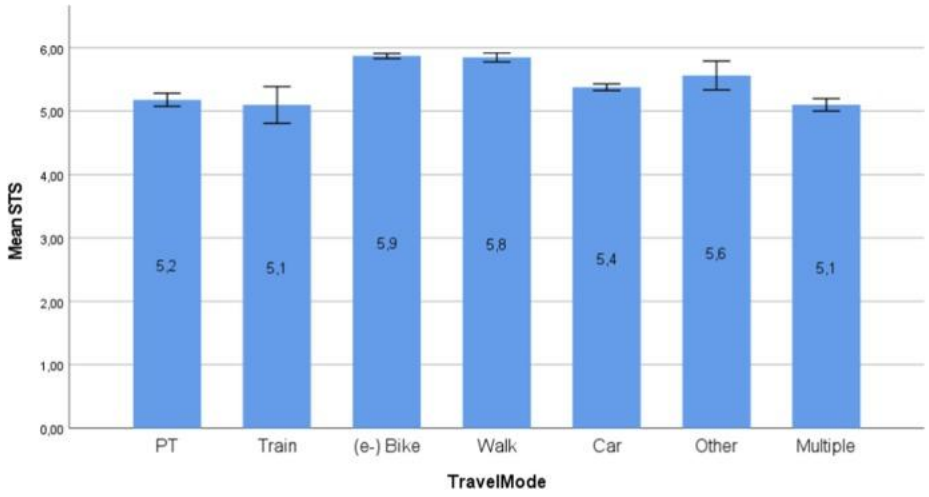

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Fig. 3. Mean travel satisfaction with 95% CI by transport mode for today's commute.

Self-reported mood has an overall mean of 4.6, with a between individual standard deviation of 0.75 and a within standard deviation of 0.77. Mood for each transport mode is displayed in Fig. 4. People travelling with train and cycling to work report the best mood.

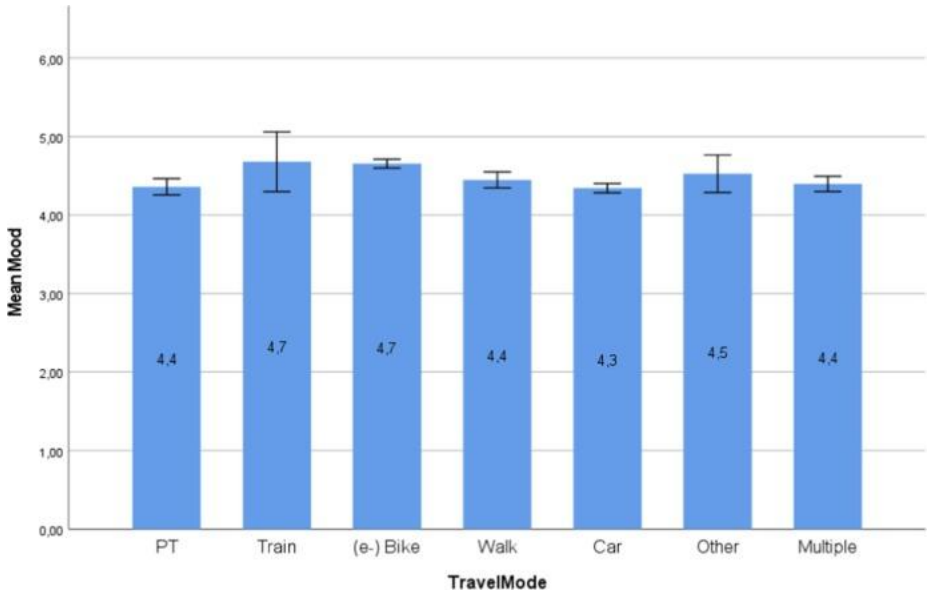

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Fig. 4. Mean mood with 95% CI by transport mode for today's commute.

Subjective performance is an index taking values between 1 and 7. Its overall mean is 4.7, while the between individual standard deviation of 0.87 and the within standard deviation is 0.97. Performance for each transport mode is shown in Fig. 5. People cycling to work report the best performance.

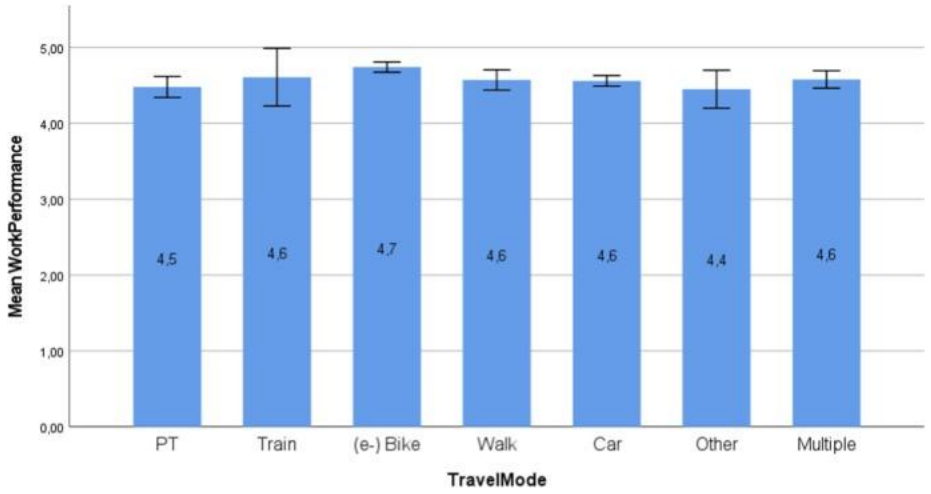

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Fig. 5. Mean subjective performance with 95% CI by transport mode for today's commute.

The bivariate correlation is 0.48 between travel satisfaction and mood, 0.30 between travel satisfaction and subjective performance and 0.40 between mood and subjective performance.

3.2. Regression results

The regression models below include several independent variables: demographics, transport and work-related characteristics, wellbeing and personality traits from the Big Five Inventory as presented in section 2.2.1. Our main independent variable is *today's mode*, which is a variable recording which transport mode the participant used to travel to work the day they answered the survey. The categories are mutually exclusive and distinguish between car (as driver or passenger), PT, train, bike including electric bike and walking. The category "other" includes for example ferry, moped and e-scooters, while "multiple" refers to people using a combination of different modes. Income and Education are two categorical variables having 6 and 4 levels respectively, in the regressions they are considered as continuous. The variables

"longer than 30 min", "flexible" and "children < 18" are dummy variables. Flexible indicates whether the respondent had to be at the office at a specific time.

We provide results in 3 steps to show how the estimated coefficients are affected by the choice of regressors. Step 1 includes several independent variables that may affect each dependent variable in a significant way. Step 2 adds relevant psychological traits, while step 3 includes relevant fixed effects (FE at the end of each table), such as time, place of residence and type of work fixed effects. In other words, we include in the regression a dummy variable for each survey wave, each place of residence and each type of work. FE are used to control for all possible unobserved characteristics that are constant across individuals but vary over time or over place of residence. Step 3 also includes travel satisfaction in Table 4, Table 5 as it is natural that a good/bad travel to work may affect daily mood and possibly performance that is recorded just a few hours after completing travel.

To explicitly test direction of causality, we also conducted a supplementary analysis (see Appendix section 7.2) employing a GLS regressions to study the determinants of mode choice, i.e., looking at the opposite direction of causality. We find that mood and performance do not impact mode choice.

3.2.1. Travel satisfaction

To test the first hypothesis (Active travel modes lead to higher travel satisfaction than passive modes), we ran an individual random-effect GLS panel regression where the dependent variable is the *travel satisfaction* index taking values between 1 and 7. Step 3 includes time and place of residence fixed effects (FE).

The results (Table 3) show that, compared to those driving to work, people who use public transport report significantly lower travel satisfaction. In contrast, those who walk, cycle, or use other transport modes such as motorbike or e-scooters to work report significantly higher travel satisfaction. These results are robust to controlling for relevant demographic variables, psychological traits and time and place of residence fixed effects.

Table 3. Random-effect GLS stepwise panel regression with travel satisfaction as dependent variable.

Travel Satisfaction	**Step 1**	**Step 2**	**Step 3**
Today's travel mode (Car baseline)			
Today's mode=1, PT	−0.25***	−0.23***	−0.24***
	(0.05)	(0.05)	(0.05)
Today's mode=2, Train	−0.00	0.01	0.01
	(0.08)	(0.08)	(0.08)
Today's mode=3, (e-)Bike	0.33***	0.34***	0.34***
	(0.04)	(0.04)	(0.04)
Today's mode=4, Walk	0.33***	0.36***	0.35***
	(0.06)	(0.06)	(0.06)
Today's mode=6, Other	0.29***	0.30***	0.29***
	(0.10)	(0.10)	(0.10)
Today's mode=7, Multiple	−0.10	−0.09	−0.08
	(0.07)	(0.06)	(0.06)
Women	−0.03	−0.02	−0.01
	(0.04)	(0.05)	(0.05)
Age	−0.03	−0.01	−0.01
	(0.02)	(0.02)	(0.02)
Age^2	0.00**	0.00	0.00
	(0.00)	(0.00)	(0.00)
Income	−0.04*	−0.07***	−0.07***
	(0.03)	(0.02)	(0.03)

Travel Satisfaction	Step 1	Step 2	Step 3
Education	−0.01	0.00	0.01
	(0.03)	(0.03)	(0.03)
Children<18	0.04	−0.01	−0.02
	(0.05)	(0.04)	(0.05)
Longer than 30min	−0.23***	−0.23***	−0.20***
	(0.04)	(0.04)	(0.04)
Physically active (index)	0.05*	0.03	0.02
	(0.03)	(0.03)	(0.03)
Trip longer than expected	−0.93***	−0.93***	−0.90***
	(0.05)	(0.05)	(0.05)
Flexible	0.23***	0.23***	0.22***
	(0.03)	(0.03)	(0.03)
Worried about Covid19		−0.04**	−0.03**
		(0.02)	(0.02)
Extraversion		0.02	0.02
		(0.02)	(0.02)
Agreeableness		0.01	0.01
		(0.03)	(0.03)
Conscientiousness		−0.01	−0.01
		(0.03)	(0.03)
Emotional stability		0.06***	0.06***
		(0.02)	(0.02)
Openness		−0.05**	−0.05**
		(0.02)	(0.02)
Wellbeing		0.11***	0.11***
		(0.03)	(0.03)
Constant	5.78***	4.94***	4.87***
	(0.38)	(0.43)	(0.43)
Time FE			YES
Place of Residence FE			YES
Observations	3,501	3,495	3,495
Number of id	1,256	1,255	1,255
R2 overall	0.26	0.29	0.30

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Looking at demographic and other potentially relevant variables, we see that age is very weakly correlated with reporting higher travel satisfaction and it has a non-linear U form (Age^2 in the table). Income is negatively correlated, while education does not seem to play a role. Those reporting a longer than expected trip and those who have longer than 30min commute report a lower travel satisfaction. While those who have flexible times at work, high general wellbeing, emotional stability and are physically active (weakly) report higher satisfaction. Being concerned about Covid-19 and high scores on openness are negatively correlated with travel satisfaction.

3.2.2. Mood

Our second hypothesis was that active travel modes leads to a better mood than passive modes. Table 4 shows an individual random-effect GLS panel regression where the dependent variable is the *mood index*, taking values 1 to 7. We provide results in 3 steps to show how the estimated coefficients are affected by the choice of regressors. Steps 2 and 3 include time and place of residence fixed effects (FE) to control for all possible unobserved characteristics that are constant across individuals but vary over time or over place of residence. Step 3 also includes travel satisfaction as a regressor. Note that people were invited to looked back at their trip and report travel satisfaction.

Table 4. Random-effect GLS stepwise panel regression with mood as dependent variable.

Mood	**Step 1**	**Step 2**	**Step 3**
Today's travel mode (Car baseline)			
Today's mode=1, PT	−0.00	0.03	0.11*
	(0.06)	(0.06)	(0.06)
Today's mode=2, Train	0.19*	0.24**	0.25**
	(0.11)	(0.10)	(0.10)
Today's mode=3, (e-)Bike	0.25***	0.22***	0.08
	(0.05)	(0.05)	(0.05)
Today's mode=4, Walk	0.15*	0.17**	0.02
	(0.07)	(0.07)	(0.07)
Today's mode=6, Other	0.23*	0.23**	0.14
	(0.12)	(0.12)	(0.11)
Today's mode=7, Multiple	0.18**	0.22***	0.25***
	(0.08)	(0.08)	(0.08)
Travel satisfaction			0.34***
			(0.02)
Women	−0.10*	−0.06	−0.05
	(0.05)	(0.05)	(0.05)
Age	−0.09***	−0.06***	−0.06***
	(0.02)	(0.02)	(0.02)
Age^2	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)
Income	0.04	0.00	0.02
	(0.03)	(0.03)	(0.03)
Education	−0.02	−0.01	−0.02
	(0.04)	(0.03)	(0.03)
Children<18	0.13**	0.05	0.07
	(0.05)	(0.05)	(0.05)
Longer than 30min	−0.09*	−0.05	0.02
	(0.05)	(0.05)	(0.04)
Physically active (index)		0.06*	0.05*
		(0.03)	(0.03)
Worried about Covid19		−0.00	0.01
		(0.02)	(0.02)
Extraversion		0.02	0.01

Mood	Step 1	Step 2	Step 3
		(0.02)	(0.02)
Agreeableness		0.03	0.03
		(0.03)	(0.03)
Conscientiousness		0.01	0.02
		(0.03)	(0.03)
Emotional stability		0.15***	0.13***
		(0.02)	(0.02)
Openness		−0.01	0.01
		(0.02)	(0.02)
Wellbeing		0.21***	0.16***
		(0.03)	(0.03)
Constant	5.74***	3.04***	1.35***
	(0.45)	(0.48)	(0.45)
Time FE		YES	YES
Place of Residence FE		YES	YES
Observations	3,502	3,496	3,495
Number of id	1,256	1,255	1,255
R2 overall	0.08	0.20	0.29

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Compared to those driving a car to work, people who walk, cycle, and ride the train to work report significantly better mood the same day. On average, people that commute with an active mode report more than 0.20 points higher mood than car drivers, ceteris paribus. These results are robust to the inclusion of time and place of residence fix effects. However, when travel satisfaction is also included (step3), we see that the effect for bike and walk modes disappears.

Age plays a role for reported mood. We find a non-linear U-shaped relationship indicating that both young and older people report better mood than those between 30 and 40years old (Age^2 in the table). Women and those who have a longer than 30min commute report a slightly lower mood (weakly significant), but these effects disappear when controlling for other factors (Step 2). Having an underage child in the household is weakly associated with better mood, but the effect disappears in Step 2. Being physically active is (weakly) associated with better mood. Mood is also positively correlated with general wellbeing, and emotional stability.

3.2.3. Subjective work performance

Our third hypothesis was that active travel modes result in higher perceived work performance than passive modes. Table 5 shows an individual random-effect GLS panel regression where the dependent variable is the *subjective performance* index taking values 1 to 7. We provide results in three steps to show how the estimated coefficients are affected by the choice of regressors. Steps 2 and 3 include time, place of residence and type of job fixed effects (FE) to control for all possible unobserved characteristics that are constant across individuals but vary over time, place of residence and over type of job. Step 3 also includes travel satisfaction as a regressor.

Table 5. Random-effect GLS stepwise panel regression with performance as dependent variable.

Subjective performance	Step 1	Step 2	Step 3
Today's travel mode (Car baseline)			
Today's mode=1, PT	−0.01	0.04	0.10
	(0.08)	(0.08)	(0.08)
Today's mode=2, Train	0.08	0.16	0.14
	(0.13)	(0.13)	(0.13)

Subjective performance	Step 1	Step 2	Step 3
Today's mode=3, (e-)Bike	0.19***	0.16**	0.03
	(0.06)	(0.07)	(0.07)
Today's mode=4, Walk	0.11	0.15	0.02
	(0.09)	(0.09)	(0.09)
Today's mode=6, Other	−0.14	0.04	−0.06
	(0.15)	(0.15)	(0.15)
Today's mode=7, Multiple	0.03	0.04	0.09
	(0.10)	(0.10)	(0.10)
Travel satisfaction			0.28***
			(0.03)
Women	−0.02	−0.04	−0.04
	(0.06)	(0.07)	(0.06)
Age	−0.07***	−0.06**	−0.06**
	(0.03)	(0.03)	(0.02)
Age^2	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)
Income	0.01	−0.07*	−0.04
	(0.04)	(0.04)	(0.04)
Education	−0.01	0.05	0.04
	(0.05)	(0.05)	(0.05)
Children<18	0.07	0.01	0.02
	(0.07)	(0.07)	(0.06)
Longer than 30min	−0.10	−0.03	0.02
	(0.06)	(0.06)	(0.06)
Physically active (index)		0.14***	0.13***
		(0.04)	(0.04)
Worried about Covid19		−0.02	−0.01
		(0.02)	(0.02)
Extraversion		0.01	0.00
		(0.03)	(0.02)
Agreeableness		0.05	0.05
		(0.04)	(0.04)
Conscientiousness		0.15***	0.15***
		(0.04)	(0.04)
Emotional stability		0.17***	0.15***
		(0.03)	(0.03)
Openness		−0.03	−0.02
		(0.03)	(0.03)
Wellbeing		0.12***	0.08**

Subjective performance	Step 1	Step 2	Step 3
		(0.04)	(0.03)
Constant	5.53***	2.81***	1.19*
	(0.55)	(0.67)	(0.65)
Time FE		YES	YES
Place of Residence FE		YES	YES
Type of work FE		YES	YES
Observations	3,502	3,268	3,267
Number of id	1,256	1,169	1,169
R2 overall	0,06	0,16	0,22

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Compared to those driving to work, people who cycle to work report significantly higher level of subjective performance (about 0.16 points) during that day. This effect is still significant when controlling for several characteristics such as being physically active and is robust to the inclusions of fixed effects. Just as for the model for mood (Table 3), the inclusion of travel satisfaction removes the effect of mode on subjective performance.

Gender and having under aged children in the household does not seem to affect subjective performance. While age (Age^2 in the table) has a small but significant non-linear (U-shaped) effect on subjective performance, indicating that both young and older people report higher subjective performance than those around 30years old. Being physically active, scoring higher in conscientiousness, emotional stability and general wellbeing are correlated with higher levels of subjective performance.

3.2.4. Delta scores on subjective mood and subjective performance in the workplace

To test our final hypothesis, we exploit the longitudinal nature of our data and select only people who report having changed transport mode during the period of observation (N=151). We aggregate cycling and walking into “active” modes and public transport, train, and car into “passive” transport modes. Herein, we report travel satisfaction, mood and subjective performance averages within individuals who over time change from active modes to passive modes or vice versa.

Fig. 6 shows that the mean score when using an active mode is higher than when using a passive one for all three indexes. The average mood score is 4.4 for passive and 4.6 for active transport use. Average subjective performance score changes from 4.5 to 4.7 when changing between passive and active modes. Similarly, the average travel satisfaction score is 5.3 when using a passive mode and is 5.7 when using an active one.

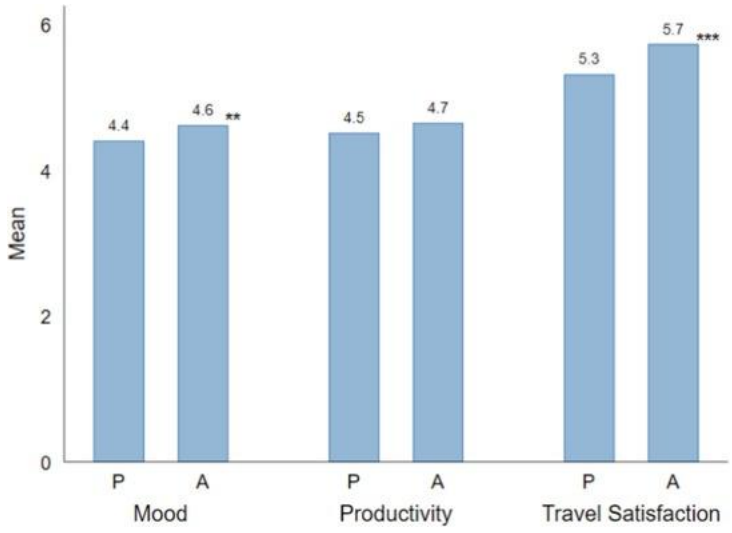

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Fig. 6. Mean mood and performance scores when using a passive or active mode for peoplethat over time change type of mode. N=151.

Paired-samples t-tests were conducted to assess whether the changes were significant. For mood and for travel satisfaction, we find a significant difference *(t(150)=-2.58, p=0.011 and t(150)=-5.70, p=0.000 respectively).* The effect sizes (*d=0.42; d=0.93 respectively*) were from medium to large according to Cohen's (2013) conventions. For performance, the observed change is not statistically significant *(t(150)=1.52, p=0.13).*[6] Similar results are also obtained with non-parametric Wilcoxon signed-rank tests: mood *(z=-2.26, p=0.024), travel satisfaction (z=-5.36, p=0.000)* and performance *(z=-1.72, p=0.086).*

4. Discussion

The current article uses the Covid-19 pandemic situation in Norway as a backdrop to study the relationship between active travel and self-reported mood and subjective work performance. We find that those who during this period commute with active modes (cycling, and to a certain extent walking) report higher degree of travel satisfaction (hypothesis 1), mood (hypothesis 2) and subjective performance (hypothesis 3) than users of passive modes (car and public transport). Our final hypothesis, that individuals who over time change travel mode report improved mood and performance when travelling with active than with passive modes, was partially confirmed. The delta score for mood was statistically significant, whereas the delta score for performance not (p=0.13).

Age is non-linearly related to travel satisfaction, mood, and performance, even though its effect is small. Women report on average lower mood than men and self-reported physical activity is important as a mediating variable for both mood and performance, but not for travel satisfaction.

The size of the effects from the regression models were large enough to be of relevance. Keeping everything else constant, those who commute with active modes report on average 0.34 points higher travel satisfaction than car drivers on a scale between 1 and 7. Similarly, active modes are associated with being in a better mood (on average 0.20 points), and with reporting higher perceived work performance (0.18 points) than car drivers. These findings are in line with previous studies, finding positive relationships from active travel to mood (Gatersleben and Uzzell, 2007, Rissel et al., 2016) as well as to perceived vitality and thereby cognitive performance and work capacity (Calogiuri et al., 2016).

In the current study we have mainly treated cycling and walking together, as different varieties of active transport. Even if a number of studies investigate the effects from these two modes separately (Celis-Morales et al., 2017, Smith, 2017), few studies actually make a point of comparing them, and they are often also just treated as "active travel" (Dinh, 2019). We did not have any hypothesis about there being a difference between the two, but still it is interesting to note that it was only cycling that had a significant effect on subjective performance.

When investigating the role of travel satisfaction for mood and performance (the final step in the regression models), most of the effect of travel modes disappears. Hence, it could be argued that the observed subjective performance effect from cycling mainly stems from the higher satisfaction this mode had above the others. However, there was no difference in mean travel satisfaction between these modes (they both ranked top in our study), as opposed to previous studies that have found a somewhat higher satisfaction for bike (Smith, 2017). It then remains to be explained why walking does not improve subjective performance, whereas cycling does, when not adjusting for satisfaction. Future research should aim at understanding the differences in perceptions about these two modes and explore to what extent these differences are related to background variables and more general preferences.

It is important to note that including travel satisfaction as an independent variable in these models does not stem from a specific research question or hypothesis, but from the fact that daily mood and performance was recorded a few hours after arriving/starting to work. Travel satisfaction was recorded in retrospect, i.e., people looked back at their trip and were invited to think about it. Nevertheless, the results indicate that people's positive and negative experiences of the everyday commute is not something that only affects them there and then, but that it may have implications on their mood and performance at least a couple of hours into the workday.

In our results, those commuting with train report being in a significantly better mood than other commuter groups. The pandemic lockdown led to reduced passenger numbers for all public transport, and it could be that train passengers benefited more from the increased space and lack of crowding than other PT users. However, train passengers were a small group, and these results should be treated carefully.

As mentioned, we used several approaches to analyse the data, and thus were able to gain sufficient control of important confounding variables. In the study we have put forward some assumptions about a direction of influences, going from choice of travel mode via travel satisfaction, then to mood and finally to performance. The stepwise regression analysis is conducted under this assumption and gives support for it, as does the GLS regression reported in the appendix.

As such, this study expands on previous studies that have found *reciprocal* relationships between these variables (Dinh, 2019, Ma and Ye, 2019). There can be several reasons for this slight discrepancy. In the current study we included more background variables, most importantly the BFI index, than the previous studies, thus some of the reciprocal relationship might have been captured by this. Further, we measured momentary (i.e., daily) mood and performance, whereas the previous studies measured more aggregate levels of these variables.

In the current study we focus on the short-term implications of travel experiences, and the momentary mood and perceived work performance effects from these. We have chosen to include wellbeing as an independent variable in our models. Some literature suggests a reverse causal relationship than what our models imply: Travel-induced moods influence each of the physical, emotional, individual and social dimensions of wellbeing and commuting satisfaction is thus seen as a "hidden" determinant of the holistic notion of wellbeing (Friman, Fujii, Ettema, Gärling, & Olsson, 2013). Still, we believe it makes sense to include wellbeing in the models like we have done, to control for the potential confounding effect of a reverse relationship, as discussed by Dinh, 2019, Ma and Ye, 2019. Future studies should aim to include an account of how immediate travel experiences have long term influences on people's well-being, e.g., with the use of prospective research design.

4.1. Strengths and limitations

A novelty of the current study is the framing of the interview situation. The survey was sent out electronically mid-morning, Participants were instructed that they should not respond if they had not started their workday. We see from control question in the survey that almost all complied with this instruction. By this, we could ensure that as many as possible of the responses were given in the middle of a typical working situation, and that people did not postpone answering until they felt like it. As has been discussed (Beute and de Kort, 2018, Gärling et al., 2020), removing self-choice in terms of response timing is essential when assessing transient states such as mood, to avoid biased results. Another strength of this study is that we use a panel design where participants are asked to respond numerous times, as has been recently called for by other scholars (Curtis et al., 2020, Gärling et al., 2020). Furthermore, the study had quite low attrition, compared to what can be expected for surveys with six reiterations. Participants responded to on average 6.4 surveys, and 68% answered the final survey.

The study sample is a convenience sample and is not meant to be representative for the general population. A quite high share of the participants are white collar workers with high education and income. Other types of workers were not explicitly excluded from responding. Still, the advertisement text as well as the questions in the T0 survey, might have discouraged several non-white collar workers to respond. The results are therefore applicable for people doing typical office work, demanding a certain level of concentration and independence.

The fact that this study was conducted during the Covid-19 pandemic is per se an extraordinary event which limits generalizability of the results. However, the lockdown can also be said to be a strength for the study design. The fact that people were forced to change their travel behaviour, resulted in more people taking up active mobility than what is normal. Transport authorities reported a slump in PT, reduced car traffic, and an increase in walking and bicycle traffic. This imposed change reduces the challenge of self-selection more than would be achieved in a "normal" situation. Still, people have a certain degree of control. Thus, we cannot rule out that some unmeasured aspects can have influenced the results. Also, we were not able to test for *directions of change*, i.e. to compare people changing from active to passive transport with people changing the other way. The study design, with seven different measurement periods, implies that there were a large number of possible ways the 151 people who changed from one to another could have changed. They could e.g. have used passive transport three times, then active two times, then passive two times, or any other of 128 (2^7) possible combinations of these two outcomes. Future research could benefit from using a randomized control design, where people are randomly assigned to groups of active and passive transport users.

In the main analysis we report estimates using panel regression with individual *random* effects because we were interested in understanding more about the relationship between our outcome variables and choice of travel mode, and relevant demographic individual characteristics and psychological traits. Importantly, we measured both psychological traits (BFI) as well as stable states (well-being). By including these potentially confounding variables, we reduced the likelihood that we are simply showing that people who reported feeling well, are more likely to be active commuters. However, our results may still be vulnerable to unobserved (individual characteristics) variables bias and possible selection effects.

5. Conclusion

Adopting measures for increased use of active mobility is beneficial for society, with higher social benefits than costs. A large part of the total sum of urban transport is commute travel. Policies to increase sustainable and active transport, will therefore be most effective when conducted in partnerships with employers. Employers will often seek justification to spend company money on measures to increase active travel among their workforce (Hill & Hupe, 2014). The current study, by showing an empirical relationship between active mobility and work performance brings arguments to the table for these employers. By e.g. subsidising bicycle parking facilities, lockers and changing rooms the business owner might get a happier, healthier, and not the least a more efficient work force.

6. Ethics statement**a

The study was approved by the Norwegian Social Science Data Services and all participants gave their informed consent before completing the questionnaire.

7. Funding**a

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CRediT authorship contribution statement

Aslak Fyhri: Conceptualization, Methodology, Investigation, Writing – review & editing, Supervision, Funding acquisition. **Alice Ciccone:** Conceptualization, Methodology, Investigation, Writing – review & editing, Data curation. **Claire Papaix:** Writing – original draft. **Katrine Karlsen:** Conceptualization, Methodology, Investigation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A.

Individual fixed effects regressions

We hereby report results for GLS panel data regression with individual fixed effect (and time fixed effect) for the three outcome variables reported in the main results. When using individual fix effects, we are evaluating the relationship between mode choice and the outcome variable of interest within an individual, hence controlling for all characteristics that are constant within a person including possible unobservable factors.

The results using individual fixed effect confirm the conclusions drawn in the main part of the analysis.

Travel satisfaction

Travel Satisfaction	**Step 1**	**Step 2**
Today's travel mode (Car baseline)		
Public Transport	−0.21***	−0.24***
	(0.07)	(0.07)
Train	0.14	0.12
	(0.12)	(0.11)
(e-)Bike	0.34***	0.32***
	(0.06)	(0.06)
Walk	0.34***	0.32***
	(0.08)	(0.08)
Other	0.39***	0.36***
	(0.13)	(0.13)
Multiple	−0.03	−0.03
	(0.08)	(0.08)
Individual FE	YES	YES
Time FE		YES
Constant	5.40***	5.43***
	(0.03)	(0.05)
Observations	3,810	3,810

Travel Satisfaction	Step 1	Step 2
R-squared	0.03	0.06
Number of id	1,319	1,319

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Mood

Mood	Step 1	Step 2	Step 3
Today's travel mode (Car baseline)			
Public Transport	0.07	0.06	0.12
	(0.09)	(0.09)	(0.09)
Train	0.31**	0.29*	0.26*
	(0.15)	(0.15)	(0.15)
(e-)Bike	0.20**	0.19**	0.10
	(0.08)	(0.08)	(0.08)
Walk	0.20*	0.19*	0.10
	(0.11)	(0.11)	(0.11)
Other	0.22	0.20	0.10
	(0.16)	(0.16)	(0.16)
Multiple	0.36***	0.35***	0.36***
	(0.11)	(0.11)	(0.11)
Travel satisfaction			0.27***
			(0.03)
Individual FE	YES	YES	YES
Time FE		YES	YES
Constant	4.34***	4.39***	2.95***
	(0.04)	(0.07)	(0.15)
Observations	3,811	3,811	3,810
R-squared	0.01	0.01	0.05
Number of id	1,319	1,319	1,319

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Subjective productivity

Subjective productivity	Step 1	Step 2	Step 3	Step 4	Step 5
Today's travel mode (Car baseline)					
Public Transport	0.15	0.15	0.19*	0.13	0.14
	(0.11)	(0.11)	(0.11)	(0.10)	(0.10)
Train	0.17	0.18	0.16	0.06	0.06
	(0.18)	(0.18)	(0.18)	(0.17)	(0.17)

Subjective productivity	Step 1	Step 2	Step 3	Step 4	Step 5
(e-)Bike	0.25***	0.24**	0.19*	0.17*	0.15
	(0.10)	(0.10)	(0.10)	(0.09)	(0.09)
Walk	0.30**	0.29**	0.24*	0.22*	0.20
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
Other	−0.21	−0.23	−0.29	−0.31	−0.33*
	(0.20)	(0.20)	(0.20)	(0.19)	(0.19)
Multiple	−0.02	−0.03	−0.02	−0.16	−0.16
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
Travel satisfaction			0.17***		0.07**
			(0.03)		(0.03)
Mood				0.39***	0.38***
				(0.02)	(0.02)
Individual FE	YES	YES	YES	YES	YES
Time FE		YES	YES	YES	YES
Constant	4.49***	4.44***	3.53***	2.73***	2.41***
	(0.05)	(0.08)	(0.19)	(0.13)	(0.20)
Observations	3,811	3,811	3,810	3,811	3,810
R-squared	0.01	0.01	0.02	0.11	0.11
Number of id	1,319	1,319	1,319	1,319	1,319

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Reverse causality

This section reports panel data GLS regressions where the outcome variable (dependent variable) is the choice of mode. The aim of this analysis is to provide evidence for (the lack of) inverse direction of causality. Looking at the first three regressors (travel satisfaction, mood and productivity) in the table below, we see that the only statistically significant relation is found for travel satisfaction, while mood and productivity do not seem to be a relevant variable for the choice of mode. In contrast being physically active and length of trip are important explanatory variables for choice of mode.

Mode choice	Step 1	Step 2	Step 3	Step 4
Travel satisfaction		0.07**		
		(0.03)		
Mood			0.01	
			(0.02)	
Subjective productivity				−0.02
				(0.02)
Women	−0.05	−0.04	−0.04	−0.05
	(0.09)	(0.09)	(0.09)	(0.09)
Age	0.00	−0.00	−0.00	−0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Income	0.07*	0.05	0.05	0.04
	(0.04)	(0.05)	(0.05)	(0.05)

Mode choice	Step 1	Step 2	Step 3	Step 4
Education	−0.03	−0.04	−0.03	−0.03
	(0.06)	(0.07)	(0.07)	(0.07)
Children<18	0.09	0.11	0.11	0.11
	(0.08)	(0.08)	(0.08)	(0.08)
Longer than 30min	−0.01	0.01	−0.01	−0.01
	(0.08)	(0.09)	(0.09)	(0.09)
Physically active (index)	−0.15***	−0.16***	−0.15***	−0.15***
	(0.04)	(0.05)	(0.05)	(0.05)
Trip longer than expected	0.11	0.21**	0.15*	0.15*
	(0.08)	(0.09)	(0.08)	(0.08)
Flexible	−0.01	−0.02	−0.01	−0.01
	(0.05)	(0.05)	(0.05)	(0.05)
Worried about Covid-19	−0.00	0.01	0.01	0.01
	(0.03)	(0.03)	(0.03)	(0.03)
Extraversion	0.00	−0.01	−0.01	−0.01
	(0.03)	(0.04)	(0.04)	(0.04)
Agreeableness	−0.01	−0.02	−0.02	−0.02
	(0.05)	(0.05)	(0.05)	(0.05)
Conscientiousness	−0.00	0.01	0.01	0.02
	(0.05)	(0.05)	(0.05)	(0.05)
Emotional stability	0.05	0.06	0.07	0.07*
	(0.04)	(0.04)	(0.04)	(0.04)
Openness	−0.00	0.02	0.02	0.02
	(0.04)	(0.04)	(0.04)	(0.04)
Wellbeing	−0.03	−0.06	−0.06	−0.05
	(0.05)	(0.05)	(0.05)	(0.05)
Constant	3.28***	3.32***	3.60***	3.66***
	(0.47)	(0.55)	(0.54)	(0.54)
Time FE	YES	YES	YES	YES
Place of Residence FE	YES	YES	YES	YES
Type of work FE	YES	YES	YES	YES
Observations	3,558	3,325	3,326	3,326
Number of id	1,278	1,190	1,190	1,190
R2 overall	0.14	0.15	0.15	0.15

Standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1.

Data availability

Data will be made available on request.

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1 Therefore, we only include a subsample of participants who answered the survey, and the sample is smaller than that mentioned in Section 2.1.

2 700 thousand Norwegian Kroner (December 2020).

3 Table 11,419 Statistic Norway (https://www.ssb.no).

4 StataCorp. 2019. Stata Statistical Software: Release 16. College Station, TX: StataCorp LLC. Dedicated panel environment “xtset”, hence using xtreg for the regression.

5 In this case OLS is not the BLUE (best linear unbiased estimator), while GLS is.

6 This lack of significance could be due to the limited number of observations. The less conservative unilateral *t*-test (when instead of the alternative hypothesis being different from 0, we have H_a: mean(P-A)<0, i.e. that the difference between passive and active score is assumed negative) gives a p-value= 0.066 providing weak support to the claim that the productivity when using a passive mode is lower than when using an active one.