Transportation Research Part A

Does active transport lead to improved mood and productivity?

A panel study of travel changes during the Covid-19 lockdown in Norway

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

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Abstract

Travel restrictions and teleworking have been imposed during the covid-19 lockdown, thus removing the need for everyday commuting. It is common wisdom that 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 as a backdrop to study the relationship between active travel and self-reported mood and workplace productivity.

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. The survey covered topics related to commute mode, experience of travel, current mood, and work productivity. 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 productivity. Finally, looking at individuals who over time *change* travel mode (N= 151), we find that they report improved mood and work productivity when travelling with active than with 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 productivity; Wellbeing; Random-effect GLS panel regression; Norway

1 Introduction

Lack of daily physical activity can have a negative effect on health, and increase the risk of diseases such as heart attack, cancer and diabetes (Bauman, 2004; Warburton & Bredin, 2017). It is therefore seen as one as one of the main challenges facing the world population today (OECD, 2020). Active mobility can be an effective way to meet this challenge, and thereby improve wellbeing (Humphreys, Goodman, & Ogilvie, 2013; Martin, Goryakin, & Suhrcke, 2014; Mytton, Panter, & Ogilvie, 2016; Oja et al., 2011). Commute travel constitutes a major part of urban transport, so involving employers in policies to increase active and sustainable mobility seems to be an effective strategy. Since employers needs to justify spending any resources that on the face of it can reduce dividend, providing solid empirical evidence about the benefits of active mobility, not just to the individual but also for the employers, is key {Hill, 2014 #8}.

Using the rise of teleworking trends in the Covid-19 era as an experimental setting, the current study sets out to investigate interactions between active mobility patterns, current mood and work productivity in Norway. As such the study taps into the notion of urban resilience - i.e. the faculty to 'adapt, bounce back or forward after a shock' - (Chelleri & Baravikova, 2021). By investigating people's opportunities to effectively perform daily activities, the study responds to calls for understanding better behavioural changes during the current sanitary context (Beck, Hensher, & Wei, 2020; Hensher, Wei, Beck, & Balbontin, 2020).

1.1 Travel satisfaction

Further than its effect on travel activity and mode preference/avoidance, the Covid-19 pandemic via anxiety, social isolation and limited physical activity (De Vos, 2020) might also influence experiences of different travel modes. In general, cars have been perceived as more "fun, lifestyle matching, and secure" than buses (Eriksson, Friman, & Gärling, 2013). In the Covid-19 context, the protection from others can along with less road congestion function to even strengthen the positive aspects of the private car. As for those not having access to a car, travelling with public transport (PT) network in the current context limits reaching key-out-of-home destinations, including arriving at work on time, whilst increasing the fear of getting infected (De Vos, 2020). However, removing a lot of the general travel demand might also have reduced stress and congestion for those who remain as passengers, since much of the capacity is fixed and has not been reduced with the same rate as the passenger volumes.

Recorded travel mood is found to be more positive for pedestrians and bicyclists engaging in interpersonal conversations, and for those exposed to various built and natural environments (Glasgow, Le, Scott Geller, Fan, & Hankey, 2019). Commuters more inclined to driving given the Covid-19 conditions might miss such aspects in the longer run. Travel duration, congestion and access- and egress trip conditions has been found to be a dominant factor in determining higher levels of commuting satisfaction for active modes, followed by safety and convenience of the trip (Lades, Laffan, Daly, & Delaney, 2020; Susilo & Cats, 2014). More specifically, the

dissonance between actual travel duration and a predefined 'ideal commute time' is found to affect commuting satisfaction the greatest. The gap is found to be the smallest for walking and cycling commutes compared to transit and car journeys, all else being equal (Ye, DeVos, & Ma, 2019). This finding further explains higher commuting satisfaction for active modes.

1.2 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 guidelines (Ainsworth et al., 2011; de Geus, De Smet, Nijs, & Meeusen, 2007). Several studies have looked at the benefits of active commuting on physical health, and these can be summarized as a lower risk of all-cause mortality and even of incidence of cancer (Celis-Morales et al., 2017). In line with general knowledge about physical activity effects, the greatest health gains from active travel can be seen among the least active (Oja et al., 2011).

However, the benefits from active transport may reach beyond improving physical health. Specifically, walking and cycling are found to be mood uplifting, by giving active travellers engaging in brief trips (10-15 minutes) twice a day important "breaks" in a daily routing characterized by prolonged sedentarism (Paul, Carlson et al. 2015). In the longer term, cycling is also associated with individuals' self-realization, in physical, psychological, and social terms (Kaplan, Wrzesinska, & Prato, 2019).

On the other hand, long-distance and PT commutes are found to make people unhappier (Lancée, Veenhoven, & Burger, 2017), though the authors' warn that living in remote locations and without cars might reduce people's wellbeing levels regardless of the travel experience *per se*. Further to that, research testing the direction of influence from life satisfaction to commuting satisfaction (Eriksson et al., 2013; Gao, Rasouli, Timmermans, & Wang, 2017) finds the proposed link to be more robust than the reverse direction of influence.

It seems that the transport experience itself, e.g., a combination of time spent, and mode used, may leave commuters with a temporary mood, which can also impact wider and longer-term aspects of wellbeing, such as life satisfaction. Still, further evidence, disentangling the effects of background variables, such as stable personally traits and general wellbeing, from more transient mood changes is called for.

1.3 Travel-induced mood and perceived work productivity

Further than life satisfaction, derived mood from the commute experience can also affect work productivity.

Generally, work productivity has been linked with life satisfaction, as well as mood states and physical health (Sirois, 2016). The Australian study of Ma and Ye (2019) is one of the first to connect, in a quantitative way, low mood and tiredness from long car commute, job absenteeism and poor work productivity on the one hand, to positive feelings and physical health of employees, job performance, satisfaction and productivity derived from active commuting on the other hand. A longitudinal study

(Dinh, 2019) confirms such results and also identifies a reciprocal causal relationship between job satisfaction and active commuting.

1.4 Dealing with transient moods and lasting traits

The links between travel mode, mood, productivity and wellbeing are intricate. Particularly due to the methodological challenges associated with studying these issues in a broader population.

As an example, age can create an ambiguous moderating effect on work productivity. On the one hand, there is a negative effect reported on work productivity due to reduction of speed and acuity (Shephard, 2000). On the other hand, there is a positive correlation, explained by the increased sense of experience and verbal abilities of older workers (Skirbekk, 2004). Personality maturation is also found to be intertwined with life satisfaction according to the study of (Hill & Roberts, 2016) with happier people being more likely to be emotionally stable, agreeable, and conscientious. However, extraversion, even if often associated with brighter moods, is found to be a predictor of higher sensitiveness to environmental stressors such as such as air quality, temperature, relative humidity and luminosity, leading to lesser work productivity when experiencing stress (Kallio et al., 2020).

A number of ways have been proposed to capture moods and emotions during the day. The Experience-Sampling Method (Csikszentmihalyi & Larson, 2014) and its cousin technique Ecological Momentary Assessment (EMA) (Beute & de Kort, 2018) are methods surveying participants moods in a systematic diary format, at random times of the day. By collecting recurrent measures of mood levels in the same day (Gärling, Ettema, Connolly, Friman, & Olsson, 2020) and designing multiple survey waves (Curtis et al., 2020) one can obtain a fair representation of participants' emotions. The circumplex model of affect (Russell, 1980, describing mood as valence (positive/negative) and arousal (calmness/intensity) is frequently used to capture emotions, and helps frame the ESM and EMA questions (Du et al., 2020).

1.5 Summary of research needs and objectives of study

With the Covid-19 travel restrictions and teleworking, some negative aspects of commuting can be assumed to be alleviated. Still, other challenges related to increased sedentarism (Warburton & Bredin, 2017) and lack of pauses in everyday routines may arise. Thus, there is a need to explore the link between physical activity and travel behaviour, considering the interaction between private life and working life (WHO 2016). There is a need to disentangle the hen-and-egg relationship between active commuting, well-being and productivity (Dinh, 2019; Ma & Ye, 2019). By gaining better control of important background variables as well as temporal relationships, it is possible to provide more validated claims about the beneficial effects of active commuting.

This calls for a longer-term panel study to investigate the relationship between commuting patterns, as mediated by sociodemographic, psychological and wellbeing-related characteristics of teleworkers, as well as Covid-19 contextual and temporal effects.

The aim of the paper is to give validated estimates of the effects of active mobility on individual wellbeing and work productivity. To this end, we investigate whether active commuters experience higher travel satisfaction, mood and subjective work productivity compared to those using passive travel modes, while controlling for influential background variables such as personality traits and general wellbeing.

The specific research question of this paper is 'to what extent does an observed change in commuting patterns during Covid-19 in Norway affect people's mood and work life productivity?'

For this, the following hypotheses are tested:

1. Active travel modes lead to higher travel satisfaction than passive modes
2. Active travel modes lead to better mood than passive modes
3. Active travel modes lead to higher productivity than passive modes
4. People changing from a passive to an active mode will report improved mood and productivity

1.6 The Covid-19 pandemic situation in Norway

Since the first patient was diagnosed on February the 26th, Norway had a rapid rise of Covid-19 cases, resulting in the government declaring a national crisis on the March the 12th. However, the increase in infections came somewhat later than in many other European states and was also far more controlled. As of December 2020, relatively few people have been infected (43,000/5.4 mill) or died (404) from coronavirus, compared to most other European countries. From March 2020, schools and kindergartens were shut down, and home office was strongly encouraged. This resulted in a dramatic change in mobility patterns overnight. A number of other restrictions were also imposed, like a ban on using holiday houses, a closing of pubs and restaurants, no large gatherings of people, and foreign travel quarantines. From late April schools and kindergartens started gradually reopening, and other restrictions were gradually lifted as well, leading to a certain normalization and also to some people returning to their daily commuting. After summer 2020, the "new normal" seemed to have been established, with foreign travel restrictions, some restricted possibilities for social gatherings, and a mix between commuting and home office for most people. This lasted until the second wave struck in late September, and restrictions were reintroduced.

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. 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 interview 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.

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, and another three during August – September. Before the first follow-up in May, and that of after the summer holidays, a preparatory e-mail was sent to all respondents with some instructions. 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. Such communication was also used to increase compliance and remind them to check for their spam folder if they did not receive the invitation. This instruction was repeated in all survey invitations and reminders. The majority of respondents complied with instructions. From T1 on, more than 90 percent report taking the survey when they had "worked a bit" or they were "about half-way" (Figure 1). Figure 1 also shows that this is not true for the recruitment stage T0, when there were no such instructions.

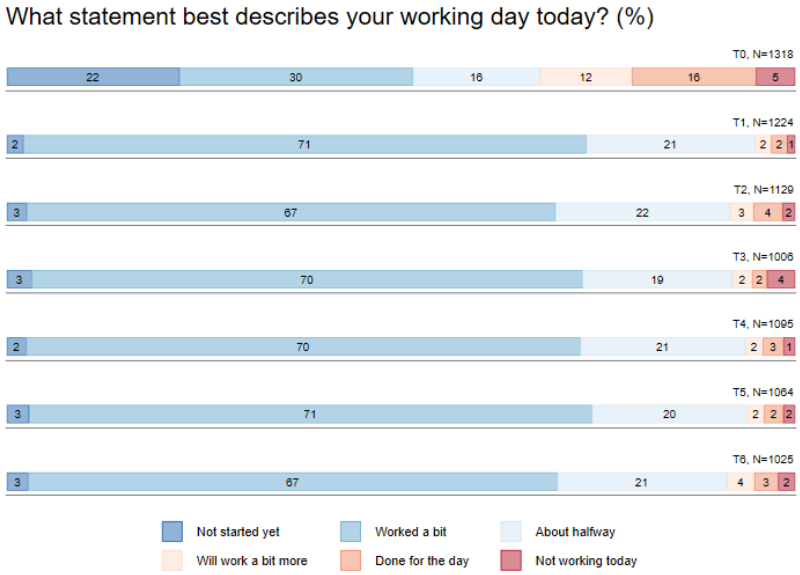

Figure 1: Compliance with instructions: when respondents answered the survey at every time period.

In this article we consider only participants who travelled to work at least once[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 less than 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,

[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.

number of respondents (in our sample of people who commuted at least once) and how many who 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

2.2 Survey items

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 productivity, physical activity and personality.

The short follow-up took approximately 2-3 minutes to complete and included questions regarding current work situation, work commute (if they did not work from home), mood and perceived productivity, as well as physical activity over the last 7 days.

2.2.1 Wellbeing, mood and personality

Wellbeing was measured using previously validated scales (WEMWEBS, 2020; WhatWorksWellbeing, 2020), from which following five items were retained or inspired by: "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". The items were measured on 7-point Likert scales anchored with completely disagree and completely agree. These items were combined into a general wellbeing scale with a Cronbach's alpha of 0.84.

In addition, mood was measured using four of the six items in the three dimensions of mood scale as done in Wilhelm and 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". The combined mood scale had an alpha of .78.

We also included four items related to Covid-19 anxiety, regarding worry that the respondents themselves, their family members and their children (if any) would get infected, as well as their worry that they would infect others. These items 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 items. 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.

2.2.2 Travel satisfaction

Travel satisfaction was measured using items from the satisfaction with travel scale. This scale has originally 9 items, but several of these were quite similar to the mood items and were excluded. We used 7-point Likert scales (completely disagree – completely agree), rather than semantic differential scales, adjusted one item to better fit with the context and added two additional items of interest. The items used were: "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 fun", (4) "was uncomfortable" and (5) "was a good separation between work/school and leisure".

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

2.2.3 Subjective productivity

The measures of subjective work productivity were created by us. Subjective work productivity was measured through the following three items: So far today, I think I am (1) "working efficiently", (2) "easily distracted", (3) "concentrating well on my tasks". These items were rated on a 7-point Likert scale and anchored with completely disagree and completely agree. The Cronbach's alpha for the productivity scale was 0.87.

2.3 Analysis procedure

Given the structure of the data we chose to use Generalized Least Squares (GLS) regressions for panel data[2]. We tested a model with individual random effects for the following three dependent variables: travel satisfaction, mood and productivity. In addition, we included fixed effects to remove the possibility of unobserved heterogeneity between different time periods in the data, place of residences and types of job. The choice of individuals random effects was made since we were mostly interested in understanding whether individual differences mattered, and which individual characteristics were most correlated with the dependent variables.

[2] The analysis was carried out with the program STATA (StataCorp. 2019. Stata Statistical Software: Release 16. College Station, TX: StataCorp LLC.) dedicated panel environment "xtset", hence using xtreg for the regression.

Individual fixed effect GLS regressions were nonetheless run to control for individual unobservable characteristics that may bias the predictor or outcome variables and they are reported in the Appendix. All our results report stepwise regression tables to show how our estimates are reliant on the choice of regressors and to illustrate the robustness of our findings. Finally, we further exploit the panel structure of our data to study changes *within* individuals who use both active and passive modes over time. We compare their reported travel satisfaction, mood and productivity for the days in which they use different (active or passive) transport modes.

3 Results

3.1 Background characteristics of sampled participants

In this section, we describe the study sample using the first questionnaire (T0) as a starting point. Table 1 shows the summary statistics for the main characteristics of the sample.

Table 1: Summary statistics of demographics and other main sample characteristics.

	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

The majority of our responders are women, living in the East part of the country, 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 and/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% respectively works in sales or service and as health workers. About 34% report

earning more than 67 thousand EUR[3] (where the average annual income in Norway is around 54 thousand EUR[4]) 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 times. As a part of their commute, 25% of respondent report bringing children to school/kindergarten, 22% chain their trip with grocery shopping and 6% with performing activities such as exercise.

3.2 Descriptive statistics results

Before reporting the results of our main analysis, we present the main independent and dependent variables below. At each period, respondents were asked to report whether they travelled to work and their transport mode of choice. Similarly, respondents also responded to several questions that were then merged into indexes: travel satisfaction, mood and subjective productivity (see in Section **Error! Reference source not found.** for more details). Travel satisfaction, mood and subjective productivity are the main outcome variables and take values that span between 1 and 7.

3.2.1 Travel mode

Figure 2 shows the percentage distribution for each mode over time (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%.

[3] 700 thousand Norwegian Kroner (December 2020).
[4] Table 11419 Statistic Norway (www.ssb.no)

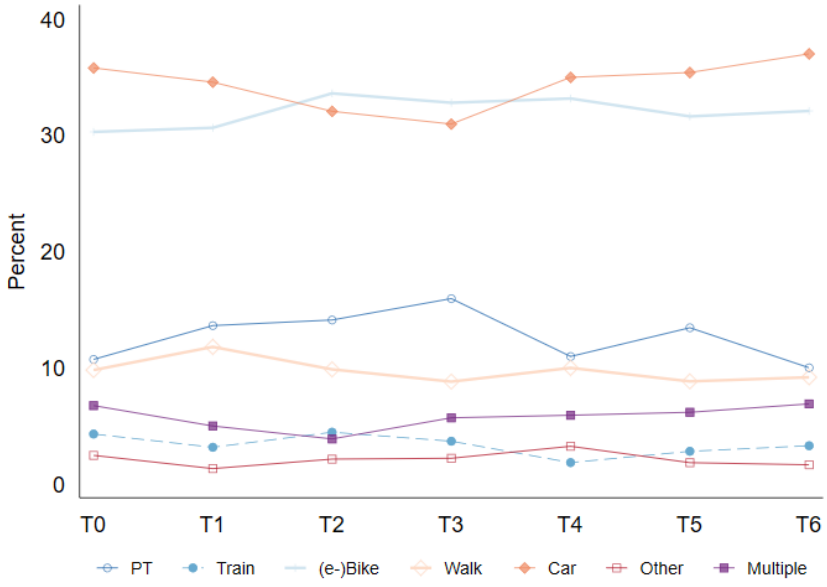

Figure 2: Travel mode use today, percentage over time.

3.2.2 Travel satisfaction

Reported travel satisfaction has an overall mean of 5.5, with a between individual standard deviation of 0.86 and a within variance of 0.49. Travel satisfaction is highly correlated with transport modes (Figure 3). Specifically, people walking and cycling to work report the highest travel satisfaction.

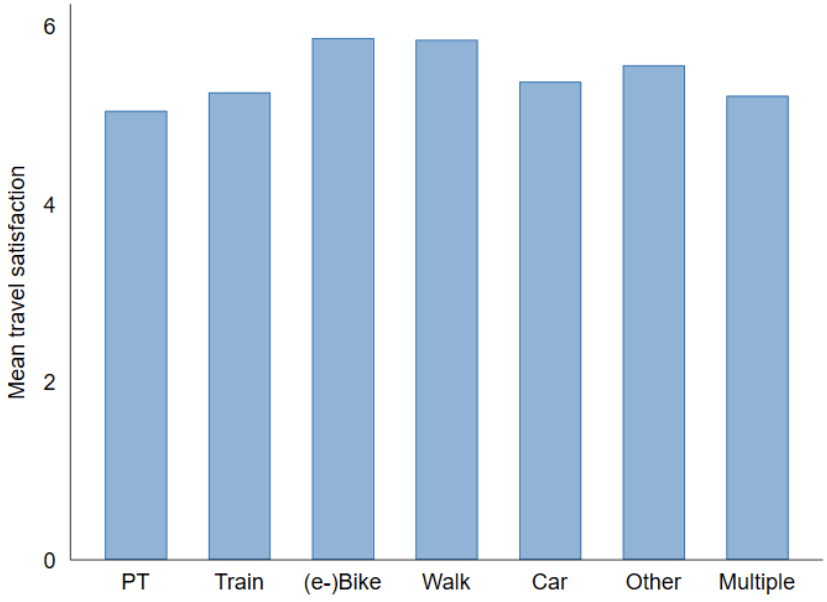

Figure 3: Travel satisfaction by transport mode

3.2.3 Mood

Self-reported mood has an overall mean of 4.6, with a between individual standard deviation of 0.75 and a within variance of 0.76. Mood also seems to be correlated with transport modes (Figure 4Figure 3).

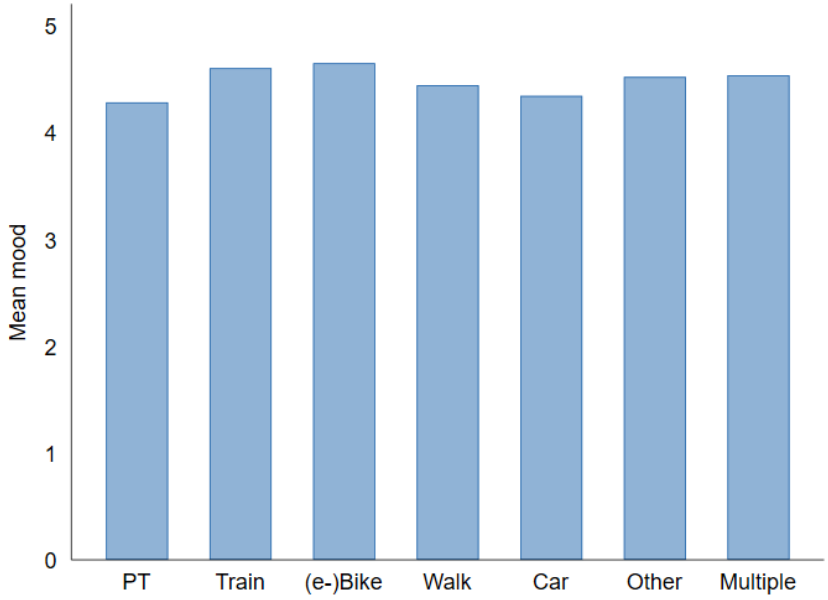

Figure 4: Mood by transport mode

3.2.4 Subjective productivity

Subjective productivity 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 variance is 0.97. Productivity seems correlated with transport modes (Figure 5Figure 3).

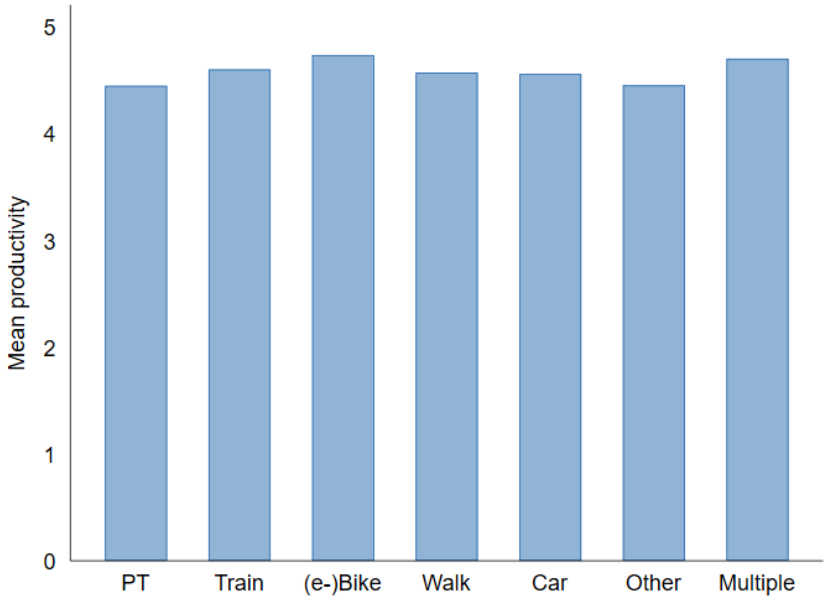

Figure 5: Subjective productivity by transport mode

3.3 Regression results

In the present section we report results from GLS panel regression to investigate the relationship between choice of transport mode and three dependent variables: travel satisfaction, mood and subjective productivity.

3.3.1 Travel satisfaction

To test the first hypothesis, we ran an individual random-effect GLS panel regression where the dependent variable is the *travel satisfaction* index taking values between 1 and 7. We provide results in 3 steps to show how the estimated coefficients are affected by the choice of regressors. Step 3 includes time and place of residence fixed effects (FE) in order to control for all possible unobserved characteristics that are constant across individuals but vary over time or over place of residence.

The results (Table 2) show that, compared to those driving or riding their cars to work, people who use public transport report significantly lower travel satisfaction (b = -0.24) compared to those who travel by car. (In contrast, those who walk, cycle or use other transport modes such as motorbike or e-scooters to work report significantly higher travel satisfaction (between 0.30 and 0.37). Age is positively correlated with reporting higher travel satisfaction, while income is negatively correlated. A negative correlation is also found for trips that exceed 30 min duration and for those that report having experienced a longer than expected trip. Travel satisfaction is positively correlated with having flexible times at work, as well as with general wellbeing and emotional stability (BFI). Being concerned about Covid-19 and high scores on openness and are negatively correlated with travel satisfaction. These results are robust

to controlling for relevant demographic variables, psychological traits and time and place of residence fixed effects.

Table 2 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	0.02
	(0.08)	(0.08)	(0.08)
Today's mode = 3, (e-)Bike	0.34***	0.35***	0.34***
	(0.04)	(0.04)	(0.04)
Today's mode = 4, Walk	0.34***	0.37***	0.36***
	(0.06)	(0.06)	(0.06)
Today's mode = 6, Other	0.31***	0.31***	0.30***
	(0.09)	(0.09)	(0.09)
Today's mode = 7, Multiple	-0.09	-0.08	-0.06
	(0.06)	(0.06)	(0.06)
Women	-0.04	-0.02	-0.02
	(0.04)	(0.05)	(0.05)
Age	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)
Income	-0.05**	-0.06***	-0.06***
	(0.02)	(0.02)	(0.02)
Education	-0.00	0.00	0.01
	(0.03)	(0.03)	(0.03)
Children<18	-0.00	-0.04	-0.05
	(0.04)	(0.04)	(0.04)
Longer than 30min	-0.22***	-0.23***	-0.19***
	(0.04)	(0.04)	(0.04)
Physically active (index)	0.04*	0.03	0.02
	(0.03)	(0.02)	(0.03)
Trip longer than expected	-0.94***	-0.94***	-0.91***
	(0.05)	(0.05)	(0.05)
Flexible	0.23***	0.22***	0.22***
	(0.03)	(0.03)	(0.03)
Worried about Covid-19		-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		0.00	-0.00
		(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***
		(0.02)	(0.02)
Constant	5.01***	4.43***	4.39***
	(0.17)	(0.24)	(0.25)
Time FE			YES
Place of Residence FE			YES
Observations	3,563	3,557	3,557
Number of ids	1,279	1,278	1,278
R2 overall	0.25	0.29	0.30

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

3.3.2 Mood

Our second hypothesis was that active travel modes leads to a better mood than passive modes. Table 3 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. Step 2 and 3 include time and place of residence fixed effects (FE) in order 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.

Confirming previous findings from the literature, results show that, 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. Older people also tend to report a slightly higher level of mood, while being female is associated with lower mood. Longer than 30 min work trips are associated with lower mood (weakly significant), while being physically active is associated with better mood. Mood is also positively correlated with general wellbeing, and emotional stability (big 5).

These results are robust to the inclusion of time and place of residence fix effects, but when travel satisfaction is also included (step3), we see that most of the effect for bike and walk modes disappears. It is important to note that travel satisfaction is highly correlated with several other regressors, in particular travel mode. Hence, travel satisfaction is an endogenous regressor that impose serious threats to the validity of our estimations. We conclude that the estimated coefficients in Step 3 are not to be interpreted as statistically valid, but they do raise the question of how important travel satisfaction is for reported mood.

Table 3 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	0.01	0.05	0.13**
	(0.06)	(0.06)	(0.06)
Today's mode = 2, Train	0.21*	0.25**	0.27***
	(0.11)	(0.10)	(0.10)
Today's mode = 3, (e-)Bike	0.26***	0.22***	0.08
	(0.05)	(0.05)	(0.05)
Today's mode = 4, Walk	0.17**	0.19***	0.04
	(0.07)	(0.07)	(0.07)
Today's mode = 6, Other	0.18	0.18	0.07
	(0.12)	(0.12)	(0.11)
Today's mode = 7, Multiple	0.18**	0.21***	0.23***
	(0.08)	(0.08)	(0.07)
Travel satisfaction			0.34***
			(0.02)
Women	-0.14***	-0.10**	-0.09**
	(0.05)	(0.05)	(0.05)
Age	0.02***	0.02***	0.01***
	(0.00)	(0.00)	(0.00)
Income	-0.02	-0.04	-0.02
	(0.03)	(0.02)	(0.02)
Education	0.00	0.00	-0.01
	(0.04)	(0.03)	(0.03)

Children<18	0.02	-0.02	0.00
	(0.05)	(0.04)	(0.04)
Longer than 30min	-0.08*	-0.04	0.03
	(0.05)	(0.05)	(0.04)
Physically active (index)		0.06**	0.06**
		(0.03)	(0.03)
Worried about Covid-19		-0.00	0.01
		(0.02)	(0.02)
Extraversion		0.03*	0.02
		(0.02)	(0.02)
Agreeableness		0.04	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		-0.02	-0.00
		(0.02)	(0.02)
Wellbeing		0.21***	0.17***
		(0.03)	(0.03)
Constant	3.74***	1.60***	0.06
	(0.20)	(0.27)	(0.26)
Time FE		YES	YES
Place of Residence FE		YES	YES
Observations	3,564	3,558	3,557
Number of ids	1,279	1,278	1,278
R2 overall	0.07	0.19	0.28

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

3.3.3 Subjective productivity

Our third hypothesis was that active travel modes result in higher work productivity than passive modes. Table 4 shows an individual random-effect GLS panel regression where the dependent variable is the *subjective productivity* index taking values 1 to 7. We provide results in four steps to show how the estimated coefficients are affected by the choice of regressors. Step 2, 3 and 4 include time, place of residence and type of job fixed effects (FE) in order to control for all possible unobserved characteristics that are constant across individuals but vary over time, place of residence and over type of job.

Once again corroborating state of the art conclusions, results show that, compared to those driving to work, people who cycle to work report significantly higher level of productivity (about 0.16 points) during that day. Similarly, those who walk report about 0.15 points higher productivity than car drivers, but this difference is weakly significant. Older individuals and those who are physically active also report higher levels of productivity. Subjective productivity is also positively correlated with conscientiousness, emotional stability and general wellbeing.

Most results are robust to the inclusions of fixed effects, but the statistical significance found for bike and walk modes disappears when mood and/or travel satisfaction is included in the analysis. As pointed out in the previous section, travel satisfaction and mood are correlated with both travel modes and some explanatory variables rending these variables endogenous. This imposes threats to the validity of our estimations.

We conclude that the estimated coefficients in Step 3 and 4 should not be interpreted as statistically valid, but they do raise the question of how important travel satisfaction and mood is for subjective productivity.

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

Subjective productivity	**Step 1**	**Step 2**	**Step 3**	**Step 4**
Today's travel mode (Car baseline)				
Today's mode = 1, PT	-0.01	0.03	-0.00	0.04
	(0.08)	(0.08)	(0.08)	(0.07)
Today's mode = 2, Train	0.08	0.15	0.04	0.05
	(0.13)	(0.13)	(0.12)	(0.12)
Today's mode = 3, (e-)Bike	0.18***	0.14**	0.04	-0.03
	(0.06)	(0.07)	(0.06)	(0.06)
Today's mode = 4, Walk	0.14	0.16*	0.06	-0.01
	(0.09)	(0.09)	(0.09)	(0.09)
Today's mode = 6, Other	-0.13	0.02	-0.10	-0.14
	(0.15)	(0.15)	(0.14)	(0.14)
Today's mode = 7, Multiple	0.03	0.04	-0.03	-0.01
	(0.10)	(0.10)	(0.09)	(0.09)
Mood			0.42***	0.38***
			(0.02)	(0.02)
Travel satisfaction				0.16***
				(0.02)
Women	-0.03	-0.04	-0.01	-0.01
	(0.06)	(0.07)	(0.06)	(0.06)
Age	0.03***	0.02***	0.02***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Income	-0.01	-0.06*	-0.03	-0.02
	(0.03)	(0.03)	(0.03)	(0.03)
Education	-0.01	0.04	0.04	0.03
	(0.05)	(0.05)	(0.04)	(0.04)
Children<18	-0.04	-0.07	-0.06	-0.06
	(0.06)	(0.06)	(0.05)	(0.05)
Longer than 30min	-0.11*	-0.05	-0.04	-0.01
	(0.06)	(0.06)	(0.06)	(0.06)
Physically active (index)		0.15***	0.13***	0.13***
		(0.04)	(0.04)	(0.04)
Worried about Covid-19		-0.02	-0.02	-0.01
		(0.02)	(0.02)	(0.02)
Extraversion		0.01	-0.00	-0.01
		(0.03)	(0.02)	(0.02)
Agreeableness		0.03	0.03	0.03
		(0.04)	(0.03)	(0.03)
Conscientiousness		0.16***	0.15***	0.15***
		(0.04)	(0.03)	(0.03)
Emotional stability		0.17***	0.10***	0.10***
		(0.03)	(0.03)	(0.03)
Openness		-0.04	-0.03	-0.02
		(0.03)	(0.02)	(0.02)
Wellbeing		0.13***	0.04	0.03
		(0.04)	(0.03)	(0.03)
Constant	3.53***	1.16***	0.21	-0.45
	(0.22)	(0.39)	(0.35)	(0.36)
Time FE		YES	YES	YES
Place of Residence FE		YES	YES	YES
Type of work FE		YES	YES	YES
Observations	3,564	3,326	3,326	3,325
Number of ids	1,279	1,190	1,190	1,190
R2 overall	0.06	0.16	0.29	0.30

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

3.3.4 Delta scores on mood and productivity

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. We here report travel satisfaction, mood and subjective productivity averages within individuals who over time change from active modes to passive modes or vice versa (Figure 6).

Figure 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 productivity 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.

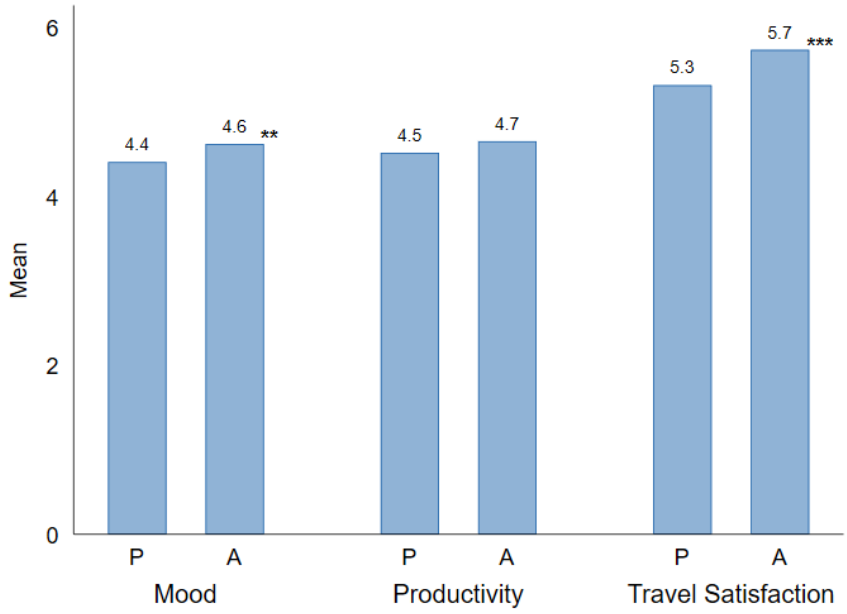

Figure 6 Mean mood and productivity scores when using a passive or active mode for people that over time change type of mode. N=151

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=.011 and t(150) = -5.70, p=.000 respectively).* For productivity, the observed change is

not statistically significant *(t(150) = 1.52, p=.13).*[5] Similar results are also obtained with non-parametric Wilcoxon signed-rank tests: mood *($\tilde{z}$ = -2.26, p=.024), travel satisfaction ($\tilde{z}$=-5.36, p=.000)* and productivity *($\tilde{z}$ = -1.72, p=.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 productivity. Using a triangulation of analytical approaches, we provide convincing evidence of the influence of active commuting on improved mood and work productivity. Multivariate models of panel data from people surveyed over a period of four months show that those who during this period commute with active modes (walking and cycling) report higher degree of travel satisfaction (hypothesis 1), mood (hypothesis 2) and subjective productivity (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 productivity when travelling with active than with passive modes, was partially confirmed. The delta score for mood was statistically significant, whereas the delta score for productivity was just above accepted levels of significance (p=0.13).

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 0.35 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 0.21 points), and with reporting higher work productivity (0.16 points) then car drivers.

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 productivity. The stepwise regression analysis is conducted under this assumption and gives support for it. To explicitly test direction of causality, we employ GLS regressions to study the determinants of mode choice, i.e. looking at the opposite direction of causality. We find that mood and productivity do not impact mode choice (see Appendix 7.2). As such, this study expands on previous studies that have found *reciprocal* relationships between these variables (Dinh, 2019; Ma & 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,

[5] 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= .066 providing weak support to the claim that the productivity when using a passive mode is lower than when using an active one.

we measured momentary (i.e. daily) mood and productivity, whereas the previous studies measured more aggregate levels of these variables.

When investigating the role of travel satisfaction for mood and productivity, most of the effect of travel modes disappears. These 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 has implications on their mood and productivity at least a couple of hours into the workday. However, it is important to note that the actual parameter estimates of these final steps of the models (where travel satisfaction is included as an independent variable) should be treated with caution, since travel satisfaction is endogenous and highly correlated with travel modes.

The aim of this study is not to investigate travel satisfaction as such or to investigate perceptions about specific travel modes. Still, some results deserve commenting. Train comes out as a positive commuting mode: train users report being in a significantly better mood than other commuter groups. The pandemic lockdown led to reduced passenger numbers for all public transport. But it could be that train passengers who had more benefit from the increased space and lack of crowding, compared with other PT users. It should be noted that train passengers were a small group, so these results should be treated carefully.

Age is positively correlated with both travel satisfaction, mood and productivity, even though its effect is small. Women report on average lower mood than men and self-reported physical activity seems to be important as a mediating variable for both mood and productivity, but not for travel satisfaction. Having children does not seem to impact mood or productivity during Covid-19 restrictions. This may be explained by most schools and kindergarten being re-opened during the period of observation.

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. Even if they were not screened out, 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 & 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. Given that we wanted to have a variety of transport mode situation for each participant, we opted for the suggested approach of collecting data in several waves (Curtis et al., 2020), rather than randomly assigning response times throughout the day (Beute & de Kort, 2018), or collecting several measures during the day (Gärling et al., 2020). This was also the most practical approach since we had a quite large sample that could not be closely monitored as individuals.

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). Added to that, the study had quite low attrition, compared to what can be expected for home surveys with as many as six reiterations.

Participants responded to on average 6.4 surveys, and as many as 68 % answered the final survey.

As for limitations, we acknowledge that our sample could be suffering from self-selection by design, given recruitment procedures. In other words, people who answered the survey could be particular people who are not representative of the population of interest and hence the results are non-generalizable. The study sample is a convenience sample and is not meant 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 ("do you travel to work or do have home office?"), as well as the questions in the T0 survey, might have discouraged several non-white collar workers to respond. This was not all unintentional, since our outcome measure was mostly related to productivity in a typical desk job, and not manual or service jobs. Further we expected that some of the beneficial effects of active mobility might be masked or washed out by being active in your work situation. The results are therefore applicable for people doing typical office work, demanding a certain level of concentration and independence. However, future studies should aim to test if similar effects can be found among a broader work force.

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 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. 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 are 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 measure both psychological traits (BFI) as well as stable states (well-being). By including these potentially confounding variables, we reduce 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. For instance, work productivity, which may be influenced by unobservable factors such as relationship with managers, colleagues, type of work environments etc. For this reason, we control for "type of job" using fixed effect, to cancel out unobservable factors that are constant within a type of job.

More generally, if people who chose a particular type of transport mode have some (unobserved) characteristics that correlates with the outcome and explanatory variables of interest, our estimates may be biased. To address this possibility, we exploit the

panel structure of our data to study changes *within* individuals who use both active and passive modes over time. Through a simple analysis we show that respondents reported significantly higher travel satisfaction, and mood the days in which they used an active transport mode than when they used a passive one. This analysis is carried out on a smaller sample as it includes only people that have changed mode over the observation period. For this reason, subjective productivity does not appear to be statistically significantly higher for active modes. To include the whole sample and at the same time control for individual unobservable characteristics, GLS panel regressions with individual fixed effects (in the Appendix 7.1) confirm the results highlighted in the main analysis: people who travel with active modes report higher travel satisfaction, mood and productivity.

Our results thus supply quite convincing evidence about the influence of active commuting on improved mood and work productivity. A more comprehensive moderation and mediation approach, such as a structural equation modelling (SEM), may be an important further step to test for these relationships. However, running SEM on panel data is a quite challenging exercise, which is beyond the scope of the current study.

4.2 Implications

A substantial part of the population has *improved fitness* as a main motivation for cycling, even if many others find this to be unimportant for their travel decisions (Fyhri, Heinen, Fearnley, & Sundfør, 2015). Looking not just at extrinsic motivations, such as financial gain or environmental concerns, but also at intrinsic *motivations* for travel is crucial to better predict travel demand (Mokhtarian, Salomon, & Singer, 2015). The current results indicated that active mobility has an effect both for intrinsic motivations such as mood, as well as more extrinsic factors, such as work productivity.

Transport is a connector between people and places that matter, according to a rather instrumental vision (Ettema et al., 2011). Travel-induced moods technically influence each of the physical, emotional, individual and social dimensions of wellbeing. Commuting satisfaction is a "hidden" determinant of the holistic notion of wellbeing facilitating e.g., social interaction, economic activity, physical exercise and needs fulfilment in a broader sense (Friman, Fujii, Ettema, Gärling, & Olsson, 2013).

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 productivity brings arguments to the table for these employers: This is not just for the common good (sic!) but can also be pure business.

5 Conclusion

The Covid-19 pandemic has been a large challenge for our society but can also be seen as an opportunity. It can be an opportunity for change, for new ways of thinking and of organizing society. The current study uses the Covid-19 pandemic situation in Norway as an opportunity to study the relationship between active travel and self-reported mood and subjective work productivity. Using multivariate models and panel data from individuals who over time change travel mode, we find that active commuting has a positive effect on both mood and work productivity. The results have implications not only for policy makers aiming to justify spending public money on measures for sustainable and active transport, but also for strengthening the public-private partnership in achieving these goals.

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7 Appendix

7.1 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.

7.1.1 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
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

7.1.2 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

7.1.3 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)
(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

7.2 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 statistical 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)
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