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Abstract

We study the effect of the COVID-19 pandemic and the associated government measures on individual mobility choices in Switzerland. Our data is based on over 1,000 people for which we observe all trips during eight weeks before the pandemic and again for up to 6 months after its onset. We find an overall reduction of travel distances by 60 percent, followed by a gradual recovery during the subsequent reopening of the economy. Whereas driving distances have almost completely recovered, public transport remains under-used. The introduction of a requirement to wear a mask in public transport had no measurable impact on ridership. We study the heterogeneity of the individual travel response to the pandemic and find that it varies along socio-economic dimensions such as education and household size, with mobility tool ownership, and with personal values and lifestyles.

JEL classification: H12, H40; I18; R41, R48

Keywords: COVID-19; mobility; tracking; causal forest; PPML.

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1 Introduction

Switzerland was hit hard and early by the COVID-19 pandemic, shortly after Northern Italy. By early April of 2020, it had among the highest infection rates per capita worldwide. Due to a series of government measures, the outbreak was contained relatively quickly. Beginning in late April, the measures were gradually removed, and by mid August, most restrictions had been lifted. In October 2020, Switzerland experienced a second wave, which necessitated new restrictions that have been gradually relaxed since March 2021.

In this paper, we examine the effect of the pandemic, and of the introduction and removal of the governmental measures, on individual mobility in Switzerland. In January 2020, we had concluded a large-scale field experiment in which we had tracked the mobility behavior of more than 3,500 participants using a smartphone-based app. After the virus outbreak, we re-contacted all participants about continuing the study, and about half of them agreed to do so. We thus have highly disaggregated mobility data for a large sample for the time before and during the pandemic. Besides mobility choices, we have detailed information about the socio-demographic characteristics of the participants as well as a wide set of preference parameters derived from two surveys. The combination of detailed GPS tracks and individual information spanning the onset of the pandemic provides us with a rare opportunity to study the effect of the COVID-19-crisis and the associated public policy measures on individual mobility.

During what is termed the “soft” lockdown in Switzerland, we observe a reduction in the overall travel distance of around 60 percent relative to the baseline. This is remarkable, given that Switzerland never formally restricted mobility. People were encouraged to stay at home, but there was no actual travel/movement ban. In this sense, staying at home can be interpreted as contributing to the public good (besides minimizing one’s own infection risk of course). By the end of August, the total distance traveled had returned to around 80 percent of its previous level. This partial overall recovery masks a significant variation over the transport modes: Whereas driving distances are almost back to pre-COVID levels and bicycling continues at a high level, the occupancy of public transport (PT) remains at around 60 percent relative to the time before the pandemic. The introduction of a formal requirement to wear a mask in PT ("mask requirement" hereafter) did not significantly alter people's propensity to use PT. The long-term reduction in PT ridership is relevant due to the important role of public transport for commuters in Switzerland. If employees were return to their work places before the trust in the safety of public transport is restored, the consequence could be a severe increase in road congestion. This is problematic from a public policy point of view, as both congestion and increasing road capacity are very costly.

We observe a pronounced heterogeneity of the response to the pandemic and policy measures in our sample. In order to better understand this heterogeneity, we engage in a machine-learning exercise based on a causal forest to identify those variables among our rich survey information that best explain the individual-level response. In a second step, we include these variables as interaction terms in a more standard regression analysis. We find that the reduction in mobility during the pandemic was more pronounced among households with children and respondents with a tertiary education and a PT subscription. In contrast, full-time employment was a predictor for increased mobility, along with personal "values" and "lifestyles" that were elicited using a standardized methodology.

In the next section, we provide some background information and section 3 presents the data. Section 4 presents our empirical framework, section 5 the regression results, and section 6 concludes.

2 Background

2.1 The COVID-19-pandemic in Switzerland

The first confirmed case of COVID-19 was registered in Switzerland on February 25, 2020. The situation deteriorated quickly and by late March, new infections exceeded 1,000 per day. By the end of our sample period (May 30, 2021), over 684,000 confirmed cases and over 10,800 deaths have been registered.[1]

[1] To put this in perspective, the population in Switzerland is currently 8.57 million.

The Swiss Federal government declared an "extraordinary situation" on March 16, 2020 and thus assumed competencies normally in the hands of the cantons.[2] Under these temporary rules, most publicly accessible and non-essential businesses were closed, along with schools and recreational facilities. Most private businesses were not affected by the ruling, but employers were asked to make home office and flexible hour arrangements possible to avoid rush hour peaks in transport. Grocery stores, health care-related institutions, post offices, banks, transport services and governmental offices were exempt. The national borders were closed with the exception of work-related travel and Swiss citizens returning from abroad.

The COVID-19-measures also targeted private individuals. Public gatherings of more than 5 were forbidden, and social distancing of 2 meters was mandated for everyone not living in the same household (this was later reduced to 1.5 m). Although strict, the measures were less severe than in many other European countries, including Switzerland's neighbors. Importantly, people were allowed to leave their homes throughout the pandemic and most of the economy remained open. Thus, the Swiss measures were labeled as a "soft" lockdown, in comparison to more stringent measures elsewhere. The first pandemic wave peaked at the beginning of April and then decreased.

Public transport service was maintained due to its high relevance for the Swiss economy. The federal government advised "individuals at risk" (i.e., those above 65 or with pre-existing health conditions believed to lead to more severe cases of COVID-19) not to travel or to use private transport if necessary.

The restrictions were gradually lifted the infection rate decreased. On April 27, 2020, a first group of businesses were allowed to re-open (including garden centers, hair salons and, somewhat idiosyncratically, tattoo parlours) and hospitals were allowed to perform non-essential procedures again. On May 11, schools re-opened for grades 1-9 and most types of businesses resumed operation, including restaurants and bars.

On June 8, the restrictions were lifted for high schools and universities, as well as for

[2] All past and present measures imposed and lifted by the federal government and cantons can be found here: https://www.bag.admin.ch/bag/en/home/krankheiten/ausbrueche-epidemien-pandemien/aktuelle-ausbrueche-epidemien/novel-cov/massnahmen-des-bundes.html

all events of up to 300 individuals. All leisure and entertainment facilities re-opened, with a limit of 1,000 individuals for sports events. The national borders to the neighboring countries were re-opened on June 15. On June 19, the extended but temporary powers of the federal government officially expired. The social distancing mandate has remained in place (now enforced by the cantons), but has been reduced to 1.5 meters.

Masks were initially not recommended by the government for healthy individuals, but eventually mandated for situations where social distancing could not be maintained (e.g. in doctors' offices or hair salons). On July 6, masks were mandated for use in public transport as well. In addition, some cantons imposed mask mandates for grocery stores and shops.

The infection and death rates remained stable over the summer months of 2020. However, in the fall the situation worsened again, resulting in the second wave of the pandemic for Switzerland. From October 19 the government mandated a ban on public gatherings of more than 15 people, that food and drink may only be consumed while sitting in restaurants and bars, and that masks must be worn inside at any publicly accessible location. These included public transport stations and stops, restaurants and bars, sports and cultural facilities and venues, supermarkets and other shopping venues, and doctor's practices, among others. On November 2, universities had to switch to remote learning, whereas schools remained open.

During December the government implemented further measures. On December 9 there was a reduction in the capacity for shops, followed by a curfew of 19:00 was added for most shops, cultural venues, and sports facilities (except bars, restaurants, and takeaway shops). Gatherings of more than 5 persons were prohibited with the exception of religious festivals, burials, and political events. From December 22 all food service locations, cultural venues, and sports facilities were closed and shops' capacities were further reduced. In January 2021, the government extended the measures from December to the end of February 2021. From January 18 home office became mandatory and non-essential shops were closed.

From March 1 the government mandated a reopening of shops, cultural venues, and sports facilities, while gatherings of up to 15 persons were allowed outside. All other measures from December were extended until March 31. On April 19 restaurants and bars were allowed to reopen their outside seating areas and universities could return to in-person learning. During May the government presented a road map for further reopening measures dependent on the pandemic situation.

For our empirical analysis, we use this timeline to divide the pandemic into 10 distinct COVID sub-periods (CPs):

CP 1: March 16 to April 26, 2020 (first lockdown)

CP 2: April 27 to May 10 (reopening of some businesses)

CP 3: May 11 to June 7 (reopening of mand. school and most businesses)

CP 4: June 8 to July 5 (reopening of all schools and recreational facilities)

CP 5: July 6 to October 18 (mask obligation in public transport)

CP 6: October 19 to December 21 (Rule of 15 people, mask mandate, remote learning)

CP 7: December 22 to January 17 (second lockdown)

CP 8 January 18 to February 28 (Lockdown extended, home office mandatory)

CP 9: March 1 to April 18 (reopening of shops, sports facilities and cultural venues)

CP 10: April 19 to May 30 (reopening of restaurants and bars)

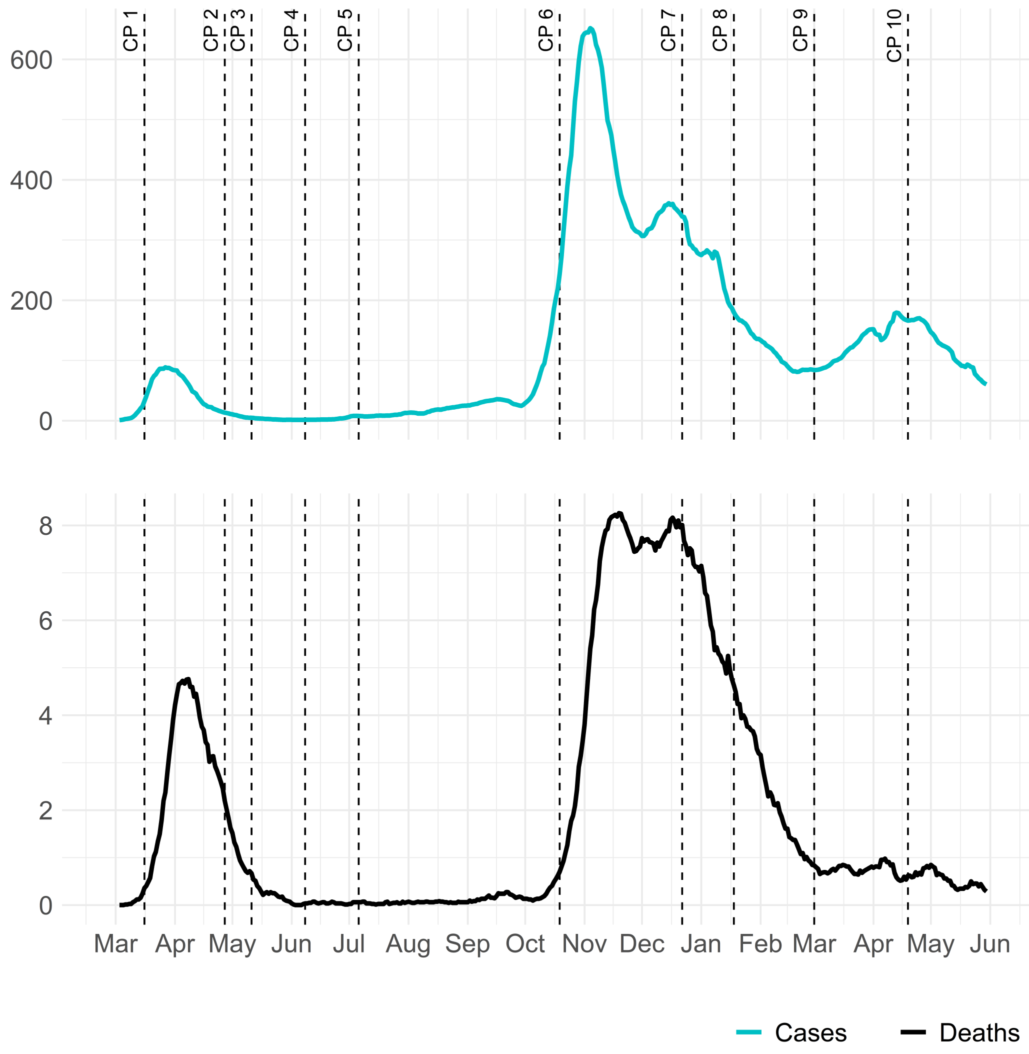
Figure 1 shows weekly new infections and COVID-related deaths per 100,000 inhabitants until the end of May 2021.

2.2 The MOBIS and MobisCovid panels

The MOBIS study is a large-scale field experiment that took place between September 2019 and January 2020. During this study, the individual mobility behavior of the participants was recorded using a smartphone-based tracking app.

A sample of 91,000 people living in urban agglomerations in both the German- and French-speaking parts of Switzerland was invited to participate in the study by letter.

Figure 1: COVID-19 Cases and Deaths (7 day incidence per 100,000 inhabitants)



Source: https://www.corona-data.ch/

Recipients were asked to complete an online survey designed to collect socio-demographic information, mobility patterns and preferences about transport policies. Respondents were filtered based on certain inclusion criteria, most importantly using a car on at least two days a week, being able to walk at least 200m and not working as a professional driver, and invited to participate in a tracking-based study.

Around 22,000 people completed the introductory survey and 7,000 qualified for tracking study, 5,466 of which registered to participate. Tracking took place by means of the Catch-My-Day GPS-tracking app developed by motion-tag, Berlin. The app records all outdoor movements, groups the GPS points into stages, trips and activities, and imputes travel modes. Although the respondents were encouraged to verify the imputation and add a trip purpose, this was not required of them. For more details about the tracking app and response rates, see Molloy et al. (2020).

3,520 participants completed the final survey after the tracking period. Some of them continued using the tracking app despite the study's end, with roughly 400 participants still tracking by mid-March 2020. The remaining participants were invited to reactivate the tracking app. Over 1,200 re-installed the app and most resumed tracking. Along with those that never switched off the app, these participants make up the MobisCovid panel. Since the beginning of April, bi-weekly reports have been produced,[3] providing detailed information on mobility patterns during the various phases of restrictions compared to the baseline MOBIS period. The original MobisCovid panel has suffered from attrition, which is mitigated by the addition of participants from LINK[4] in the fall of 2020, with over 700 individuals having delivered tracking information up to the end of May 2021. The panel has further been augmented with a series of online surveys where respondents were asked about current working and living arrangements and asked to assess their own and others' risk of contracting a severe case of COVID-19. Up until May 30 2021, the MobisCovid panel has over 450,000 person-day observations from over 2,400 participants.

2.3 Other COVID-19 mobility studies

The COVID-19 pandemic has had a global impact, with countries around the world responding in various ways in response. A growing number of studies has examined the impacts of the initial lockdowns on mobility behaviour in various countries, and then the changes resulting from corresponding easing of restrictions.

During the initial lockdowns in early 2020, large reductions in kilometers travelled were observed around the world. In Australia, a reduction of over 50% in weekly trips was observed, based on an online survey panel of 1073 persons (Beck and Hensher, 2020a). Follow-on analysis by Beck and Hensher (2020b) covering the period from early May to

[3]Updates of the reports are available in English, German, and French at https://ivtmobis.ethz.ch/mobis/covid19/en/

[4]https://www.link.ch/en/products/the-link-internet-panel/

mid-June indicated that travel had increased but is still below pre-COVID levels. They also observed that car usage rebounded faster and stronger than other modes.

Yabe et al. (2020) also observed a reduction in human mobility of over 50% in Japan in the early days of the pandemic. Pepe et al. (2020) report a reduction of inter-regional trips of a similar magnitude. In Sweden, reductions of between 40% and 60% were observed in public transport ridership (Jenelius and Cebecauer, 2020).

Further studies used mobile phone data to investigate country wide changes in Austria (Heiler et al., 2020), Finland (Järv et al., 2021), China (Jia et al., 2020) and the United States (Xiong et al., 2020).

3 Data

Table 1 shows the composition of the MobisCovid sample (split into the original MOBIS sample and the LINK sample) in comparison to the Swiss transport Microcensus (Swiss Federal Office of Statistics and Swiss Federal Office of Spatial Development, 2017), which is a representative survey about travel behavior that takes place every 5 years. Our sample is similar along some dimensions (e.g., gender), but there are also differences. For example, our sample focuses on people below the age of 65 and excludes the Italian-speaking part of the country. Our participants have, on average, a higher level of employment, education and income and live in larger households than the general population. These differences can be explained by self-selection and by the focus of the MOBIS study on working-age people that drive at least two days a week and live in urban agglomerations in the German- and French-speaking regions of Switzerland. For example, the employment rate among people aged 18-65 in the Microcensus is 71.2%, which is very close to the rate in MobisCovid.

Table 1: MobisCovid, MOBIS, LINK, and Microcensus (2015) Sample Comparison

		Share (%)			
Variable	Value	MobisCovid	MOBIS	LINK	Microcensus
Access to car	Yes	82.5	90.5	65.1	75.8
	Sometimes	12.1	8.6	19.8	18.1
	No	5.3	0.8	15.1	6.2
Age	Under 18	0.3		0.3	13.2
	[18, 25]	13.1	12.6	14.2	9.0
	(25, 35]	15.8	13.8	20.3	14.2
	(35, 45]	24.1	23.5	25.6	15.4
	(45, 55]	23.8	26.1	18.9	16.7
	(55, 65]	19.5	22.3	13.5	12.9
	66 and older	3.5	1.7	7.3	18.5
Education	Mandatory	5.4	5.8	4.6	19.3
	Secondary	46.9	46.3	48.4	49.5
	Higher	47.6	47.9	47.1	31.2
Employment	Employed	73.5	73.0	74.7	48.2
	Self-employed	5.4	6.8	2.5	7.2
	Apprentice	0.7	0.6	0.9	2.6
	Unemployed	3.1	3.7	1.7	2.5
	Student	5.5	5.1	6.3	3.7
	Retired	5.4	4.1	8.3	19.3
	Other	6.4	6.7	5.6	16.5
Gender	Female	48.2	50.6	43.1	50.7
	Male	51.8	49.4	56.9	49.3
Household size	1	14.8	12.4	19.9	34.0
	2	33.8	33.3	35.0	35.4
	3	18.9	20.4	15.7	13.0
	4	23.9	25.7	19.9	12.5
	5 or more	8.6	8.2	9.4	5.1
Income	4 000 CHF or less	6.3	5.6	7.7	17.8
	4 001 - 8 000 CHF	28.9	28.9	29.1	32.8
	8 001 - 12 000 CHF	30.5	30.0	31.5	17.4
	12 001 - 16 000 CHF	16.2	16.3	15.9	6.8
	More than 16 000 CHF	9.5	10.5	7.5	4.5
	Prefer not to say	8.6	8.7	8.4	20.7
Language	German	72.3	69.0	79.3	68.4
	French	21.6	22.8	18.9	25.3
	English	6.2	8.2	1.8	
	Italian				6.3
Nationality	Switzerland	97.9	97.9		75.9
	Other	2.1	2.1		24.1

Notes: Sample descriptive statistics shown for MobisCovid (n = 2,412), MOBIS (n = 1,649), LINK (n = 763), and Swiss Microcensus 2015 (n = 57,090) samples.

Because weather information is an important predictor for some modes, especially in the leisure context, we complement our tracking data with data about temperature, precipitation and sunshine hours from MeteoSwiss.[5] The data are provided on a 1 x 1 km grid resolution.

To allow for a nonlinear effect of temperature on travel choices, we define periods of heat and cold (in terms of degree days) for a trip j on day t as follows:

$$Heat_{jt} \equiv \max\{tmaxd_{jt} - 25,\, 0\} \tag{1}$$

$$Cold_{jt} \equiv \max\{10 - tmind_{jt},\, 0\} \tag{2}$$

The variables $tmaxd_{jt}$ and $tmind_{jt}$ refer to the daily maximum and minimum temperature, respectively, recorded in degrees Celsius at the grid point closest to the departure location for trip j.[6] In addition, we include precipitation and the number of sunshine hours, recorded on the same grid. To compute the corresponding values per person and day, we take the average of the heat, cold, precipitation and sunshine values across all trips taken by person i on day t.

Table 2 shows average daily distances, duration and trip counts for our sample, along with information about the weather and infection rates. The values are given for the whole period (September 2019 through August 2020), as well as the different sub-periods defined above. Descriptive statistics for additional variables entering the causal forest and regression analyses described below are presented in Table A.1.

[5] See `www.meteoswiss.admin.ch`

[6] The grid is based on the Swiss CH1903 coordinate system, which necessitates a conversion from the standard GPS coordinates obtained from the tracking data to the Swiss coordinate system.

Table 2: Descriptive statistics for selected variables

Variable	Mode	Phases		
		All	Baseline	COVID
Infections (weekly per 100k)	Total	0.00	0.00	123.90
		(0.00)	(0.00)	(146.83)
Distance (km)	Total	38.91	47.15	36.45
		(55.34)	(59.54)	(53.79)
	Car	29.11	33.97	27.65
		(47.56)	(49.31)	(46.91)
	PT	6.24	10.05	5.11
		(29.07)	(35.89)	(26.65)
	Bicycle	1.07	0.72	1.18
		(5.77)	(4.22)	(6.15)
	Walking	2.00	2.02	1.99
		(3.45)	(3.62)	(3.40)
Duration (min)	Total	81.86	92.27	78.71
		(84.18)	(96.05)	(79.97)
	Car	40.37	47.83	38.12
		(53.38)	(56.44)	(52.22)
	PT	9.07	16.35	6.90
		(35.59)	(54.42)	(27.20)
	Bicycle	3.81	2.32	4.25
		(18.34)	(13.13)	(19.61)
	Walking	27.60	25.18	28.30
		(49.84)	(55.50)	(47.87)
Trips	Total	4.17	4.55	4.07
		(3.10)	(2.95)	(3.14)
Cold	Total	5.92	6.30	5.79
		(4.89)	(4.47)	(5.01)
Heat	Total	0.24	0.03	0.30
		(1.01)	(0.26)	(1.13)
Sunshine (hours)	Total	5.59	3.67	6.16
		(4.86)	(3.49)	(5.06)
Precipitation (mm)	Total	2.71	2.80	2.67
		(5.49)	(4.94)	(5.62)

Notes: Values calculated as daily means for the full sample ("All", n = 450,794), the baseline period ("Baseline", n = 102,442), and the COVID period from 09.3.2020 to 30.05.2021 ("COVID", n = 345,985). Standard deviations in parentheses.

4 Empirical framework

We estimate the proportional change of outcome variable Y_{it} for person i on day t as a function of a set of explanatory variables. To obtain the average effect of the COVID-subperiods on mobility choices, we start with the following regression:

$$ln(Y_{it}) = c + \alpha \cdot CW_t + \beta \cdot ln(W_{it}) \times [\mathbf{1} \quad WE_t] + \gamma \cdot X_{it} + \delta \cdot D_t + \mu_i + u_{it} \qquad (3)$$

The vector CW_t contains a series of "COVID Week" dummies. The first dummy, to which we refer to as "Week 0", is equal to one during the week starting on March 9, 2020; the second dummy marks the week starting on March 16, and so on. The sample ends on May 30, which is the last day of COVID Week 63. In addition to these CW dummies, we include additional dummies for the first week of March and for week-ends and holidays in the vector D_t. The baseline time period thus consists of work days from September to February, which is captured by the constant c and the person FE. The estimated vector of coefficients $\hat{\alpha}$ measures the proportional change in Y_{it} during each week of the pandemic, relative to the person-specific baseline and corrected for weather.

The vector W_{it} contains weather information associated with the trips that are included in Y_{it}. This allows for an interpretation of the other coefficients at the average weather a person was exposed to during our observation period. Because the effect of weather on mobility could differ between work days and week-ends, we enter the weather information by itself (the unit vector in the first position in the brackets) and interacted the weekend-dummy WE_t. In some regressions, we also include additional variables in the vector X_{it}, in particular the infection rate.

We include person fixed effects (μ_i) to absorb unobserved heterogeneity that is constant across time. The error term u_{it} has an expectation of zero, but we allow for correlations within individuals and within calendar days by imposing a two-way clustering.

Rather than estimating (3) in a log-linearized form, we exponentiate the equation and estimate it using a Poisson pseudo-maximum likelihood (PPML) model.[7] The PPML

[7]We use Stata's ppmlhdfe command developed by Correia et al. (2019) and Correia et al. (2020).

estimator only requires that conditional mean is correctly specified, but no additional assumptions need to be made about the distribution of the error term (Gourieroux et al., 1984; Correia et al., 2020). Furthermore, estimating the model with PPML solves the problem with zeroes and also addresses a potential bias that can arise in the presence of heteroskedasticity; see Santos Silva and Tenreyro (2006) for a discussion.[8]

The problem associated with having no control group (i.e., the impact of dynamic unobserved factors that drive the dependent variable independently of COVID) is arguably mitigated in the current context. The pandemic and the lockdown measures were extremely salient, such that we expect all other unobserved determinants of mobility to be of second-order importance. This is true especially in the beginning of our sample period. In contrast, mobility during the second lockdown was probably affected also by the Christmas period.

The approach outlined above allows us to estimate the average proportional change in the dependent variable during the pandemic. But the overall effect is only a part of the story, as we observe a pronounced heterogeneity in the response to the pandemic and the governmental measures. Understanding the drivers of the observed this heterogeneity will be useful for policy makers in anticipating the distributional consequences of future policy measures for subgroups of the population.

Including all possible variables in a joint regression could lead to spurious results due to multi-collinearity. To pre-select the variables that predict the heterogeneity best among the large set from the various surveys, we therefore make use of a machine learning algorithm. The causal forest (CF) algorithm proposed by Wager and Athey (2018) is an ensemble method based on the random forest (RF) algorithm proposed by Breiman (2001).[9] Once a CF is trained, a test for calibration and potential heterogeneity in the

[8]Briefly, the expected value of the logarithm of a random variable depends both on its mean and its variance. If the variance of $e^{u_{it}}$ depends on the regressors, which is quite plausible given that no negative values for y_{it} are allowed, then u_{it} will depend on (the log of) these regressors too, which would lead to a bias.

[9]A CF is trained in the standard way by growing trees from random samples of the data to estimate an expected outcome (here, the change in the average distance traveled after vs. before the pandemic). The final estimate is a weighted average of the estimates for each leaf in the tree. A key difference in the CF algorithm compared to other RF algorithms is how the quality of the splits at each node in a tree is determined. With the ultimate aim of explaining potential treatment effect heterogeneity, the splits at each node are made such that the difference in treatment effects across all "child" nodes in the tree is

estimated treatment effect can be applied using the approach of Chernozhukov et al. (2018). The variables that drive the potential heterogeneity are those where the most splits occurred while training the CF and provide a measure of "variable importance".

Consistent with our regression framework, we use September 2019 to February 2020 as the control period and the entire COVID period as well as CP 1 (first lockdown) and CP 7 and CP 8 (second lockdown) as the treatment periods. As we are comparing COVID-subperiods to a baseline period without a contemporaneous control group, we cannot claim to identify causal effects of the measures on mobility behaviour. Nonetheless, by controlling for a large set of covariates, the estimates from the CF and the resulting indicator of variable importance can inform the specification of regression models to uncover potentially heterogeneous responses to the COVID-19 measures.

Using the information from the CF, we specify the following regression.

$$ln(Y_{it}) = c + \alpha \cdot CP_t + \beta \cdot CP_t \times Z_i + \mu_i + \mu_t + u_{it} \tag{4}$$

Here, CP_t is a vector of 10 COVID period dummies, and Z_i contains the person-specific variables identified by the CF algorithm to be relevant drivers of the observed heterogeneity. This includes information about socio-demographics, mobility tool ownership, personal values and lifestyles.

To elicit personal values, we used the scale originally developed by Schwartz (1992) and adapted by De Groot and Steg (2010) and Steg et al. (2014). The respondents were asked to what extent they consider the 16 value items as *guiding principle in their lives* (Schwartz 1992). Responses were recorded on a Likert scale and aggregated to 4 meta-values particularly relevant for explaining environmentally relevant behavior: egoistic, altruistic, hedonic and biospheric.[10]

maximised.

[10]These values are based on the following items: Egoistic: social power (control over others, dominance), wealth (material possessions, money), authority (the right to lead or command), influential (having an impact on people and events) and ambitious (hard-working, aspiring). Altruistic: equality (equal opportunity for all), a world at peace (free of war and conflict), social justice (correcting justice, care for the weak) and helpful (working for the welfare of others). Hedonic: pleasure (joy, gratification of desires), enjoying life (enjoying food, sex, leisure etc.) and self-indulgent (doing pleasant things). Biospheric: respecting the earth (harmony with other species), unity with nature (fitting into nature), protecting the environment (preserving nature) and preventing pollution (protecting natural resources).

To capture respondents' "lifestyle" we applied the typology developed by Otte (2008), who defines two lifestyle-defining dimensions: (1) modernity and biographical perspective[11] and (2) endowment level (including both material and cultural wealth).[12] The two dimensions are constructed based on the sub-items measured on a 4-point scale and then trichotomized taking the values 2 and 3 as the threshold values and defining the levels of modernity and biographical perspective as traditional (dimension index 1 to 2), semi-modern (dimension level 2 to 3) and modern (dimension level 3 to 4) and the levels of endowment as low (dimension index 1 to 2), middle (dimension index 2 to 3) and high (dimension index 3 to 4). The Otte lifestyle types result from the 9 possible pairs of dimension levels: (1) traditional workers (traditional, low endowment), (2) home-centered (semi-modern, low endowment), (3) entertainment-oriented (modern, low endowment), (4) conventionalists (traditional, middle endowment), (5) advancement-oriented (semi-modern, middle endowment), (6) hedonists (modern, middle endowment), (7) conservatives (traditional, high endowment), (8) liberals (semi-modern, high endowment) and (9) reflexives (modern, high endowment). Summary statistics of values and lifestyles are given in Table A.1.

5 Results

5.1 Effect on overall mobility

Figure 2 plots the coefficients of the COVID Week dummies from using total travel distance as the dependent variable in (3), including the weather.[13] The corresponding coefficient estimates are shown in the second column of Table 3. The vertical dashed lines in the figure mark the start of the COVID phases defined in section 2.1. The red line

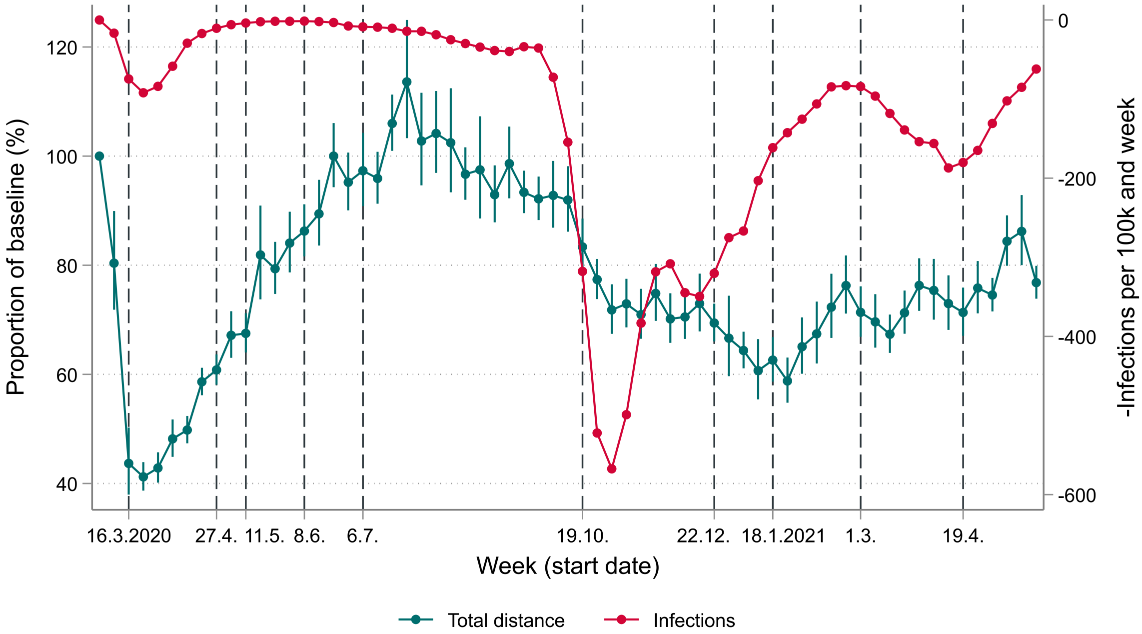
[11]This dimension is measured based on the following 4 items: (i) I enjoy my life to the fullest degree, ii) I live according to the religious principles, (iii) I hold on my family's old traditions and (iv) I go out often.

[12]This dimension is measure based on the following 5 items: (i) I cultivate an upscale standard of life, (ii) Restaurant expenditures, (iii) Visiting art exhibitions and galleries, (iv) Reading books and (v) Reading a nationwide newspapers.

[13]While the weather is significant in explaining some of the variance, it has a minor influence on the point estimates of the COVID week dummies, as can be seen in column 1 of Table 3. For the remainder of the paper, we therefore focus on the results that include the weather controls.

without confidence intervals plots the negative weekly infection rates.

Figure 2: Change in total distance traveled



Notes: This figure shows the estimated coefficients α in eq. (3) (left axis, with 90% confidence intervals), along with the infection rates (right axis). The vertical dashed lines mark the COVID periods defined in Section 2.1. The sample period ends on May 30, 2021.

The first lockdown was associated with a reduction in overall mobility by around 60% relative to the baseline period. By summer 2020, mobility had recovered to pre-COVID-levels, and in some weeks even exceeded the baseline. It decreased again with the onset of the second and wave and did not fully recover by the very end of the sample period. Note that the mobility response to the second wave was significantly smaller, despite the higher infection rates.

The overall response of travel to the pandemic can be separated into an intensive margin (i.e., the change in travel distance, conditional on person i travelling on day t) and an extensive margin (the change in the probability of person i to travel on day t). The latter is computed using a logit model. Columns 2-3 in Table 3 indicate that initially, both margins of travel were reduced relative to the baseline: The proportional effects from the PPML model are less than unity and the marginal effects from the logit model are negative. In the summer of 2020, the intensive margin became briefly positive (i.e., the

Table 3: Effect of the pandemic on total travel distance

	Overall margin	Overall margin	Intensive margin	Extensive margin
Week 0	0.828*	0.804*	0.795*	0.023*
Week 1	0.444*	0.437*	0.512*	-0.112*
Week 2	0.451*	0.412*	0.464*	-0.100*
Week 3	0.490*	0.429*	0.458*	-0.071*
Week 4	0.535*	0.482*	0.508*	-0.056*
Week 5	0.535*	0.498*	0.528*	-0.060*
Week 6	0.595*	0.586*	0.612*	-0.045*
Week 7	0.587*	0.608*	0.626*	-0.032*
Week 8	0.698*	0.672*	0.689*	-0.033*
Week 9	0.696*	0.675*	0.688*	-0.023*
Week 10	0.859'	0.819*	0.822*	-0.008°
Week 11	0.873*	0.794*	0.805*	-0.019*
Week 12	0.831*	0.841*	0.851*	-0.013*
Week 13	0.828*	0.863*	0.860*	0.002
Week 14	0.901'	0.894*	0.904*	-0.017*
Week 15	0.964	1.000	1.002	-0.003
Week 16	0.961	0.952	0.958	-0.011'
Week 17	0.982	0.973	0.982	-0.006
Week 18	0.982	0.959	0.970	-0.014*
Week 19	1.011	1.060'	1.067'	-0.016*
Week 20	0.985	1.136'	1.166*	-0.033*
Week 21	0.994	1.028	1.051	-0.031*
Week 22	0.959	1.042	1.053	-0.016*
Week 23	0.959	1.025	1.021	0.004
Week 24	0.920'	0.967	0.97	-0.011'
Week 25	0.951	0.975	0.983	-0.005
Week 26	0.955	0.929'	0.947	-0.023*
Week 27	0.944°	0.986	0.991	-0.013'
Week 28	0.890*	0.934*	0.937*	-0.007
Week 29	0.903*	0.922*	0.937'	-0.023*
Week 30	0.891'	0.928°	0.959	-0.039*
Week 31	0.891*	0.920'	0.949	-0.040*
Week 32	0.833*	0.834*	0.876*	-0.051*
Week 33	0.754*	0.774*	0.823*	-0.063*
Week 34	0.695*	0.718*	0.771*	-0.068*
Week 35	0.754*	0.729*	0.778*	-0.066*
Week 36	0.740*	0.710*	0.758*	-0.069*
Week 37	0.750*	0.748*	0.784*	-0.053*
Week 38	0.697*	0.702*	0.742*	-0.061*
Week 39	0.700*	0.705*	0.742*	-0.055*
Week 40	0.722*	0.730*	0.775*	-0.063*
Week 41	0.685*	0.694*	0.754*	-0.071*
Week 42	0.656*	0.666*	0.730*	-0.082*
Week 43	0.680*	0.644*	0.692*	-0.072*
Week 44	0.622*	0.607*	0.662*	-0.080*
Week 45	0.648*	0.626*	0.683*	-0.076*
Week 46	0.579*	0.588*	0.650*	-0.082*
Week 47	0.625*	0.651*	0.721*	-0.087*
Week 48	0.732*	0.674*	0.726*	-0.074*
Week 49	0.782*	0.723*	0.771*	-0.064*
Week 50	0.797*	0.763*	0.801*	-0.059*
Week 51	0.736*	0.714*	0.755*	-0.057*
Week 52	0.707*	0.696*	0.746*	-0.068*
Week 53	0.699*	0.674*	0.720*	-0.067*
Week 54	0.780*	0.713*	0.757*	-0.058*
Week 55	0.836*	0.763*	0.809*	-0.062*
Week 56	0.789*	0.754*	0.804*	-0.063*
Week 57	0.765*	0.730*	0.782*	-0.068*
Week 58	0.797*	0.714*	0.758*	-0.058*
Week 59	0.745*	0.758*	0.806*	-0.060*
Week 60	0.796*	0.745*	0.794*	-0.062*
Week 61	0.814*	0.844*	0.885*	-0.051*
Week 62	0.883'	0.862*	0.882*	-0.026*
Week 63	0.809*	0.768*	0.801*	-0.043*
Weekend	0.995	0.851*	0.907*	-0.061*
Heat		0.973*	0.973*	0.000
Cold		1.006*	1.006*	-0.001*
Precipitation		1.001	1.001	-0.001*
Sunshine		1.007*	1.007*	0.000*
Weekend*Heat		0.969'	0.971'	-0.002°
Weekend*Cold		1.006'	1.006'	0.001*
Weekend*Precipitation		1.001	1.002	0.000
Weekend*Sunshine		1.021*	1.018*	0.002*
Pseudo-R_2	0.204	0.208	0.214	
N	367,432	367,432	335,329	362,528
Participants	1,649	1,649	1,649	1,649

Notes: *: $p < 0.01$, ': $p < 0.05$, °: $p < 0.1$. Standard errors are clustered by person and day. The overall and intensive margins are estimated using a PPML model. The coefficients have been exponentiated to derive proportional effects relative to the baseline (a value of 1.00 indicates no effect). The results shown for the extensive margin are the marginal effects from a Logit regression. For a definition of overall, intensive and extensive margins, see main text.

people that left their home on a given day travelled longer distances) while the probability of travel has been decreased throughout the pandemic. With the onset of the second wave in October of 2020, the intensive margin switched back to negative, such that by the end of the sample period, both margins of travel remained depressed relative to the baseline.

The COVID week dummies capture the joint effect of the government measures and personal choices in the presence of high infection rates. To disentangle these two sources of behavioral change, we estimate a model in which we replace the COVID week dummies in (3) with ten COVID period dummies that mark the periods discussed above and, additionally, include infection rates in the regression. In order to allow for nonlinear and differential effect across waves, as suggested by Figure 2, we include square terms and interactions with a wave-2-dummy. The results are shown in Table 4. Controlling for the governmental measures, the marginal effect of the infection rate is negative and highly significant during the first wave (CP 1-5), but not during the second wave (CP 6-10). This implies that in the beginning of the pandemic, people reduced their mobility not only in response to the governmental measures but also in response to increasing infection rates. In wave 2, this was no longer the case; in fact, the marginal effect of infection rates, conditional on the COVID periods, is *positive*. One possible reason behind this result is that as the general level of mobility increased in the population (of which the participants constitute but a small sample), infection rates increased as a consequence.[14]

The additional columns in Table 4 display reduced versions of the full model. These versions capture less variation, as evidenced by the lower pseudo- R squared and the increased Bayesian Information Criterion. The most significant drop in model fit comes from dropping the COVID period dummies (columns 4, 6 and 7). Removing the weather (columns 2, 5 and 6) also worsens the model fit. In contrast, removing infection rates from the model only marginally impacts the fit. This indicates that most of the change in mobility behavior is captured by the governmental measures, whereas a variation in infection rates within a period did not have a meaningful impact on people's travel choices.

[14]Our sample of $<$1,700 people is insufficient to drive infection rates in Switzerland. For this reason, we treat infection rates as exogenous in the regression. However, if our participants are representative of the broader population, which we assume is the case, then such a feedback loop is possible.

Table 4: Relative relevance of government measures and infection rates

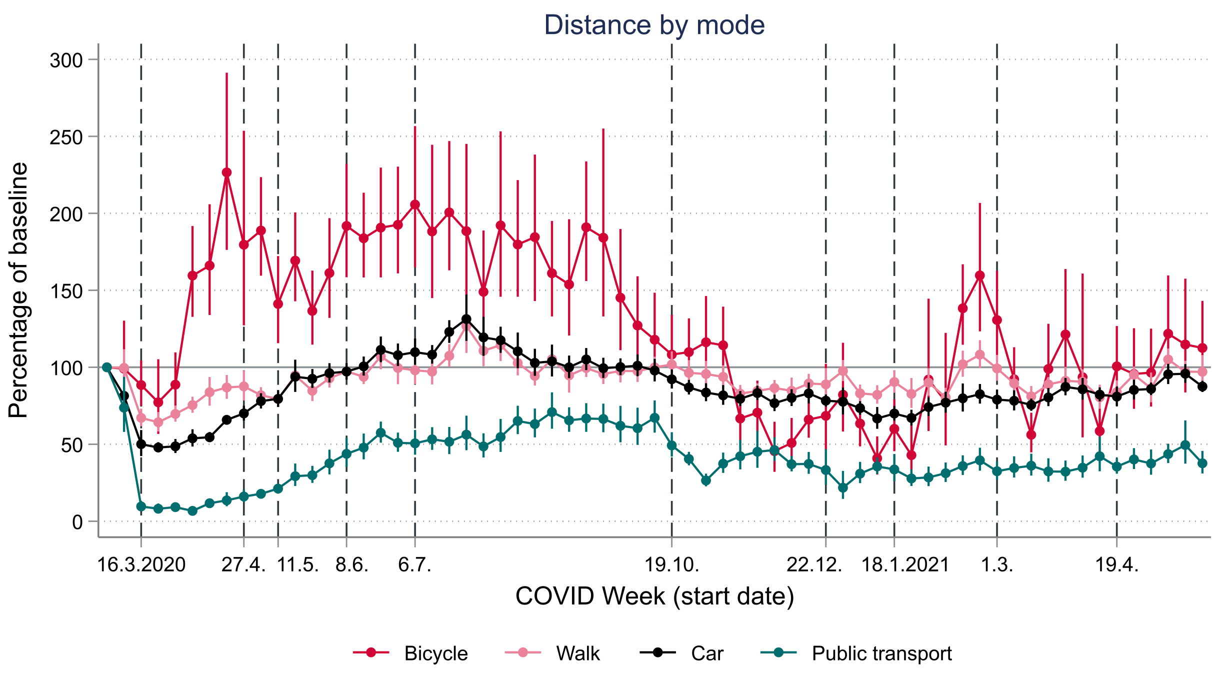
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CP 1	0.515*	0.566*	0.476*		0.519*		
	(0.017)	(0.015)	(0.014)		(0.013)		
CP 2	0.640*	0.655*	0.626*		0.643*		
	(0.018)	(0.024)	(0.018)		(0.024)		
CP 3	0.768*	0.818*	0.758*		0.813*		
	(0.023)	(0.026)	(0.022)		(0.027)		
CP 4	0.901*	0.918*	0.884*		0.911*		
	(0.022)	(0.023)	(0.021)		(0.022)		
CP 5	0.996	1.007	0.938*		0.954*		
	(0.022)	(0.018)	(0.018)		(0.016)		
CP 6	0.594*	0.584*	0.745*		0.740*		
	(0.032)	(0.032)	(0.016)		(0.017)		
CP 7	0.560*	0.548*	0.676*		0.662*		
	(0.029)	(0.029)	(0.022)		(0.021)		
CP 8	0.626*	0.632*	0.688*		0.695*		
	(0.024)	(0.027)	(0.020)		(0.023)		
CP 9	0.658*	0.685*	0.729*		0.760*		
	(0.021)	(0.022)	(0.017)		(0.019)		
CP 10	0.705*	0.734*	0.769*		0.809*		
	(0.022)	(0.024)	(0.019)		(0.02)		
Weekend	0.863*	0.997	0.862*	0.816*	0.997	0.981	0.802*
	(0.028)	(0.017)	(0.028)	(0.037)	(0.018)	(0.022)	(0.041)
Heat	0.983*		0.985*	1.021*			1.023*
	(0.005)		(0.005)	(0.005)			(0.005)
Cold	1.002		1.000	0.994*			0.988*
	(0.002)		(0.002)	(0.002)			(0.003)
Precipitation	1.000		1.000	0.996’			0.997°
	(0.001)		(0.001)	(0.002)			(0.002)
Sunshine	1.009*		1.010*	0.996’			0.993’
	(0.001)		(0.001)	(0.002)			(0.003)
Weekend × Heat	0.973’		0.973’	0.984			0.984
	(0.013)		(0.013)	(0.011)			(0.012)
Weekend × Cold	1.006’		1.006’	1.011*			1.012*
	(0.003)		(0.003)	(0.004)			(0.005)
Weekend × Precip.	1.002		1.002	1.005°			1.005°
	(0.002)		(0.002)	(0.003)			(0.003)
Weekend × Sunshine	1.018*		1.018*	1.020*			1.022*
	(0.003)		(0.003)	(0.004)			(0.005)
Infections	0.998*	0.998*		0.994*		0.994*	
	(0.000)	(0.000)		(0.001)		(0.001)	
Infections^2	1.000*	1.000*		1.000*		1.000*	
	(0.000)	(0.000)		(0.000)		(0.000)	
Infections × Wave2	1.003*	1.003*		1.005*		1.005*	
	(0.000)	(0.000)		(0.001)		(0.001)	
Infections^2× Wave2	1.000*	1.000*		1.000*		1.000*	
	(0.000)	(0.000)		(0.000)		(0.000)	
Marg. effect Wave 1	0.999*	0.999*		0.996*		0.996*	
	(0.000)	(0.000)		(0.000)		(0.000)	
Marg. effect Wave 2	1.001*	1.001*		0.999*		0.999*	
	(0.000)	(0.000)		(0.000)		(0.000)	
N	367,432	367,432	367,432	367,432	367,432	367,432	367,432
Participants	1,649	1,649	1,649	1,649	1,649	1,649	1,649
BIC	1.542E+10	1.548E+10	1.543E+10	1.580E+10	1.550E+10	1.583E+10	1.569E+10
Pseudo-R^2	0.206	0.203	0.206	0.187	0.202	0.185	0.178

Notes: *: $p < 0.01$, ’: $p < 0.05$, °: $p < 0.1$. Standard errors are clustered by person and day. Model (1) is the full model. The marginal effects for waves 1 and 2-3 are functions of the infection-related regression coefficients. Models (2)-(7) are reduced versions that omit one or two groups of variables.

5.2 Change in distance by mode

Figure 5 displays the change in distance by mode in response to the different waves of the pandemic. These results are derived by using distance by mode as the dependent variable in (3). The reduction in travel distance was particularly pronounced for public transport, which plunged to below 10% of the baseline at the beginning of the lockdown period and remains at much lower levels than before the pandemic even at the end of the sample period. Car and walking distances decreased too, but recovered very quickly and, during the summer of 2020, even exceeded pre-baseline levels. Last, we observe a remarkable increase in bicycle distances during the first wave, but not during the second. Note that even though we control for the weather in our regressions, the fact that our pre-pandemic information starts only in September 2019 makes this control imperfect, such that some of the increase in cycling in the Spring of 2020 may a consequence of the warm weather.

Figure 3: Change in distance travelled by mode



Notes: This figure shows the estimated coefficients α in eq. (3), with distance by mode as the dependent variable. The vertical bars mark 90%-confidence intervals. The vertical dashed lines mark the COVID periods defined in Section 2.1. The sample ends on May 30, 2021.

Interestingly, there is no visible uptick in public transport ridership once the mask requirement was introduced on July 6, 2020, which corresponds to the first day of COVID Week 17. This visual impression is confirmed by a series of statistical tests: The coefficient on COVID Week 16 in the PT-regression (i.e., the last week before the mask requirement) is not statistically different from those on COVID Weeks 17-19.[15] Since the PT mask requirement was the only COVID-related measure that changed on this date, we interpret this as an indication that any negative and positive effects of the mask requirements on PT ridership cancelled each other.

Drivers responded to the lockdown both on the intensive and the extensive margins. Starting in week 10, however, the intensive margin becomes insignificant and then switches direction: Conditional on driving on a given day, the panel participants drove *longer* distances in the summer of 2020 than during the baseline. In contrast, the propensity to drive has been affected negatively throughout. Therefore, the (more than complete) recovery of overall car travel after the first wave can be explained by fewer people driving longer distances, which suggests that some medium- and long-distance train trips were replaced by car trips. This may have been a "catch-up" phenomenon after the first lockdown, as in the second wave, both margins of travel remained consistently reduced.

For public transport, the reduction took place along both the intensive and the extensive margins. Although PT travel recovered somewhat from its first-wave drop, it remains significantly depressed throughout the sample period.

Bicycling significantly increased during much of 2020, along both margins. However, the level of cycling decreased towards winter and dropped below the baseline.[16] No clear picture emerges for walking, as this can be a stand-alone mode (people walking to work) or serve as a first step for PT.

5.3 Effect heterogeneity

Figure 4 shows the distribution in the change of total distances and distance by mode for the entire COVID period and separately for the two lockdowns, using the CF algorithm.

[15] The lowest p-value from this series of tests is 0.66, such that the null hypothesis of equal coefficients cannot be rejected by a long shot.

[16] This clear seasonality suggests that our weather "control" is imperfect, presumably because of the limited data before the onset of the pandemic.

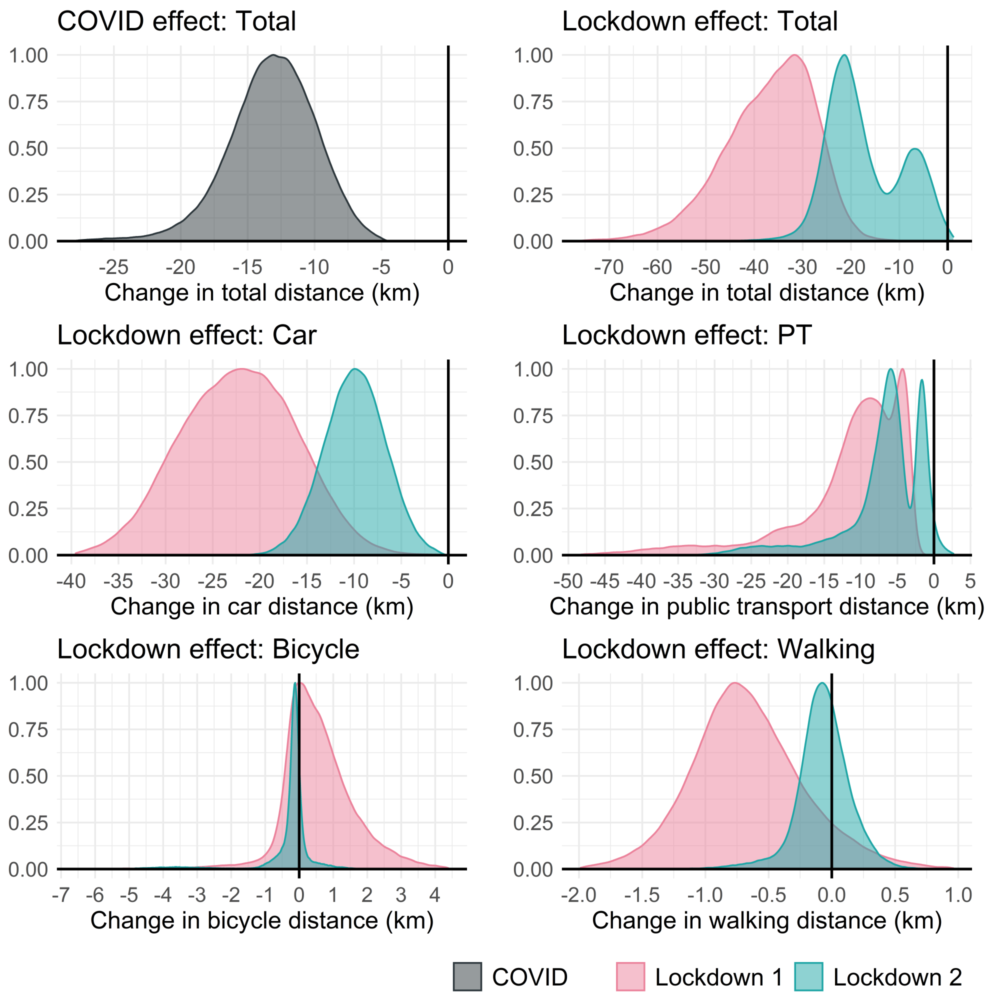
Table 5: Effect of the pandemic on different modes

	Car			Public Transport			Walking			Bicycle		
	Overall	Intensive	Extensive	Overall	Intensive	Extensive	Overall	Intensive	Extensive	Overall	Intensive	Extensive
Week 0	0.815*	0.814*	0.002	0.738’	0.884	-0.040*	0.996	0.987	0.008	0.991	0.897	0.018*
Week 1	0.501*	0.729*	-0.223*	0.096*	0.413*	-0.226*	0.672*	0.832*	-0.162*	0.885	1.022	-0.008
Week 2	0.479*	0.670*	-0.212*	0.081*	0.499*	-0.285*	0.643*	0.772*	-0.163*	0.773	0.934	-0.032*
Week 3	0.487*	0.629*	-0.172*	0.092*	0.514*	-0.272*	0.697*	0.794*	-0.132*	0.887	0.939	-0.012*
Week 4	0.539*	0.686*	-0.160*	0.067*	0.355*	-0.256*	0.755*	0.854*	-0.120*	1.596*	1.136°	0.026*
Week 5	0.546*	0.690*	-0.158*	0.117*	0.535*	-0.253*	0.838*	0.947	-0.117*	1.661*	1.206*	0.025*
Week 6	0.659*	0.791*	-0.134*	0.136*	0.590*	-0.239*	0.869*	0.957	-0.103*	2.266*	1.335*	0.049*
Week 7	0.700*	0.785*	-0.085*	0.161*	0.511*	-0.213*	0.876’	0.959	-0.087*	1.796*	1.306*	0.021*
Week 8	0.780*	0.853*	-0.071*	0.178*	0.528*	-0.190*	0.819*	0.892*	-0.091*	1.888*	1.259*	0.032*
Week 9	0.795*	0.845*	-0.047*	0.212*	0.585*	-0.176*	0.794*	0.860*	-0.078*	1.411*	1.109°	0.016*
Week 10	0.939	0.974	-0.036*	0.293*	0.614*	-0.141*	0.947	0.997	-0.052*	1.693*	1.155*	0.041*
Week 11	0.926°	0.941°	-0.017*	0.299*	0.665*	-0.137*	0.847*	0.899’	-0.062*	1.367*	1.060	0.032*
Week 12	0.962	0.999	-0.032*	0.376*	0.722*	-0.117*	0.928°	0.982	-0.053*	1.612*	1.210*	0.038*
Week 13	0.972	0.987	-0.016*	0.438*	0.759*	-0.103*	0.973	0.990	-0.032*	1.918*	1.214*	0.045*
Week 14	1.006	1.029	-0.023*	0.478*	0.793*	-0.096*	0.939’	0.980	-0.051*	1.838*	1.188*	0.046*
Week 15	1.113’	1.131*	-0.011°	0.575*	0.879’	-0.081*	1.071	1.106’	-0.036*	1.907*	1.202*	0.052*
Week 16	1.079°	1.066°	0.007	0.510*	0.777*	-0.079*	0.996	1.047	-0.054*	1.926*	1.208*	0.049*
Week 17	1.098’	1.110*	-0.009	0.506*	0.780*	-0.083*	0.980	1.025	-0.039*	2.057*	1.253*	0.059*
Week 18	1.082’	1.095*	-0.016’	0.532*	0.811*	-0.080*	0.972	1.038	-0.066*	1.882*	1.235*	0.048*
Week 19	1.230*	1.246*	-0.011	0.517*	0.825’	-0.094*	1.074°	1.127*	-0.058*	2.006*	1.290*	0.047*
Week 20	1.314*	1.389*	-0.032*	0.563*	0.939	-0.097*	1.269*	1.328*	-0.067*	1.885*	1.360*	0.033*
Week 21	1.194*	1.235*	-0.025*	0.486*	0.810’	-0.095*	1.107°	1.156*	-0.059*	1.490*	1.248*	0.017*
Week 22	1.176*	1.226*	-0.028*	0.547*	0.834’	-0.085*	1.144’	1.170’	-0.041*	1.922*	1.304*	0.036*
Week 23	1.104	1.127’	-0.017’	0.651*	0.906	-0.071*	1.028	1.037	-0.020*	1.797*	1.231*	0.042*
Week 24	1.029	1.042	-0.016’	0.631*	0.918	-0.074*	0.944	0.959	-0.021*	1.846*	1.185°	0.046*
Week 25	1.038	1.071	-0.024*	0.709*	0.904	-0.060*	1.053	1.054°	-0.017’	1.611*	1.050	0.044*
Week 26	1.000	1.053	-0.040*	0.656*	0.914	-0.068*	0.947	0.976	-0.044*	1.538*	1.154°	0.036*
Week 27	1.051	1.076’	-0.020’	0.667*	0.867’	-0.060*	0.995	1.017	-0.035*	1.910*	1.241*	0.052*
Week 28	0.994	1.016	-0.021*	0.664*	0.918	-0.060*	0.957	0.971	-0.026*	1.842*	1.195’	0.039*
Week 29	1.002	1.020	-0.019’	0.620*	0.874	-0.065*	0.977	0.982	-0.023*	1.452’	1.169°	0.024*
Week 30	1.010	1.056°	-0.036*	0.605*	0.922	-0.074*	0.975	1.000	-0.035*	1.272°	1.118	0.013’
Week 31	0.979	1.026	-0.043*	0.672*	0.941	-0.074*	1.000	1.006	-0.019*	1.179	0.947	0.024*
Week 32	0.922’	1.003	-0.066*	0.493*	0.793*	-0.105*	1.018	1.034	-0.025*	1.083	1.027	0.011’
Week 33	0.869*	0.964	-0.080*	0.405*	0.740*	-0.105*	0.964	0.999	-0.045*	1.099	1.093	-0.001
Week 34	0.836*	0.937*	-0.090*	0.265*	0.584*	-0.139*	0.956	1.004	-0.051*	1.163	1.048	0.012’
Week 35	0.818*	0.910’	-0.084*	0.374*	0.819*	-0.135*	0.938	0.978	-0.047*	1.143	1.074	0.007
Week 36	0.796*	0.865*	-0.074*	0.422*	0.758*	-0.118*	0.828*	0.874*	-0.055*	0.667’	0.901	-0.020*
Week 37	0.833*	0.893*	-0.061*	0.452*	0.835’	-0.117*	0.847*	0.888*	-0.053*	0.705’	0.876°	-0.018*
Week 38	0.767*	0.840*	-0.076*	0.463*	0.751*	-0.104*	0.865*	0.905*	-0.051*	0.455*	0.726*	-0.037*
Week 39	0.801*	0.865*	-0.060*	0.371*	0.703*	-0.126*	0.848*	0.888’	-0.049*	0.508*	0.778*	-0.037*
Week 40	0.830*	0.929’	-0.080*	0.372*	0.718*	-0.126*	0.895*	0.948	-0.062*	0.660*	0.992	-0.035*
Week 41	0.783*	0.901*	-0.089*	0.333*	0.728’	-0.145*	0.889°	0.977	-0.086*	0.685	0.940	-0.033*
Week 42	0.776*	0.944	-0.123*	0.218*	0.651’	-0.191*	0.976	1.056	-0.084*	0.822	1.000	-0.027*
Week 43	0.735*	0.831*	-0.096*	0.309*	0.672*	-0.152*	0.831*	0.891’	-0.070*	0.635*	0.958	-0.037*
Week 44	0.667*	0.804*	-0.131*	0.356*	0.759*	-0.145*	0.822*	0.884*	-0.069*	0.409*	0.774°	-0.051*
Week 45	0.700*	0.828*	-0.114*	0.337*	0.813°	-0.161*	0.905’	0.950	-0.061*	0.600*	0.877°	-0.031*
Week 46	0.671*	0.806*	-0.128*	0.278*	0.676*	-0.156*	0.828*	0.905	-0.085*	0.429*	0.866	-0.048*
Week 47	0.742*	0.889*	-0.120*	0.285*	0.659*	-0.155*	0.900°	0.977	-0.084*	0.920	1.158	-0.027*
Week 48	0.770*	0.862*	-0.087*	0.312*	0.646*	-0.151*	0.805*	0.859*	-0.071*	0.776	1.378’	-0.044*
Week 49	0.799*	0.900’	-0.084*	0.359*	0.731*	-0.144*	1.020	1.077	-0.070*	1.383*	1.138	0.023*
Week 50	0.825*	0.918’	-0.087*	0.396*	0.770*	-0.125*	1.082	1.125’	-0.049*	1.597*	1.210’	0.024*
Week 51	0.790*	0.895*	-0.089*	0.325*	0.580*	-0.103*	0.993	1.016	-0.038*	1.307’	1.200’	0.009
Week 52	0.783*	0.887*	-0.091*	0.346*	0.609*	-0.118*	0.896*	0.935°	-0.056*	0.922	1.069	-0.016*
Week 53	0.756*	0.847*	-0.084*	0.361*	0.693*	-0.123*	0.812*	0.857*	-0.067*	0.562*	0.883°	-0.042*
Week 54	0.804*	0.900*	-0.080*	0.324*	0.646*	-0.112*	0.889*	0.926*	-0.050*	0.989	1.144	-0.009°
Week 55	0.873*	0.966	-0.074*	0.322*	0.605*	-0.109*	0.912	0.944	-0.038*	1.213	1.225*	-0.002
Week 56	0.857*	0.955	-0.077*	0.348*	0.672*	-0.111*	0.906°	0.954	-0.063*	0.936	1.121	-0.018*
Week 57	0.823*	0.917’	-0.084*	0.422*	0.749*	-0.079*	0.805*	0.855’	-0.070*	0.586*	0.952	-0.037*
Week 58	0.810*	0.886*	-0.067*	0.355*	0.683*	-0.090*	0.838*	0.875’	-0.046*	1.006	1.117	-0.012’
Week 59	0.853*	0.951	-0.074*	0.401*	0.698*	-0.092*	0.952	0.992	-0.049*	0.957	1.093	-0.014’
Week 60	0.859*	0.928°	-0.057*	0.375*	0.689*	-0.097*	0.864’	0.901	-0.047*	0.965	1.050	-0.013’
Week 61	0.954	1.037	-0.061*	0.436*	0.701*	-0.087*	1.051	1.073	-0.037*	1.218	1.259°	-0.010
Week 62	0.958	0.992	-0.031*	0.495*	0.800°	-0.072*	0.972	0.971	-0.012	1.148	1.249°	-0.015’
Week 63	0.875*	0.963	-0.069*	0.377*	0.720*	-0.085*	0.971	1.004	-0.040*	1.126	1.065	0.003
Weekend	0.923’	1.009	-0.063*	0.600*	0.944	-0.076*	0.979	1.080’	-0.086*	0.807°	1.071	-0.041*
Heat	0.966*	0.962*	0.001	1.005	1.004	0.000	0.950*	0.952*	-0.000	0.991	0.981’	0.002’
Cold	1.006*	1.007*	-0.001*	1.003	0.998	0.001*	1.016*	1.015*	0.001*	1.017	1.008°	0.001*
Precipitation	1.002°	1.002°	0.000°	0.999	1.000	0.000	0.996*	0.997*	-0.001*	0.981*	0.996	-0.001*
Sunshine	1.005*	1.007*	-0.001*	1.006°	1.007*	-0.001*	1.016*	1.014*	0.001*	1.065*	1.024*	0.004*
Weekend*Heat	0.975°	0.971’	0.001	0.994	0.997	-0.003	0.945*	0.955*	-0.007*	0.963	0.993	-0.002
Weekend*Cold	1.006’	1.009*	-0.001*	0.999	1.000	-0.001*	1.006’	1.004	0.001*	1.021’	0.999	0.002*
Weekend*Precip.	1.001	1.002	-0.001’	0.995	1.000	-0.001*	1.000	1.001	-0.000	1.019’	1.006	0.001*
Weekend*Sunshine	1.015*	1.015*	0.001*	1.009	1.005	0.001*	1.024*	1.020*	0.003*	1.055*	1.020*	0.004*
Pseudo R^2	0.208	0.206		0.379	0.440		0.208	0.215		0.412	0.506	
N	367432.000	259132.000	367384.000	364950.000	75526.000	364950.000	367432.000	287071.000	366986.000	332927.000	38389.000	332927.000
Participants	1,649	1,649		1,630	1,608		1,649	1,649		1,432	1,293	

Notes: *: $p < 0.01$, ’: $p < 0.05$, °: $p < 0.1$. For additional notes, see Table 3.

The figure implies a significant reduction of travel distances during the COVID period as a whole (top, left panel). There is a wide range of heterogeneity both within and across modes for lockdowns 1 and 2, as shown by the distributions.

Figure 4: Distribution of Change in Distance Traveled (km/day)



Note: This figure shows the heterogeneity of the response in travel distance to the pandemic over the entire COVID period (09.03.2020 - 30.05.2021, top panel), and during Lockdown 1 (CP 1, 16.03.2020 - 26.04.2020 and Lockdown 2 (CP 7 and CP 8, 22.12.2020 - 28.02.2021) by mode (remaining panels). The effect is computed using the CF algorithm by Wager and Athey (2018) and implemented in the R package "grf" (R Core Team, 2020; Tibshirani et al., 2020).

Figure A.1 in the appendix contains the variables from the CF analysis for the entire COVID period with a "better than random" information contribution to the model.[17] We combine the covariates identified by the CF in the vector Z_i and include them as inter-

[17]We generate a natural cutoff for the information contribution of each variable by adding two random variables. The continuous and dichotomous random variables capture random variation and, as such, all variables with a lower variable importance ranking represent nothing more than white noise.

action terms in eq. (4), separately for each of the ten COVID period dummies CP_t. The included variables can be grouped into socio-demographics (gender, age, language, household size, income, education, employment); variables capturing mobility tool ownership and habits (access to PT and road network; PT subscription and car ownership; regular use of car, PT or bicycle); personal values; and lifestyles (see above). One category is always omitted as it will be captured by the constant (reference category). Note that Z_i is not included by itself as it would be absorbed by the person fixed-effects μ_i. Because we are not interested in a variation across "non-personal" variables that were identified by the CF as relevant, such as the weather or zip codes, we do not include these in Z_i.

We start by estimating the full model and then gradually reduce its scope by eliminating variables for which the interactions with the ten COVID periods do not meet a threshold for a joint significance test.[18] After estimation, we remove the variables that have a joint p-value of more than 0.4. We then re-estimate the model and proceed to make cuts at p=0.3 and, finally, at p=0.2. The final model includes 21 interaction variables, which are shown in Figure 5. For exposition purposes, we only include the results for 5 of the 10 COVID periods; the full results are shown in Table A.2 in the Appendix.

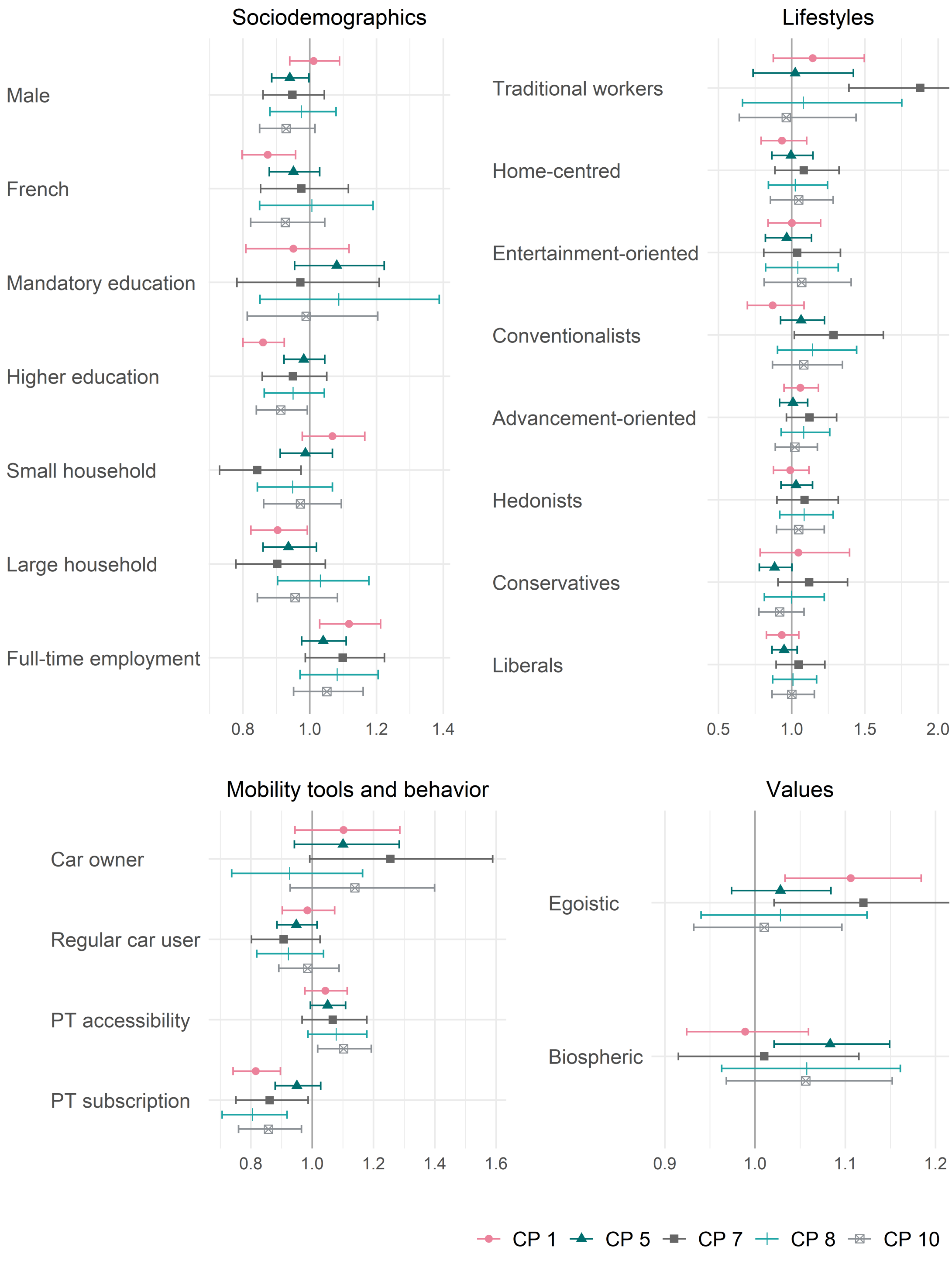
The reduction in mobility was particularly pronounced for people with a tertiary education and those living in large households. This is likely due to the presence of children, which is important due to school closures during the first wave. Men also travelled less than women, especially in the later periods of the pandemic. As could be expected, those with full employment travelled more than others.

We find that the study participants that hold a public transport subscription reduced mobility by more than those that do not.[19] This is consistent with the facts that regular PT users tend to have a subscription and that PT use remains reduced. On the other hand, living in a zip code with high access to PT is associated with increased mobility.

[18]The number of the involved dummies depends on the dimension in question. For the gender dimension, we include 10 interaction terms (one "male" dummy multiplied by each CP), the coefficients of which are tested jointly. For lifestyles, the resulting number of coefficients is 80, as there are 8 separate lifestyle dummies included in the model (the ninth serving as the reference).

[19]By "subscription" we mean either a "general abonnement" allowing for unrestricted use of the Swiss transport system or a line- or region-specific transport pass. We do not interpret half-fare cards as a subscription as the vast majority of Swiss hold such a card.

Figure 5: Response heterogeneity



Notes: Error bars represent 95% confidence intervals. The reference categories (in order) are: female, German-speakers, secondary education, household with 3 members, not working full time, not owning a car, using the car on fewer than 3 days per week, living in a zip code that does not have "high PT access" as defined by an index holding a PT subscription, belonging to the lifestyle category "reflexives" and having a below-median index for "egoistic" and "biospheric" values. The coefficient estimates are shown in Table A.2.

This is not as expected, but it is possible that "PT accessibility" is correlated with urban density, which is not reflected in our data, and which may be associated with an increased mobility during the pandemic. Owning a car is associated with a lower reduction of travel during the pandemic, as could be expected.

Respondents that scored highly on the values dimensions "egoistic" and "biospheric" traveled more than others during the pandemic. The former result is consistent with the interpretation of reducing mobility as a public good during a pandemic, whereas the latter is somewhat unclear. Last, the lifestyle category assigned to the respondents explained a significant part of the response heterogeneity. Conservatives reduced their travel by more than the reference category (reflexives), whereas traditional workers reduced it by less, presumably due to a limited flexibility in work hours and options to work from home.

6 Discussion and Conclusions

Using tracking data collected through a smartphone-based tracking app, we find that people cut their travel distances at the onset of the COVID-19 pandemic by an average of 60 percent. This large reduction was not obvious given that the Swiss federal government never imposed a formal stay-at-home rule, but instead appealed to the population to act "responsibly" meaning to stay at home if possible. The reduction in travel was therefore a combination of policy (e.g., the closing of schools and of businesses with public access), voluntary firm measures and people choosing not to travel in the face of the virus threat. Other researchers also identify the role of voluntary measures and individual response in reducing mobility (Maloney and Taskin, 2020; Yabe et al., 2020). The Swiss case is proof that individual mobility can be significantly reduced without the formal travel bans that have been instituted in many countries. To the extent that "soft" lockdowns are easier to implement than "hard" ones in the long run, the Swiss response to COVID-19 could serve as a blueprint for the regulation of mobility in future pandemics.

Travel distances increased as the economy was re-opened, but the recovery was incomplete and unequal across the different modes of transport. This was also observed elsewhere (Beck et al., 2020). Whereas driving distances are (almost) back at pre-pandemic levels, public transport continues to be under-used. Remarkably, the introduction of a mask mandate did not have a measurable effect on PT ridership, at least not during the first 6 weeks. If and when most firms return to workplace presence, the reluctance to use PT suggests a threat of increased road congestion if the average daily travelled kilometers return to their pre-pandemic levels without a corresponding return to public transport (Hu et al., 2020; Li et al., 2021). However, it is also possible that a permanent shift towards working-from-home will take place, which could more than offset the increase in private car usage (Beck et al., 2020; Beck and Hensher, 2021).

The mobility response to the second wave (starting in October 2020) was qualitatively quite different from the first wave. Although infection rates were much higher, the decrease in mobility was much less pronounced, implying that people were reluctant to limit their activity to the same degree, and or that the opportunity cost of reducing certain activities increases more than proportionally with time. Most of us have felt this: Whereas reducing mobility for a couple of months is burdensome but more or less feasible (depending on the personal situation of course), doing the same for over a year is much harder. For the same reason, it becomes increasingly difficult to contain the pandemic, at least as long as vaccination rates are insufficiently high.

We measure a large heterogeneity of travel responses to the pandemic. It is evident that the capacity for an individual response is restricted by socio-demographic factors such as the type of profession or income (Bonaccorsi et al., 2020). People with a tertiary education reduced their travel (and thus their risk of infection) by more than others, along with households with children. Other researchers have also observed such discrepancies across socio-economic groups (Abdullah et al., 2020; Barbieri et al., 2021). We furthermore find that the decision to stay at home is at least partly driven by pro-social preferences and personal "lifestyles". The distributional implications of the pandemic and of the governmental measures in terms of the consequences for individual behavior should be considered when implementing the public response in the future. For example, pandemic relief measures should be means-tested, schools left open as long as possible, and an increased (decreased) response by PT users (car owners) should be anticipated.

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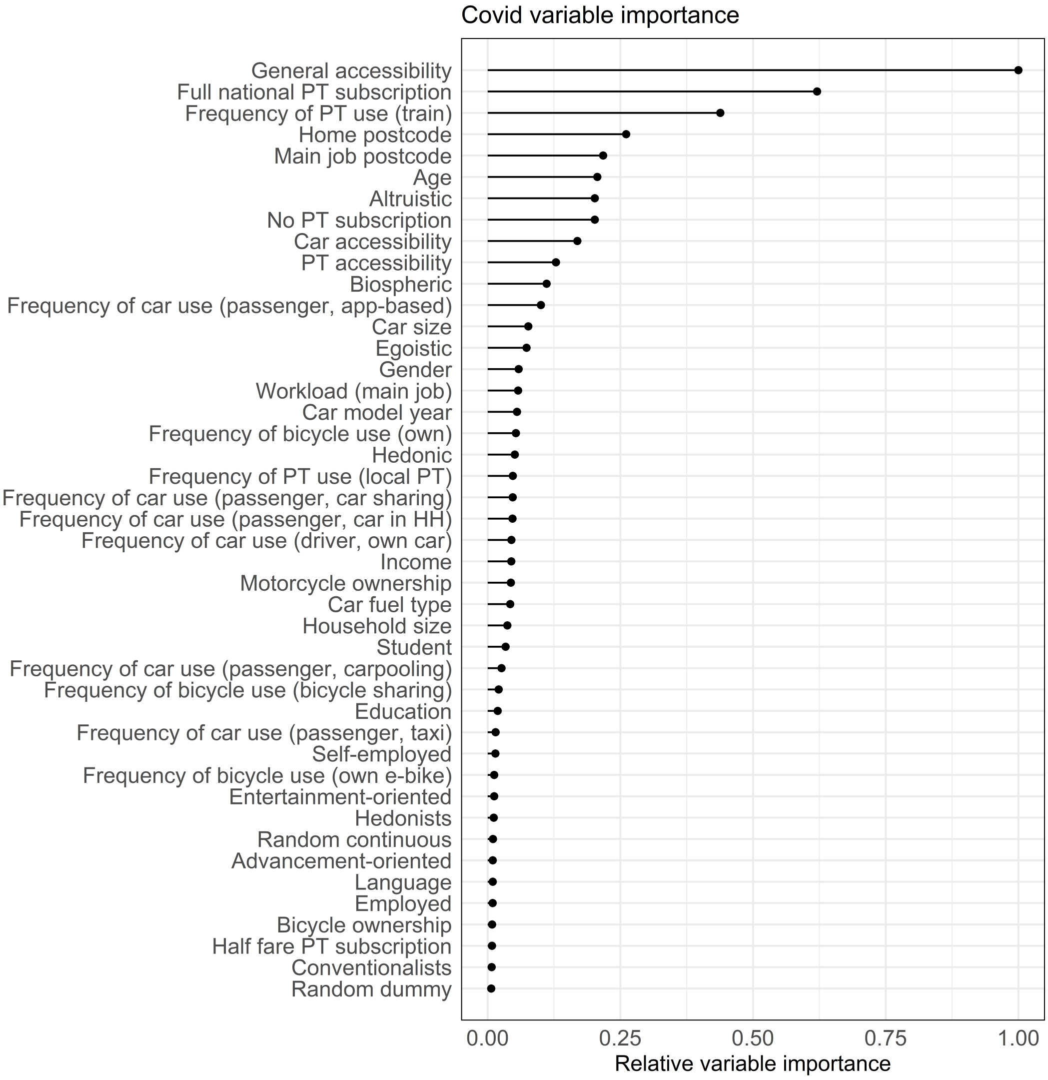
A Additional Tables and Figures

Figure A.1: Variable importance from CF approach for entire COVID period



Note: The figure shows variable importance measure from the causal forest approach using the baseline period and the entire COVID period. The variable importance is normalised relative to the "most important" variable. For more information about the included variables, refer to Tables 1, 2 and A.1.

Table A.1: Additional descriptive statistics for MobisCovid sample

Variable	Subcategory	Level	Value
Car characteristics	Fuel	Gasoline	58.9%
		Diesel	33.8%
		Hybrid (gasoline/diesel + electric)	4.6%
		Electric	2.1%
		Other	0.5%
	Model year	2015 or later	43.5%
		2011 - 2014	28.5%
		2006 - 2010	19.0%
		2001 - 2005	5.9%
		1997 – 2000	1.8%
		Don't know	1.0%
		1993 - 1996	0.2%
		1992 or earlier	0.1%
	Size	Medium to large	47.4%
		Small	25.5%
		Off-road	16.5%
		Minivan	8.4%
		Luxury or sports coupé	2.3%
Mobility tool use		Regular car user	72.1%
		Regular PT user	26.3%
		Regular bicycle user	14.3%
PT subscription		Full or regional subscription	22.1%
Mobility access		High general access	38.8%
		High car access	39.7%
		High PT access	41.7%
Lifestyle		Advancement-oriented	30.9%
		Liberals	20.0%
		Hedonists	16.8%
		Reflexives	14.0%
		Home-centred	8.2%
		Entertainment-oriented	5.0%
		Conventionalists	2.4%
		Conservatives	1.5%
		Traditional workers	1.1%
Values		Altruistic	64.5%
		Egoistic	61.6%
		Hedonic	56.9%
		Biospheric	67.5%
Employment		Full-time	71.3%

Notes: Additional descriptive statistics for variables used in causal forest analysis and regressions using the MobisCovid sample (n = 1,649). The "Values" variables are measured on a continuous scale and individuals with a number strictly above the median are assigned the respective "Value". All individuals have entries for all values. In contrast, individuals are only assigned to one lifestyle category. High general, MIV and PT access denote participants living in postcodes that are in the top two quintiles of an index constructed based on the connectivity of a particular postcode for public transport and the road network.

Table A.2: Effect heterogeneity: Final model

Variable	CP 1	CP 2	CP 3	CP 4	CP 5	CP 6	CP 7	CP 8	CP 9	CP10
Male	1.012	0.939	0.958	1.009	0.940’	0.976	0.948	0.975	0.922°	0.929
	(0.038)	(0.038)	(0.036)	(0.035)	(0.028)	(0.040)	(0.047)	(0.050)	(0.042)	(0.042)
Education (Tertiary)	0.860*	0.860*	0.878*	0.923’	0.982	0.916’	0.950	0.950	0.939	0.913’
	(0.032)	(0.035)	(0.031)	(0.032)	(0.031)	(0.038)	(0.049)	(0.046)	(0.040)	(0.039)
Education (Primary)	0.951	0.95	1.066	1.062	1.081	0.980	0.972	1.087	1.055	0.989
	(0.078)	(0.081)	(0.075)	(0.069)	(0.068)	(0.089)	(0.108)	(0.136)	(0.107)	(0.099)
Large Household	0.904’	0.843*	0.926	0.902’	0.936	0.941	0.903	1.032	0.981	0.956
	(0.043)	(0.044)	(0.044)	(0.045)	(0.041)	(0.054)	(0.068)	(0.069)	(0.061)	(0.061)
Small Household	1.068	1.035	1.008	1.004	0.987	0.963	0.843’	0.949	1.026	0.972
	(0.048)	(0.051)	(0.045)	(0.047)	(0.040)	(0.051)	(0.062)	(0.057)	(0.058)	(0.059)
Full-time job	1.118*	1.119*	1.116*	1.046	1.040	1.119*	1.099°	1.082	1.084°	1.051
	(0.046)	(0.048)	(0.044)	(0.039)	(0.034)	(0.048)	(0.060)	(0.060)	(0.052)	(0.053)
French Speaker	0.874*	0.927	0.967	0.936°	0.951	1.012	0.975	1.006	1.000	0.927
	(0.041)	(0.046)	(0.041)	(0.036)	(0.039)	(0.061)	(0.067)	(0.086)	(0.064)	(0.056)
PT Subscription	0.816*	0.825*	0.804*	0.852*	0.950	0.889’	0.861’	0.805*	0.855*	0.857’
	(0.039)	(0.043)	(0.037)	(0.039)	(0.038)	(0.049)	(0.06)	(0.054)	(0.051)	(0.052)
Car Owner	1.102	1.212’	1.199’	1.185’	1.100	0.975	1.255°	0.926	0.979	1.139
	(0.087)	(0.103)	(0.092)	(0.092)	(0.087)	(0.094)	(0.151)	(0.108)	(0.102)	(0.120)
Reg. Car	0.984	0.941	0.906’	0.868*	0.948	1.003	0.907	0.922	0.955	0.985
	(0.044)	(0.043)	(0.037)	(0.035)	(0.033)	(0.047)	(0.057)	(0.055)	(0.046)	(0.050)
OEV Access	1.043	1.051	1.036	1.014	1.050°	1.090’	1.067	1.078°	1.021	1.102’
	(0.035)	(0.039)	(0.032)	(0.032)	(0.029)	(0.042)	(0.054)	(0.049)	(0.042)	(0.045)
Egoistic	1.106*	1.083’	1.027	1.030	1.028	1.053	1.120’	1.028	1.057	1.010
	(0.039)	(0.040)	(0.033)	(0.031)	(0.028)	(0.041)	(0.053)	(0.047)	(0.042)	(0.042)
Biospheric	0.989	1.056	1.039	1.016	1.083*	1.039	1.01	1.057	1.056	1.056
	(0.034)	(0.039)	(0.035)	(0.035)	(0.033)	(0.042)	(0.051)	(0.050)	(0.044)	(0.047)
Traditional worker	1.144	1.059	1.002	0.813	1.023	1.938*	1.877*	1.079	1.401°	0.962
	(0.157)	(0.184)	(0.145)	(0.120)	(0.172)	(0.387)	(0.287)	(0.266)	(0.244)	(0.198)
Home-centered	0.934	0.961	0.987	0.956	0.995	0.944	1.082	1.023	1.016	1.048
	(0.079)	(0.076)	(0.079)	(0.068)	(0.071)	(0.079)	(0.111)	(0.102)	(0.094)	(0.109)
Entertainment-oriented	1.001	0.987	0.911	0.964	0.965	0.979	1.038	1.041	1.012	1.068
	(0.091)	(0.096)	(0.083)	(0.084)	(0.080)	(0.11)	(0.132)	(0.125)	(0.137)	(0.15)
Conventionalists	0.870	0.888	0.916	0.881	1.064	1.061	1.286’	1.142	1.020	1.082
	(0.098)	(0.092)	(0.083)	(0.084)	(0.076)	(0.118)	(0.154)	(0.136)	(0.127)	(0.121)
Advancement-oriented	1.059	1.001	1.063	0.993	1.009	1.073	1.122	1.082	1.02	1.021
	(0.060)	(0.059)	(0.054)	(0.050)	(0.049)	(0.066)	(0.087)	(0.084)	(0.071)	(0.073)
Hedonists	0.990	1.003	0.985	1.053	1.029	1.034	1.088	1.085	0.995	1.047
	(0.062)	(0.065)	(0.055)	(0.059)	(0.055)	(0.08)	(0.106)	(0.093)	(0.076)	(0.083)
Conservatives	1.046	1.106	0.995	1.05	0.883°	0.904	1.119	0.997	0.851°	0.918
	(0.154)	(0.142)	(0.105)	(0.079)	(0.057)	(0.113)	(0.121)	(0.103)	(0.077)	(0.078)
Liberals	0.932	0.906	0.931	0.960	0.948	1.000	1.047	1.009	0.984	1.000
	(0.057)	(0.058)	(0.051)	(0.048)	(0.044)	(0.063)	(0.084)	(0.076)	(0.072)	(0.074)
Pseudo-R^2	0.212									
N	350,747									
Participants 1	1,568									

Notes: *: p < 0.01, ’: p < 0.05, °: p < 0.1. Standard errors are clustered at the person-day level. This is the result from the final estimation of (4), after removing coefficients that did not meet a joint significance threshold of p¡0.2. The omitted categories (in order) are: female, secondary education, household with 3 members, participants working less than full time, non-French speakers, not holding a PT subscription, not owning a car, using the car on fewer than 3 days per week, living in a zip code that does not have “high PT access” as defined by an index, having a below-median index for “egoistic” and “biospheric” values, and belonging to the lifestyle category “Reflexives”. The model was estimateded using PPML. Standard errors are clustered on the participant level.