Time use rebound effects from adopting time efficient practices in Germany: a zero-inflated negative binomial approach

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Zusammenfassung

Zeitnutzungs-Rebound-Effekte werden beobachtet, wenn Zeiteffizienz zu einem Anstieg der Nachfrage nach einer Dienstleistung führt. Wir identifizieren direkte Zeitnutzungs-Rebound-Effekte durch die Einführung von 14 zeiteffizienten Praktiken in den Bereichen Mobilität, Ernährung und Digitalisierung sowie durch allgemeine zeiteffiziente Praktiken. Dazu schätzen wir Semi-Elastizitäten über null-inflationäre negative Binomialmodelle.

Im Bereich Mobilität identifizieren wir einen Zeitnutzungs-Rebound-Effekt von 18 % durch zügiges Fahren. Im Bereich Ernährung finden wir keine direkten Zeitnutzungs-Rebound-Effekte, sondern negative Effekte, die darauf hindeuten, dass die Zeiteffizienz bei der Zubereitung von Mahlzeiten effektiv an Take-Away-, Restaurant- oder Kantinendienste ausgelagert wird. Im digitalen Bereich finden wir einen Zeitnutzungs-Rebound-Effekt durch werbefreie Online-Dienste von 8 %. Im Hinblick auf allgemeine zeiteffiziente Praktiken finden wir Zeitnutzungs-Rebound-Effekte durch Multitasking und das Füllen von Wartezeiten mit Aktivitäten von 3 %.

Unsere Ergebnisse deuten auf eher moderate direkte Zeitnutzungs-Rebound-Effekte durch zeiteffiziente Praktiken hin. Gleichzeitig können wir für die meisten analysierten Praktiken nicht feststellen, dass Zeiteffizienz zu direkten Zeiteinsparungen führt.

Abstract

Time use rebound effects are observed when time efficiency leads to an increase in service demand. In this article, we identify direct time use rebound effects from adopting 14 time efficient practices across the mobility, nutrition and digital domain as well as from general time efficient practices. Therefore, we estimate semi-elasticities via zero-inflated negative binomial models. The empirical data is derived from a representative survey among people at working age in Germany.

In the mobility domain, we identify a time use rebound effect of 18 % from the time efficient practice of driving fast. In the nutrition domain, we do not find direct time use rebound effects. Here, the adoption of time efficient practices in meal preparation coincides with a decrease in the number of self-prepared meals, suggesting that people employing time efficient meal preparation practices also tend to outsource meal preparation to take away, meal delivery, restaurant or canteen services. In the digital domain we find a time use rebound effect from ad-free online services of 8 %. In terms of general time efficient practices, we find time use rebound effects from multitasking and filling waiting time with activities of 3 %.

Our results suggest rather low to moderate direct time use rebound effects from individual time efficient practices. However, taking all time efficient practices together, the direct time use rebound effect may amount to significant increases of service demand. At the same time, for the most practices analysed, we cannot conclude that time efficiency leads to direct time savings.

Inhaltsverzeichnis

1 Introduction

Consumption is often represented as the purchase of products and services. Hence, rebound effects are economically derived from expenditure data. Yet, there are shortcomings by focusing on expenditure as a proxy for consumption. As Jalas (2015) elaborates extensively, it is consumer engagement in terms of time spent on activities rather than expenditure on products and services that yields utility. This approach is informed by household economics (Becker 1965) which aims to go beyond analysing the purchase of goods and services in favour of analysing their actual use in everyday life by introducing a temporal budget constraint to household production.

Binswanger (2001, p. 128) introduced rebound effects with respect to time. He argued that "if a service can be produced with less time" [via time-saving technological progress], households will demand more of that service". In this regard, Binswanger (2001, p. 128) suggests that "the rebound effect with respect to time is similar to the rebound effect with respect to energy efficiency". If there is an increase in time (instead of energy) efficiency, it implies a decrease of the time (instead of energy) input for the production of a service leading to a higher demand of the service and thus offsetting the time (instead of energy) savings. Jalas (2002, p. 112) stressed further that preferences are expressed under a temporal budget constraint rather than an expenditure budget constraint. Jalas (2002) was the first to highlight with regards to rebound effects that consumption should be regarded as a set of temporal activities in which consumers engage with the various products. Jalas (2002, 2005) did not estimate time use rebound effects, but offered a framework for analysing time use rebound effects with time use data.

Further, with respect to an accelerating pace of life according to Rosa (2013), Buhl and Acosta (2016a,b) highlight that potential opportunities (like trips, going out, cooking, or sports) emerge at an increasing pace in an experience-oriented society (Schulze 2013). Hence, the opportunity costs of consumer decisions increase and the efforts to decrease the costs by applying time saving innovations gain relevance (Buhl and Acosta 2016a, p. 165).

In conclusion, two reasons highlight the importance of a time use approach to rebound effects. A time use approach considers 1) consumption as a goal-oriented proxy to utility and 2) the increasing relevance of temporal budget constraints for consumer preferences.

Kim et al. (2020) report that empirical studies on time use rebound effects between 2002 and 2018 have been applied to either home technologies (4 studies), information and communication technologies (2 studies), high-speed transport (1 study) or reduced working hours (2 studies). However, most studies analyse changes in time use and energy use, but do not define and report time use rebound effects. Thus, we only summarise those studies which actually claim to report direct time use rebound effects. In contrast to energy efficiency rebound effects, only few empirical work is dedicated to estimate (direct) time use rebound effects with differing methodological approaches.

For instance, Takahashi et al. (2004) briefly describe a potential direct time use rebound effect from video-conferencing by attending more video-conferences compensating for substituted business trips. They find a time use rebound effect of 10 % including additional beverage consumption and paper use

due to additional video-conferencing. Spielmann et al. (2008) examine the impact of adopting high-speed railway services on further transportation services from public transport to cycling in Switzerland. They analyse in different scenarios how time savings from high-speed railway use is spent on further transportation services and find time use rebound effects from 11 to 114 %. Brencic and Young (2009) report direct time use rebound effects from adopting time saving household appliances. They show the impact of dishwashers and washing machine ownership on the intensity of washing machine and dishwasher use. They find that low (high) income households show about 11 (16) % greater intensity of washing machine (dishwasher) use in an average week for households that own a washing machine (dishwasher) compared to those that do not.

Santarius and Bergener (2020) analyse the use of information and communications technologies (ICT) on online activities and developed a General Acceleration Scale (GAS) on the basis of Rosa's theory of social acceleration. They find that ICT usage decreases the hours spent on stationary and mobile internet use, but increases the frequency and areas of online activities. What´s more, they find that the use of ICT increases Rosa's four dimensions of time efficient practices - multitasking, filling waiting time with activities, performing activities faster and replacing slow with fast activities. With respect to time use rebound effects, they found that respondents intend to use ICT in order to save time. They conclude that their findings do not imply that time is saved to do less, or to have more time off for relaxing or contemplation. But most important, they introduce general time efficient practices in connection to time use rebound effects.

In this study, we follow Sorrell und Dimitropoulos' (2008, p. 645) definition of time use rebound effects based on Binswanger (2001). They argue that rebound effects with respect to time efficiency exist parallel to rebound effects with respect to energy efficiency. Improvements in time efficiency are associated with a particular service lowering the cost of that service. Consequently, there should be a corresponding increase in service demand that will offset the potential time savings. For instance, the potential time savings from faster modes of transport may be partly or wholly taken back by traveling further. Direct time use rebound effects are then defined by the increase of the service demand following time efficiency gains delivering those services as opposed to indirect effects, delivering other services. Eventually, expected savings in terms of energy or resource use are compensated.

Sorrell und Dimitropoulos (2008, p. 638) state that that an efficiency elasticity of the demand for useful work is "commonly taken as a direct measure of the rebound effect". Useful work of cars may be indicated by vehicle kilometres or travel distance as applied by Frondel et al. (2008) and Frondel and Vance (2013). More recently Stapleton et al. (2016) and Andersson et al. (2019) identify direct rebound effects with respect to travel distance due to increased fuel efficiency in Sweden. They propose that effects with respect to time may be defined as a time efficiency elasticity similar to conventional rebound effects with respect to energy efficiency (see section 2.2 for a more detailed definition of the time use rebound effect).

Against this theoretical background, we indicate useful work, i.e. service demand by time use (e.g. leisure travel time instead of kilometres travelled) and take a time efficiency elasticity (e.g. the leisure travel time in relation to faster transportation modes) as the direct measure of time use rebound effects.

This way, we aim at contributing to the empirical literature by 1) estimating direct time use rebound effects from adopting time efficient services in the mobility, food and digital domain and 2) estimating the effects from adopting time efficient practices on time use. We aim to complement research on time use rebound effects from time efficient technologies by estimating effects from time efficient practices.

The following paper is structured as following: Section 2 describes the data, hypotheses and methods, definitions used. Section 3 presents the results. Section 4 summarises the findings and discusses the data and method.

2 Data and Methods

2.1 Data

We carried out a representative survey of the German population at working age to take stock of time use patterns and practices as well as the usage of time efficient technologies and services. We surveyed 2,015 people aged between 18 and 67 years in February 2020. A quota system was applied to respondents representing the German population regarding age, gender, education level and provincial state.

The following table presents the outcome and predictors used to identify time use rebound effects. The data table is structured as following. First, the outcome variables are presented with respect to mobility, meal preparation (i.e. the proxy for nutrition), internet time use and time use for rest in addition to sleep. Next, the predictor variables are shown, representing time efficient practices in the mobility, nutrition (meals), digital domain as well as general time efficiency practices according to the General Acceleration Scale. Last, relevant socio-economic features are reported by gender, age, working hours per week, number of children in the household, and net monthly household income.

Predictors of direct time use rebound effects should hypothetically incorporate potential time efficiency gains in relation to the respective time use. Time efficient mobility practices are (1) taking the fastest transportation mode and (2) driving fast. Time efficient nutrition services are (1) usage of frozen or cooled food and (2) take away, meal delivery, restaurant, or canteen services. In the digital domain, potential time efficiency gains relate to time spent online via (1) a focused use of online services as well as (2) the use of ad-block and ad-free online services. General time efficient practices are derived from Bergeners and Santarius´ (2021) General Acceleration Scale (GAS) representing (1) multitasking, (2) replacing time consuming by time saving activities (shorter), (3) performing activities faster, (4) filling breaks or waiting time with activities (filling pauses) (see the supplementary material for a detailed item description).

The use of online services as well as mobility practices are surveyed in 5 categories from never to always. The use of cooled and frozen food is surveyed in 7 categories from never to multiple times a day. Here, we opted to split respondents in one group which performs the aforementioned activities relatively often and a respective reference group. The first group should not represent extreme cases, but a population of at least 20 %. Due to the distribution of cases, the first group may as well represent more than half of the population.

General time efficiency practices (multitasking, shorter, faster, filling pauses) are surveyed each via two items on a 5-point Likert scale from 1 (not agreeing at all) to 5 (totally agreeing). We opted to build a sum score for each time efficient practices ranging from 2 to 10 respectively.

We control for socio-economic features which may affect time use. We included age, gender, children in household, working hours and household monthly net income in order to take individual heterogeneity into account.

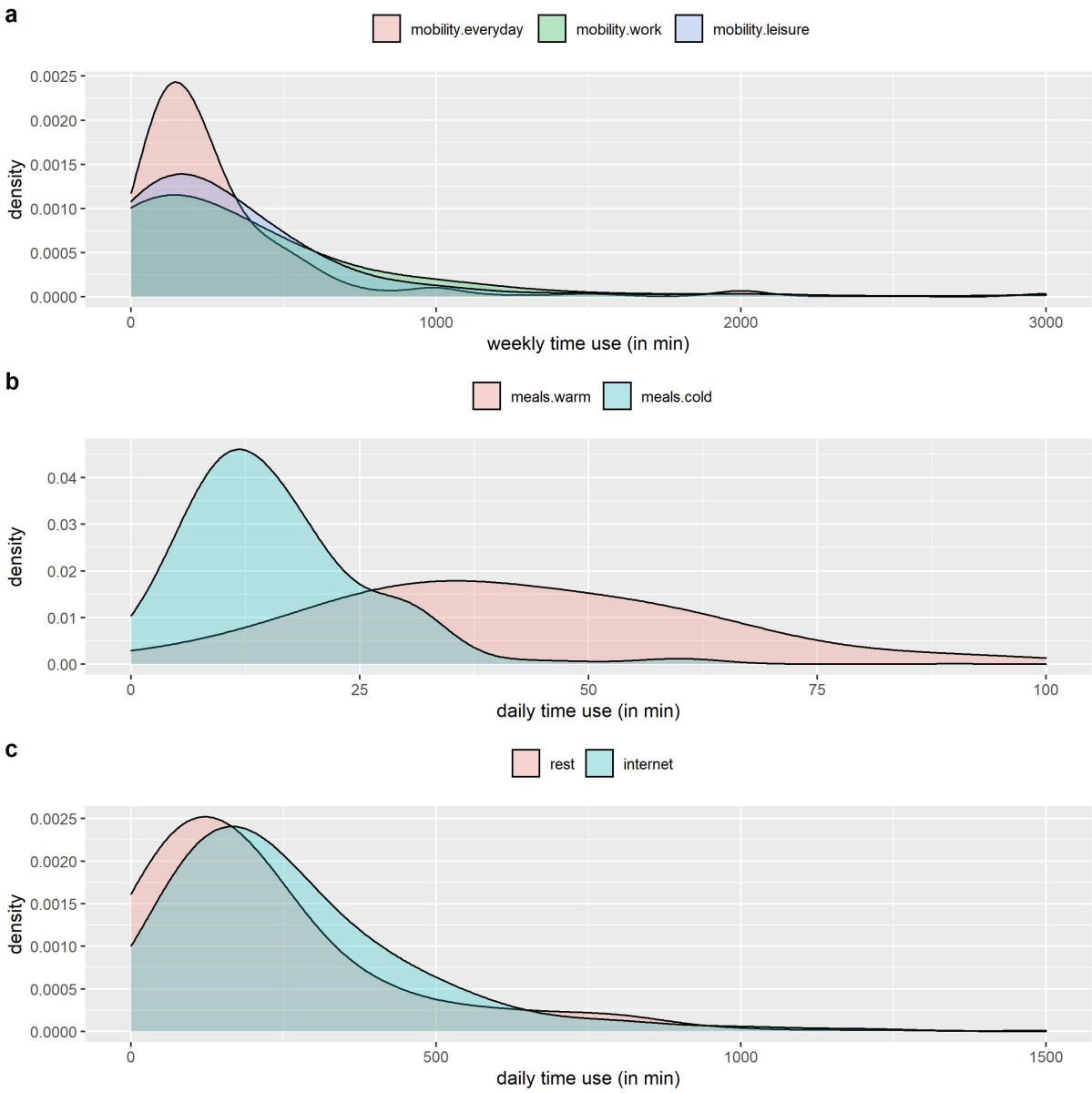
Tab. 1. Descriptive statistics of outcome and predictor variables

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
mobility: everyday (h per week)	1,994	4.20	9.50	0.00	1.00	3.90	168.00
mobility: work (h per week)	1,999	5.70	15.00	0	0.3	5	168
mobility: leisure (h per week)	1,999	4.80	11.00	0	1	5	168
meals: warm (min per meal)	1,649	42.00	20.00	0.00	30.00	60.00	99.00
meals: cold (min per meal)	1,582	16.00	10.00	0.00	10.00	20.00	90.00
time use: internet (h per day)	1,999	2.70	2.30	0	1	3	24
time use: rest (h per day)	1,999	2.20	2.30	0	1	3	22
mobility: fast driving always	1,705	0.22	0.41	0.00	0.00	0.00	1.00
mobility: fastest mode always	1,769	0.31	0.46	0.00	0.00	1.00	1.00
meals: take away (num per week)	1,999	1.50	4.30	0	0	1	100
meals: restaurant (num per week)	1,999	0.56	1.50	0	0	1	21
meals: canteen (num per week)	1,999	0.61	1.60	0	0	0	21
meals: delivery (num per week)	1,999	0.36	1.20	0	0	0	21
meals: frozen food (ref. less than once a week)	1,993	0.57	0.50	0.00	0.00	1.00	1.00
meals: cooling shelf (ref. less than once a week)	1,995	0.45	0.50	0.00	0.00	1.00	1.00
internet: focused (ref. less than often)	1,985	0.37	0.48	0.00	0.00	1.00	1.00
internet: ad-block (ref. less than often)	1,992	0.38	0.49	0.00	0.00	1.00	1.00
general: mutlitasking	1,981	6.60	1.90	2.00	5.00	8.00	10.00
general: shorter	1,978	6.40	1.50	2.00	6.00	7.00	10.00
general: faster	1,983	7.50	1.50	2.00	6.00	8.00	10.00
general: fill pauses	1,977	6.70	1.60	2.00	6.00	8.00	10.00
gender (ref. male)	1,992	0.51	0.50	0.00	0.00	1.00	1.00
age	1,999	44.00	14.00	18	32	56	67
children in household (num)	1,999	0.37	0.74	0	0	0	5
working time (h per week)	1,999	20.00	18.00	0	0	36	57
household monthly net income (in thou. EUR)	1,622	2.90	1.40	0.75	1.80	3.80	6.20

Figure 1 shows density estimates of the outcome variables for mobility, nutrition and for rest and internet time use. The density estimates show right skewed distributions and potentially exceeding zero observations and influential outliers. For plausibility reasons we excluded time use exceeding 24 hours a day. Besides, we did not opt to identify a threshold for theoretically supposable time use, but

opted to rather identify and cope with influential outliers statistically. We derive appropriate models in the methods section.

Fig. 1. Density of a) weekly time use for everyday, work, leisure mobility; b) daily time use for hot and cold meal preparation and for c) rest and internet time use



Respondents report relatively high time use for mobility, nutrition, internet use as well as for rest. As argued in the introduction, time intensive services are theoretically prone to time saving ambitions and thus time use rebound effects. Time efficient practices should hypothetically lead to decreased time use respectively. In cases where time efficiency does actually come with increased time use, we identify time use rebound effects.

In the mobility domain, we test the following hypotheses *H(m)* in order to identify direct time use rebound effects:

H(m)1: Taking the fastest transportation mode decreases a) everyday, b) work, c) leisure travel time.
H(m)2: Driving fast decrease a) everyday, b) work, c) leisure travel time.

In the food domain we test the following hypotheses *H(f)* in order to identify direct time use rebound effects:

H(f)1: a) Frozen and b) chilled food decrease (hot, cold) meal preparation time.
H(f)2: Outsourcing meal preparation to a) take away, b) delivery, c) restaurant, d) canteen services decreases (hot, cold) meal preparation time.

In the digital domain we test the following hypotheses *H(d)* in order to identify direct time use rebound effects:

H(d)1: Focused internet use decreases internet time use,
H(d)2: Using ad-blocks and ad-free e-mailing decreases internet time use.

In order to identify effects of general time efficiency practices, we hypothesise according to Santarius and Bergener (2020) that

H(b)1 Multitasking,
H(b)2 replacing time consuming with time saving activities,
H(b)3 performing activities faster and
H(b)4 filling waiting time with activities decreases time use in terms of rest and time-outs.

General time efficient practices cannot be attributed to a single service or time use. However, theoretically, General Acceleration practices refer to an accelerated pace of life at cost of down times in terms of rest times and take-outs. At the same time, rest times are consistently associated with the least environmental pressure in terms of carbon or resource intensity (Druckman et al. 2011, Buhl and Acosta 2016a, 2017, Jalas 2015, Smetschka 2019, Lorenz and Pfaff 2021, upcoming). In case rest times are decreased due to General Acceleration practices, it is justified to conclude that General Acceleration practices do come with time use rebound effects in terms of increasing service demand and thus also environmental impacts.

2.2 Method

According to Sorrell und Dimitropoulos (2008, p. 645), the rebound effect with respect to time may be defined as an efficiency elasticity in a similar manner to the conventional rebound effect as introduced by Binswanger (2001). As described by Sorrell und Dimitropoulos (2008, p. 638) for rebound effects as an efficiency elasticity, we describe rebound effects with respect to time analogously: The change in demand for time use T following a small change in time efficiency θ may be measured by the efficiency elasticity of the demand for time use $\eta_\theta(T)$. In the absence of a time use rebound effect, the demand for time use would be proportionally reduced to the increased time efficiency ($\eta_\theta(T) = -1$). However, increased time efficiency lowers the input cost (e.g. time in hours) per unit of useful work S (e.g. distance travelled in km), thus altering $\eta_\theta(T)$ respectively. This change in demand for useful work following a small change in time efficiency may be measured by the efficiency elasticity of the demand for useful work $\eta_\theta(S)$. The relationship between the efficiency elasticity of the demand for time use $\eta_\theta(T)$ and the efficiency elasticity of the demand for useful work $\eta_\theta(S)$ is then given by

$$\eta_\theta(T) = \eta_\theta(S) - 1 = \frac{\partial S}{\partial \theta}\frac{\theta}{S} - 1 \quad (1)$$

As proposed by Frondel et al. (2008, p. 148), only if $\eta_\theta(S)$ equals zero, there is no rebound effect. Then, $\eta_\theta(T)$ equals -1 indicating that 100 % of time savings due to time efficiency are actually realised. For example, if $\eta_\theta(S)$ equals 0.1 than only 90 % of time savings are actually realised and 10 % of time savings are reallocated (elsewhere). Consequently, $\eta_\theta(S)$ is the rebound effect.

Following Sorrell und Dimitropoulos (2008), we define a rebound effect with respect to time as an increase in the amount of time allocated to service demand S (mobility, nutrition, digital) resulting from the adoption of time efficient practices (e.g. driving speed, multitasking), that hypothetically incorporate time efficiency (θ).

The definition is a staple in rebound economics and applied widely, e.g. in the mobility domain by Frondel et al. (2008), Frondel and Vance (2013) by regressing fuel efficiency on kilometres driven in Germany, more recently applied by Stapleton et al. (2016) on travel distance in Great Britain and Andersson et al. (2019) in Sweden.

According to Sorrell et al. (2020, p. 2) the rebound effect with respect to time can be negative if the techniques or modes are actually not more time efficient, e.g. motorised transport by car compared to cycling in cities. A negative rebound effect is given when $\eta_\theta(S) < 0$ and $\eta_\theta(T) > 1$, indicating that an increase in time efficiency leads to less time allocated. Negative effects may indeed occur, e.g. due to time efficient modes of transport. However, the saved time is likely reallocated elsewhere, eventually leading to indirect time us rebound effects. For instance, time efficient modes of transport may come with less time spent on leisure mobility (e.g. time to get to locations for hobbies), but more time is therefore spent on the actual leisure activities (e.g. time spent on hobbies). We thus opted to only identify $\eta_\theta(S) > 0$ as direct time use rebound effects.

We estimate semi-elasticities in a log-linear model. It makes sense to estimate a semi-elasticity that gives a percentage increase in outcome y from a unit increase in x for a better interpretation of the given proxies for time efficiency. For instance, in the mobility domain, time efficiency is not measured e.g. by travelling distance per hour driven (ratio), but proxied by adopting mobility modes (using fastest transportation mode or driving fast) from never to always (ordinal).
However, we cannot identify the log of zero. Hence we opt for a generalised Poisson regression. This way we treat the allocated time per day as count data in minutes. A Poisson process is given by

$$P(y_{ij}) = \frac{e^{\lambda}\lambda_{ij}^{y_{ij}}}{y_i!} \quad (2)$$

Where P is the probability of subject i allocating time y to time use category j per day. λ is the Poisson parameter which equals the expected mean time use $E(y_{ij})$. Poisson regression models commonly assume a log-linear relationship between Poisson parameter y and explanatory variables:

$$\lambda_{ij} = E(y_{ij}|X_{ij}) = e^{\beta X_{ij}} \tag{3}$$

Where X_i is a vector of explanatory features, β is a vector of unknown regression coefficients estimated by maximum likelihood.

However, Poisson processes require the mean being equal to the variance. If $E(y_{ij}) < Var(y_{ij})$ we identify overdispersion. In such a case, the mean-variance restriction will fail to hold when the expression for λ contains an error. In reality, overdispersion is common. That's why we add an error term that loosens that restriction in a negative binomial (NB) regression. Moreover, a negative binomial model fits better to highly right skewed distributions due to zeros. Based on residual analysis, residual deviance and the Akaike information criteria (AIC), we find that negative binomial regression models fit better than poisson regressions. The negative binomial model is an extension that adds a gamma-distributed error ε_i in order to loosen the mean-variance restriction

$$\lambda_{ij} = E(y_{ij}|X_i, \varepsilon_i) = e^{\beta X_i + \varepsilon_i} \tag{4}$$

In this study we regress time use y_{ij} on time efficient practices X_i and further socio-economic explanatory features Z

$$\lambda_{ij} = E(y_{ij}|X_n, Z_k, \varepsilon_i) = e^{\beta_o + \beta_n X_{ijk} + \beta_k Zk_{ij} + \varepsilon_i} \tag{5}$$

Hence, $\eta_\theta(S) = \lambda_{ij} = E(y_{ij}|X_n, Z_k, \varepsilon_i)$, where S is the service unit proxied by time use j and θ is time efficiency proxied by time efficient practices X.

For cases where we observe excess zeroes, that is a higher probability of zeroes than expected under NB distributions, we apply zero-inflated models (ZINB). ZINB models have been applied recently with respect to time use in Efthekar et al. (2016). For instance, respondents may have children and do not spend time for them or respondents do not have children and thus are not susceptible to spend time for child care. Greene (1994) suggests to identify the observed count y_{ij} in zero inflated models as a product of a binary process z and y' following a NB or Poisson distribution ($y_{ij} = z_{ij} y'_{ij}$).

Conceptually, we divide individuals i into people who are are not susceptible to time use with probability q and people who potentially may or may not spend time in time use category j with probability $1 - q$ as predicted under distribution f.

$$P(y_{ij}) = \begin{cases} q_{ij} + (1 - q_{ij}) f(0), & y_{ij} = 0 \\ (1 - q_{ij}) f(y_{ij}), & y_{ij} \geq 0 \end{cases} \tag{6}$$

Where q is the logistic link function $q_{ij} = \frac{\theta_{ij}}{1+\theta_{ij}}$, where $\theta_{ij} = e^{\gamma_m w_{mij}}$. Note that w may or may not represent the same set of predictors identifying λ_{ij}. f follows the negative binomial probability distribution for y_{ij}:

$$f(y_{ij}) = \frac{\Gamma(y_{ij} + 1/\alpha)}{\Gamma(y_{ij} + 1)\Gamma(\frac{1}{\alpha})} \frac{(a\lambda_{ij})^{y_{ij}}}{(1 + a\lambda_{ij})^{y_{ij}+1/a}} \tag{7}$$

The negative binomial model is also referred to as a mixed Poisson-gamma model, where Γ denotes the gamma distribution with α as dispersion parameter handling overdispersion and $\lambda_{ij} = E(y_{ij})$ is the mean to be estimated as a linear combination of covariates (X, Z) as denoted in eq. 5.

Further, in order to cope with the highly right skewed distribution of time use, we identify influential outliers for each model by approximating Cooks distance according to Williams (1987) and exclude observations with a distance $> 4/n$ from the analysis.

3 Results

Table 2 reports the semi-elasticities $\eta_\theta(S)$ of adopting time efficient practices on time use in the mobility, nutrition and digital domain and of adopting general time efficient practices on time use for rest.

We find that in the mobility domain, respondents who always drive fast spend 18 % more time for everyday mobility. People who always take the fastest transportation mode spend 10 % less time for everyday mobility.

With respect to nutrition, we find that take away services reduce cold meal preparation time by 1 %. Every other meal per week in restaurants reduces the time for hot meal preparation by 4 %. Every other meal in canteens per week reduces hot meal preparation time by 2 % and cold meal preparation time by 4 %. Respondents who buy food from the cooling shelf like sliced vegetables reduce hot meal preparation time by 6 %; frozen food by 5 %.

In the digital domain, we find that a more focused internet use (at least sometimes) does lead to less internet time use by 14 %. Using ad-block and ad-free online services coincides with an 8 % higher internet time use.

In general, replacing time consuming with shorter activities increases time use for rest by 3 % per unit on the General Acceleration scale. Multitasking does show decreasing effects on take-outs and time use for rest by 3 % per unit. Filling waiting time with activities (filling pauses) does show a decreasing effect by 3 % per unit of time use for rest.

However, for the most time efficiency predictors across domains, we do not find significant decreasing time use, thus cannot conclude that those actually lead directly to increased or decreased time use.

Socio-economic features have been introduced in order to take individual heterogeneity into account. Age shows positive effects except for mobility to work and internet time use. Time use for mobility to work decreases by 2 % per year of age; internet time use decreases by less than 1 % per year of age. Women allocate less time to mobility for leisure purposes and internet time use. Children in households have an increasing effect on cold meal preparation time, but negative effects on internet time use and for rest. Weekly working hours have negative effects on all time use categories except for mobility to work. Monthly household net income shows negative effects on everyday mobility and time use for internet and rest. We do not find counterintuitive effects of socio-economic features on

time use, but do not delve further into interpreting the results since no hypotheses have been formulated.

Tab. 2. Semi-elasticities of the demand for mobility, meals, internet and rest time from adopting time efficient practices

	mobility: everyday	mobility: leisure	mobility: work	nutrition: warm meals	nutrition: cold meals	internet	rest
Predictors	*Estimate*	*Estimate*	*Estimate*	*Estimate*	*Estimate*	*Estimate*	*Estimate*
mobility: fast driving	0.18 *** (0.05 – 0.31)	-0.01 (-0.12 – 0.10)	-0.08 (-0.22 – 0.06)				
mobility: fastest mode	-0.10 * (-0.22 – 0.01)	-0.04 (-0.13 – 0.06)	-0.05 (-0.17 – 0.08)				
meals: take away				0.00 (-0.00 – 0.01)	-0.01 * (-0.02 – 0.00)		

meals: restaurant				-0.04 *** (-0.06 – -0.02)	0.00 (-0.02 – 0.03)		
meals: canteen				-0.02 ** (-0.04 – -0.00)	-0.04 *** (-0.06 – -0.01)		
meals: delivery				0.01 (-0.02 – 0.04)	0.01 (-0.03 – 0.04)		
meals: frozen food				-0.05 * (-0.11 – 0.00)	-0.03 (-0.09 – 0.04)		
meals: chilled food				-0.06 * (-0.11 – 0.00)	0.04 (-0.02 – 0.11)		
internet:focused						-0.14 *** (-0.22 – -0.07)	
internet:ad-block						0.08 ** (0.00 – 0.16)	
general: mutitasking							-0.03 *** (-0.06 – -0.01)
general: shorter							0.03 ** (0.00 – 0.05)
general: faster							0.00 (-0.02 – 0.03)
general: fill pauses							-0.03 *** (-0.06 – -0.01)
age	0.01 *** (0.00 – 0.01)	0.00 *** (0.00 – 0.01)	-0.02 *** (-0.02 – -0.01)	0.00 *** (0.00 – 0.01)	0.01 *** (0.00 – 0.01)	-0.00 *** (-0.01 – -0.00)	0.00 * (-0.00 – 0.01)
female	0.06 (-0.04 – 0.16)	-0.13 *** (-0.21 – -0.04)	0.00 (-0.11 – 0.12)	0.05 * (-0.01 – 0.11)	0.12 *** (0.05 – 0.18)	-0.23 *** (-0.31 – -0.16)	0.01 (-0.07 – 0.08)
children in household	0.03 (-0.03 – 0.10)	-0.01 (-0.07 – 0.05)	-0.00 (-0.07 – 0.07)	0.03 (-0.01 – 0.06)	0.07 *** (0.03 – 0.11)	-0.13 *** (-0.18 – -0.08)	-0.05 ** (-0.10 – -0.00)
working hours	-0.01 *** (-0.01 – -0.00)	-0.00 ** (-0.01 – -0.00)	0.03 *** (0.02 – 0.03)	-0.00 *** (-0.00 – -0.00)	-0.00 (-0.00 – 0.00)	-0.01 *** (-0.01 – -0.00)	0.00 (-0.00 – 0.00)
household net income	-0.08 *** (-0.11 – -0.04)	-0.00 (-0.04 – 0.03)	0.03 (-0.01 – 0.07)	0.01 (-0.01 – 0.03)	0.01 (-0.02 – 0.03)	-0.07 *** (-0.10 – -0.05)	-0.05 *** (-0.07 – -0.02)
Observations	1238	1253	1281	1316	1249	1601	1581

*Notes: Standard errors in parantheses; * p<0.1 ** p<0.05 *** p<0.01*

Table 3 summarises the findings with respect to the formulated hypotheses. The first column summarises the hypotheses, the second column summarises the respective semi-elasticities in the mobility, nutrition and digital domain as well as from adopting General Acceleration practices. Effects are either negative, non-significant or positive. Negative effects corroborate the hypothesis that decreased time use follows an increase of time efficiency. In the mobility, nutrition and digital domain, only positive effects are considered as time use rebound effects. When it comes to the effect of general time efficient practices on rest times, only negative effects are considered as time use rebound effects.

Direct time use rebound effects are identified for driving fast, for ad-free online services and for general time efficient practices (multitasking and filling waiting time). At the same time, for most of the practices, we cannot conclude that time efficiency comes with time savings.

Tab. 3. Summary of test results for time use rebound effects

Hypotheses	Effect
H(m)1: taking the fastest transportation mode decreases travel time for a) everyday, b) leisure, c) work mobility	- / 0 / 0
H(m)2: driving fast decreases travel time for a) everyday, b) leisure, c) work mobility	+ / 0 / 0
H(f)1: a) frozen and b) chilled food reduce hot (cold) meal preparation time	- (0) / - (0)
H(f)2: outsourcing meal preparation to a) take away, b) restaurants, c) canteen, d) delivery services decreases hot (cold) meal preparation time	0 (-) / - (0) / - (-) / 0 (0)
H(d)1: focused internet use decreases internet time use	-
H(d)2: using adblock and adfree online services decreases internet time use	+
H(b)1: multitasking decreases relaxing time use for rest	-
H(b)2: replacing time consuming with shorter activities decreases time use for rest	+
H(b)3: doing activities faster decreases time use for rest	0
H(b)4: filling waiting time with activities decreases time use for rest	-

Notes: 0 no significant effect, + time use rebound effect, - negative effect (*i.e.* time use rebound effect for *H(b)*)

4 Summary and Conclusion

We estimated semi-elasticities via zero-inflated negative binomial models in order to identify direct time use rebound effects from adopting time efficient practices in the mobility, nutrition and digital domain.

In the mobility domain, we find a direct time use rebound effect for driving practices as well as negative effects. People who always drive fast spend 18 % more time for everyday mobility. The time use rebound effect of driving fast is 18 %.

In the nutrition domain, we find negative effects from adopting time efficient services and no direct time use rebound effects. Every other meal per week in restaurants reduces the time for hot meal preparation by 4 %. Every other meal in canteens per week reduces hot meal preparation by 2 %. Respondents who buy food from the cooling shelf like sliced vegetables reduce hot meal preparation time by 6 %.

In the digital domain, we find direct time use rebound effects as well as negative effects. A more concentrated smart phone use (at least sometimes) does lead to less internet time use by 14 %. Ad-free and ad-block services come with 8 % more internet time use.

Regarding general time efficient practices, we observe time use rebound effects as well as positive effects. Replacing time consuming with shorter activities increases time use for rest by 3 % per unit on the General Acceleration scale. Multitasking and filling waiting times with activities show decreasing effects on relaxing time use for rest by 3 % per unit. These results are mirrored by recent results on subjective experience on time wealth. Geiger et al. (submitted) found that multitasking and filling pauses were negatively related to the subjective impression of having enough free time in everyday life, while performing activities faster was positively related. The current data corroborates this subjective impression with the actual time-use data on rest times.

In a nutshell, we find rather few and low to moderate direct time use rebound effects from 3 % for general time efficient to 14 % of time efficient mobility practices. At the same time, for most of the surveyed time efficient practices we do not find significant time-saving effects either. Here we can conclude that we did not find enough evidence that time efficient practices actually do lead to time savings.

We conclude that our results do not indicate that direct time use rebound effects are as relevant as direct energy efficiency rebound effects at the individual application level. For instance in the mobility domain, Frondel et al. (2008) find direct rebound effects in the mobility domain due to fuel efficiency range between 57 % and 67 %. However, taking all time efficient practices together, the direct time use rebound effect may amount to significant increases of service demand distributed over a number of different services.

However, there are a number of shortcomings that need to be taken into consideration when interpreting the results. First, cross-sectional studies are susceptible to endogeneity and causality may be reversed. For instance, in the mobility domain, people who need more work travel time may travel fast more often. As well, effects may be overestimated due to omitted variables. We considered the socio-economic features age, gender, children in household, working hours and monthly household net income which may impact time use. The socio-economic features show ambiguous effects, but affect time use as expected. For instance, working hours affect time use negatively, as well does household net income. However, further predictors may affect time use relevantly, but have not been covered. For instance, infrastructural conditions may infer with time use for mobility and moderate time efficiency predictors significantly. Ad-free and ad-block services may not entail time efficiency, but may rather distinguish people who spent more time online from more casual users. Unobserved subscriptions or connection speed of users may render the effect of ad-free and ad-block services insignificant. Future research should thus be conducted based on panel or experimental designs in order to control for unobserved heterogeneity, endogeneity and reverse causality properly.

Second, the surveyed data allowed only to test for direct time use rebound effects. At the same time, we observed negative effects which may be interpreted as time efficiency gains leading to actual time savings. However, it is likely that time savings due to time efficiency gains may be rather reallocated

across domains, eventually leading to indirect time use rebound effects. We encourage future research to account for indirect time use rebound effects in order to test whether negative effects are cancelled out by indirect time use rebound effects.

What is more, time „saved“ can also be used to stretch services over a longer period of time without increasing or - or even decreasing - environment impacts (e.g. time saved by using frozen food can be spent for driving more slowly). Taking these different time spending modes into account, Erdmann and Pfaff (2021, upcoming project report) investigate the environmental implications of direct and indirect time spending.

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Supplementary Material

Questionnaire and item description of items on time use and time efficiency

Question and item	Item description	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
How far are your ways and how long do you need for them?								
mobility: everyday (h per week)	Routes for everyday errands (shopping, visits to authorities, ...)	1,994	4.20	9.50	0.00	1.00	3.90	168.00
mobility: work (h per week)	Routes to work or training	1,999	5.70	15.00	0	0.3	5	168
mobility: leisure (h per week)	Routes for leisure, including short weekend getaways	1,999	4.80	11.00	0	1	5	168
How much time do you spend on meals at home?								
meals: warm (min per meal)	for the preparation of a warm main meal	1,649	42.00	20.00	0.00	30.00	60.00	99.00
meals: cold (min per meal)	for the preparation of a cold main meal	1,582	16.00	10.00	0.00	10.00	20.00	90.00
How many hours per day do you spend on the following activities on an average working day?								
time use: internet (h per day)	Internet usage (e.g. surfing, streaming, smart tv)	1,999	2.70	2.30	0	1	3	24
time use: rest (h per day)	Resting and time-outs (without night sleep)	1,999	2.20	2.30	0	1	3	22
How do you usually travel?								
mobility: fast driving always	When I take the car, I drive fast.	1,705	0.22	0.41	0.00	0.00	0.00	1.00
mobility: fastest mode always	I take the fastest available means of transport for each route.	1,769	0.31	0.46	0.00	0.00	1.00	1.00
How many main meals (breakfast, lunch, dinner) are in a typical week…								
meals: take away (num per week)	…take away, (including stand-up snack)	1,999	1.50	4.30	0	0	1	100
meals: restaurant (num per week)	…in the dining restaurant with service	1,999	0.56	1.50	0	0	1	21
meals: canteen (num per week)	…in the self-service restaurant (including canteen / cafeteria)	1,999	0.61	1.60	0	0	0	21
meals: delivery (num per week)	…delivered	1,999	0.36	1.20	0	0	0	21
How do you do your kitchen work at home?								

meals: frozen food (ref. less than once a week)	I use frozen food (e.g. french fries, frozen vegetables).	1,993	0.57	0.50	0.00	0.00	1.00	1.00
meals: cooling shelf (ref. less than once a week)	I use products from the refrigerated shelf (e.g. chilled pasta, freshly cut vegetables).	1,995	0.45	0.50	0.00	0.00	1.00	1.00
How do you usually use digital media?								
internet: focused (ref. less than often)	I focus only on the initial reason to look on the internet	1,985	0.37	0.48	0.00	0.00	1.00	1.00
internet: adblock (ref. less than often)	I use ad blockers and / or ad-free email inboxes.	1,992	0.38	0.49	0.00	0.00	1.00	1.00
Think about your everyday life in general. Usually…								
general: mutlitasking	1) I do multitasking. 2) I do several things at the same time.	1,981	6.60	1.90	2.00	5.00	8.00	10.00
general: shorter	1) I replace time-consuming activities with less time-consuming ones. 2) I prefer to choose activities that only take a short time than those that take a long time.	1,978	6.40	1.50	2.00	6.00	7.00	10.00
general: faster	1) I get things done as quickly as possible. 2) I do things as quickly as possible.	1,983	7.50	1.50	2.00	6.00	8.00	10.00
general: fill pauses	1) I use waiting time for other activities. 2) I try to use breaks as productively as possible.	1,977	6.70	1.60	2.00	6.00	8.00	10.00