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Allocation of Time and Weather Dependency of Recreational Activities: A Survey with Empirical Focus on Styria.

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Abstract

Leisure goods are characterized by the feature that time as well as money is needed for their consumption. Models of time allocation account for this fact and explain how households allocate their time to activities. We suppose that the allocation of leisure time is highly weather dependent and modify familiar utility functions in order to extend the existing time allocation models. The weather dependency of leisure time allocation can be established by the statistical evaluation of daily attendance data of 52 recreational sites in Styria. A Poisson regression enables reliable short term predictions of attendance levels on an aggregate level by using maximum temperature, precipitation and air pressure as weather variables. We find that the average leisure time allocation is strongly affected by calendrical and weather related factors. A Multinomial Logit model points out that leisure activities act as substitutes with regard to the time spent on it whereas weather determines their substitutability.

Author’s Declaration

Unless otherwise indicated in the text or references, or acknowledged above, this thesis is entirely the product of my own scholarly work. Any inaccuracies of fact or faults in reasoning are my own and accordingly I take full responsibility. This thesis has not been submitted either in whole or part, for a degree at this or any other university or institution. This is to certify that the printed version is equivalent to the submitted electronic one.
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Chapter 1

Introduction and Literature Survey

1.1 Introduction

It is undisputed that economic activity as well as human behavior are strongly affected by climatic or weather related factors. Everybody has 3 hours and 23 minutes per day of pure leisure at his disposal.\footnote{This was pointed out by the Time Use Survey 2008/09 conducted by Statistics Austria and published by Ghassemi-Bönisch (2011).} How is the way we spend this time affected by weather conditions? We believe that the development of an understanding of the weather dependent time allocation, especially for leisure time, is an important sociological as well as economic issue and deserves further investigation.

Aguiar and Hurst (2007) document a substantial increase in leisure time between 1965 and 2003 and discuss the determinants of this increase. We however pay attention to the way households allocate their time on various recreational activities with regard to weather conditions. The way agents allocate their leisure time has impact on economic sectors and gives rise to further questions. It is obvious that weather acts as a driving factor in the economic calculation of households, for example for the decision how much leisure is consumed and which types of recreational activities are actually carried out. Arnberger and Brandenburg (2001, p. 124) for example point out that ‘although one can always achieve thermal comfort by adjusting one’s clothing, weather has still a major influence on the way we spend leisure and our recreational behavior.’ The focus of this thesis is on the weather dependence of leisure time allocation in the province of Styria. Of course, this is not the first attempt in analyzing the human time allocation.

The theoretical pioneering work of Becker (1965) shows that households do not only consume in order to obtain utility but should better be interpreted as producers of commodities, which in turn generate utility at consumption. From this point of view, market goods and time serve as inputs in the production process. In accordance to this literature, leisure commodities are considered as those, where time cannot be easily substituted for goods. On the basis of this insight, it is straight forward to use these models as a starting point for a study of the recreational behavior. We will consider the work of Becker (1965) and Gronau (1977) in more detail in chapter 3. In this chapter, a simple modification of familiar utility functions allows us to analyze the weather dependent allocation of time and money to different activities.

Steedman (2001) points out that the act of consumption must be analyzed within the context of time, simply because goods require time for consumption. Standard consumer theory typically pays a lot of attention to money as the only scarce resource. Undoubtedly, this is true in the first place but in the course of spending income, the time component gains attention. This idea is especially applicable on the consumption of recreational goods since one needs time and money in order to undertake leisure
activities. In spite of these findings, it makes sense to understand time as the more important factor. Juster and Stafford (1991) put it this way:

‘It can be argued that the fundamental scarce resource in the economy is the availability of human time, and that the allocation of time to various activities will ultimately determine the relative prices of goods and services, the growth path of real output and the distribution of income.’ (Juster and Stafford, 1991, p. 1)

We will not go that far but as we are interested in the allocation of time and money to leisure activities, we discuss consumer behavior models under consideration of time as an additional resource constraint and stress its importance for microeconomic theory. The theoretical framework of Steedman (2001) is used to analyze the effects of money and time constraints when recreational goods are consumed.

In the long run, it makes sense to understand the market wage rate as the opportunity cost of leisure and therefore the determinant for the time split between market work and non-work. In line with this, Jara-Díaz et al. (2008) develop a microeconomic model of time allocation in order to estimate the value of leisure and motivate the interest in this area as follows:

‘Thus, the value of leisure is of great importance to fully understand the effect of transport projects. After all, understanding time allocation is just as understanding life itself.’ (Jara-Díaz et al., 2008, p. 946)

We suppose that the evaluation of leisure depends on weather conditions as well, since they might determine its marginal utility. The wage rate however as opportunity cost is left unchanged. Therefore, weather conditions should be of great importance for the allocation of time between work and non-work, at least in the short run. We are interested in the factors that influence the total amount of leisure that one can enjoy and further the way how this leisure is spent. It turns out that weather has a considerable impact on the allocation of time and that the short term mix of leisure activities may differ substantially from the average.

It is obvious that all types of leisure branches are exposed to weather related risk and experience booms and recessions caused by weather conditions. As a consequence, firms are interested in the precise impact of weather on demand for their goods. Therefore, a higher predictability of recreational activities is not only an end in itself but is highly relevant for the entire leisure industry. Our model could utilize weather forecasts to generate reliable predictions on the recreational time use and the economic consequences that arise from the actions taken by households. The prognosis of attendance levels for single recreational facilities or the entire industry could lead to significant reductions in cost through a more efficient supply of public transport or a clever management of resources in recreational destinations or firms engaged in catering.

Surprisingly, the existing literature pays little attention to weather dependent time allocation to recreational activities and the demand for leisure goods. Our work adds to two branches of the existing literature. On the one hand, we follow the theoretical and empirical literature on time allocation. On the other hand, we tie in with the work on the impact of weather and climate change on matters of tourism and leisure or travel behavior. We briefly review these contributions to the literature in the following section. The main contribution of this thesis is to merge these two branches through the prediction of recreational behavior and the daily time use for the entire province of Styria from a short run perspective. In doing so, we identify weather as an important determinant of daily time use, the magnitude of total leisure time and its breakdown into single activities.

First, we look for a theoretical justification for a potential weather dependence of time allocation. In chapters 2 and 3 we discuss the fact that consumption of leisure goods can only be analyzed within
the context of time and illustrate models in which households maximize utility with respect to time
constraints. Description of the data is presented in chapter 4, chapter 5 illustrates the empirical framework
and chapter 6 discusses the results. Chapter 7 concludes. The empirical focus is on Styria, a province in
Austria with about 1.2 million inhabitants and 16,400 km².

1.2 References to Literature

A literature review reveals a rather scattered field of research. Basically, we detect two branches. The
first examines the allocation of time per se, without the consideration of weather conditions. The second
branch investigates the effects of weather and climate change on various issues, e.g. tourism, recreation
or travel behavior, but not on time allocation. Therefore, this master’s thesis provides a synthesis of both
branches. We begin by discussing the literature on time allocation.

Schreyer and Diewert (2013) extend the framework of Becker (1965) and Gronau (1977) and develop
a model of household production in order to evaluate the economic value of own account production by
households. In doing so, the work carried out by households is not only considered as an input but also
as a potential source of (dis-)utility itself. They present theoretical justifications for two approaches:
the replacement cost and the opportunity cost approach. Whereas the first suggests to evaluate the
time spent in household production by use of perfect substitutes offered by the market, the opportunity
cost approach proposes to evaluate the labor input by the (forgone) market wage rate. The System
of National Accounts (SNA) only records the acts of production and consumption that are subject to
market transactions. Therefore, particularly with regard to measuring economic welfare, it is important
to evaluate the own account production of households.

Aguiar and Hurst (2007) pool data from five time use surveys and document a similar and consistent
increase in different measures of leisure time. They distinguish between four uses of time (market work,
nonmarket production, child care and pure leisure) and create four different measures for leisure. Even
in this classification, measures for leisure time may take on a broad spectrum, ranging from narrow
(including only activities that yield direct utility) to broad (leisure time is the time spent neither in
market nor in nonmarket production). The increase in leisure is basically caused by a reduction of
market and nonmarket work: between 1965 and 2003, the sum of market and nonmarket work declined
by 8.3 hours for men and 7.8 hours per women per week. In return, total leisure increased by about
4 - 8 hours per week, depending on which leisure measure is used. For example, leisure measure 2-
which includes leisure activities that yield direct utility plus time spent sleeping, eating and personal
care - increased by 5.5 hours per week. Aguiar and Hurst (2007) provide two arguments that even this
increase may be underestimated. First, their sample did not include retired individuals. Given the fact
that expectancy of life is increasing, the growing amount of leisure enjoyed by retired persons is not
considered here. Second, they argue that the nature of time spent at work has changed and that more
leisure type activities (surfing the web) are carried out while at work.

Juster and Stafford (1991) review theoretical issues of time allocation and pool various time use surveys
for different countries and discuss the different results and their comparability. Regarding data collection
methods, they argue that keeping diaries represents the only reliable method that yields unbiased results.
Biddl and Hamermesh (1990) analyze the allocation of time with regard to sleep. They provide evidence
that the amount of sleep is a choice variable over which individuals optimize since it offers direct utility
and enhances market and nonmarket productivity.

The second branch of literature that investigates the influence of weather and climate on leisure
and tourism is nicely reviewed by Hamilton and Tol (2004). This type of literature is formed by the
insight that climate change has considerable effects on the leisure and tourism sector since tourism is based predominantly on spending time outdoors or enjoying sun or landscape. They distinguish between tourism and recreation in the way ‘that the former includes at least one overnight stay away from home.’ (Hamilton and Tol, 2004, p. 3) Qualitative impact studies provide information about the likely direction of the change of tourism demand, whereas quantitative impact studies provide concrete estimates of changes in demand. Of course, studies are available for winter as well as summer tourism destinations. While all studies differ in investigation periods, methods and places, one common message arises: ‘Climate change could well have substantial effects on tourism and recreation.’ (Hamilton and Tol, 2004, p. 13) A study about how tourism demand in skiing areas in Austria is affected by climate change is provided by Toeglhofer et al. (2011).

Thorsson et al. (2004) analyze the recreational use of park sites in urban areas of Sweden by methods of structured interviews and combination of mean radiant temperature and park visitors. They document a positive relation between thermal comfort and park use. The necessity of visitor monitoring in general is outlined by Arnberger et al. (2006). They point out that visitor monitoring is an important instrument for the urban administration to provide attractive recreational areas. Arnberger and Brandenburg (2001) also focus on the use of recreational outdoor sites and stress the importance of visitor monitoring as well because leisure activities provokes problems in public areas. They investigate the weather dependence of visitors in the Danube Flood Plains National Park, a protected area near Vienna. Video monitoring is used to count visitors and to distinguish between separate user categories: joggers, dog walkers and hikers. They find that the Physiological Equivalent Temperature (PET) has considerable influence on the total number of visitors as well as on the number of bikers and hikers.2 The day of the week has the greatest influence on all types of user categories, whereas weather variables have small impact on the number of joggers and dog walkers. They did not consider swimmers as a separate user group as the sample size was too small. Since we analyze the behavior of swimmers in Styria at length, our work constitutes a suitable supplement to Arnberger and Brandenburg (2001). Furthermore, Ploner and Brandenburg (2003) compare two kinds of prediction models for the same recreational area.

There are several papers that consider the influence of weather on leisure activities. Brandenburg et al. (2007) provide a study for the weather dependence of cycling in Vienna and point out that in urban and suburban recreation areas, a conflict of interest exists between various user groups. The different speeds of motion of cyclists and walkers constitute a challenge for park management. Furthermore, they distinguish between commuting and recreational cyclists and apply multiple regression to show that a positive relationship exists between the PET index and the number of cyclists (commuters as well as recreational cyclists). They also control for the thermal perception by including a weather index of the previous six days.

The link between weather and the number of cyclists is further investigated by Miranda-Moreno and Nosal (2011) for Montreal, Gebhart and Noland (2013) for Washington DC, Thomas et al. (2013) for the Netherlands and Tin et al. (2012) for Auckland. While the first three papers consider a nonlinear relationship between weather and the number of cyclists, the fourth considers a linear model. Scott and Jones (2006) consider the impact of weather on golf participation in the greater Toronto area. Li and Lin (2011) investigate the influence of weather conditions on hiking. Shih and Holecek (2009) and Damm et al. (2014) consider the influence of weather variables on the number of daily visitors in ski areas. The daily participation in recreational outdoor activities for Finland is examined by Vaara and Matero (2011). By using data from a time diary set, they find that the time spent on outdoor activities is mainly

2The Physiological Equivalent Temperature constitutes a thermal comfort index. Therefore, the thermic conditions felt in the open air are compared with the experience gained indoors. (Arnberger and Brandenburg, 2001, p. 124)
influenced by the variables age, dog ownership and seasons. In contrast to our work, their paper does not consider any weather variables.

Some papers discuss the impact of weather on travel behavior. A literature review on this topic is provided by Böcker et al. (2013). Cools et al. (2010) perform a descriptive analysis of weather dependent travel behavior which reveals that the willingness to change the travel mode in response to weather conditions depends on the trip purpose. They find that for leisure or shopping trips, more people alter their transport mode during warm temperatures than during cold temperatures. Saneinejad (2010) estimates a multinomial logit model to explore the relationship between weather and the type of transportation mode in the city of Toronto. Furthermore, a scenario of climate change is presumed to assess the impact on travel behavior.

A synthesis of the last two types (effects of weather on recreational behavior and travel behavior) is provided by Shih and Nicholls (2011). They investigate the weather dependence of the traffic volume caused by leisure activities for a location in the US state of Michigan. A model for daily leisure traffic is built and reveals that unsurprisingly, temperature and the availability of leisure time had positive, significant influence on leisure traffic, whereas precipitation does not have significant influence. Similarly, Horanont et al. (2013) study the effects of weather (temperature, rainfall and wind) on the activity patterns by using GPS traces of mobile phones to investigate the places people go and the time spent there. They find that stops people make while traveling substantially increase on very cold or calm days, whereas these stops most often concern meals in restaurants or shopping tours in malls. Furthermore, activities tend to be more variable on warm days, i.e. they engage in a wider range of activities, especially in warm nights.
Chapter 2

Consumption Takes Time

Ian Steedman in his work ‘Consumption takes Time’ (2001), fabulously points out that standard consumer theory fails to account for the fact that the money budget constraint is not the only important one. Already Gossen (1854) had in mind that time - not money - is the ultimate scarce resource: utility arises from the time spent on certain activities and even in the land of plenty, time is scarce and one is urged to allocate it carefully. In this section, some ideas of Steedman (2001) are illustrated in order to build a theory why people spend their leisure in the way they do. We will also discuss some implications and pitfalls when we start to include time constraints into models of consumer theory.

Consider the money budget constraint in figure 2.1(b). In standard microeconomic theory, the dotted area usually represents the set of feasible consumption bundles. But it is not appropriate to discuss the set of feasible consumption bundles, ignoring the fact that the time in which to consume them cannot be bought by anyone. Since ‘it takes two hours to watch a two hour long film, a variable length of time to watch a professional golf match, to read a given book or to eat a dish of tagliatelle’ (Steedman, 2001, p. 4), one is unable to consider combinations of goods that blow up the time frame in discussion. Of course, one could be able to buy any amount of goods, but it is never guaranteed that he is also able to consume them. Linder (1970) already points out: ‘Such pleasures as a cup of coffee or a good stage play are not in fact as pleasurable, unless we can devote time to enjoying them.’ He was right by saying that ‘one cannot regard consumption as an instantaneous act without temporal consequences.’ The act of buying cannot be separated from the act of consumption, especially in a discussion about recreational goods. Under this view, even figure 2.1(a) is just not able to represent the set of all feasible bundles of

![Figure 2.1: The Money Budget Constraint and the Set of Feasible Consumption Bundles](image-url)
leisure activities, because time constraints are inescapable.

The same is true for indifference curves and the ranking of bundles: how can one assign utility levels to consumption bundles, given the fact that the consumption of goods (or activities) in different proportions will change the total time requirement? First, is it plausible to assume that if one is able to eat one pizza in 12 minutes, he was able to eat five pizzas within one hour? And second, which is even more important: could one experience the same utility level from the visitation of a museum by dedicating two hours to it than from dedicating three hours to the visit? At this point we recognize that the concept of utility functions begins to dangle once we allow for time in the consumption context.

Henry Ford remarked that ‘the waste of time is the easiest of all dissipation’. But given the fact that no one is able to spend more or less than 168 hours per week or 1440 minutes per day, how is it possible to ‘waste’ any time at all? Anyone is literally forced to spend the whole day in any way. Therefore, we cannot decide whether to spend the next 37 minutes as they will pass anyway. We can only decide upon how to spend our time. Steedman argues that there is no ‘free disposal’ of time, hence we must spend our time by doing something. Since first, the ranking of commodity bundles whose consumption takes more than 168 hours per week is meaningless, second, the fact that utility changes at different consumption rates and third, there is no way of not using time, our set of commodity bundles could reduce for example to a line like $X'$ in figure 2.1(c).

As we cannot abandon a certain amount of time because it will pass anyway, all feasible consumption bundles must lie on $X'$, which could be nonlinear due to varying consumption rates. No meaningful bundle can lie north-east of $X'$ - since this would require more than 168 hours per week. Nor south-west of $X'$ because (given our assumption) there is no third way of using time than by consuming $x_1$ and $x_2$. Hence, it is better to think of the time constraint in figure 2.1(c) as an identity rather than an inequality. We can decide whether to spend or save money, but their is no analogous decision regarding time, since the next few minutes must be spent immediately and cannot be postponed. In fact, there is no savings regarding the resource time. The familiar money budget constraint in figure 2.1(b) is actually fine and is not bothered by the inclusion of time constraints. It can be satisfied as a weak inequality.

In general when we use formulations like needing time, wasting time or loosing time, it is not easy to be clear about its meaning. According to Steedman (2001, p. 6), time is conceptually hard to grasp - and that difficulty is naturally not irrelevant to careful economic analysis. Winston (1987) points out that time, treated as a thing, is misleading. It is better considered as ‘the context, within which’ household production takes place. In this spirit it is misleading to define time as an input in the production process. In a production process, one can decide about the usage of many inputs but time is not under control of anyone: the next 7 hours cannot be accumulated or stored, they will pass regardless. Not that ‘one can only do some things and not others within the context of those 7 hours.’

In what follows, we will put time in the center of the analysis and consider the expenditure constraint only in a subordinate role. Of course, time and money itself are strongly related, since money arises from the time spent at work. As it is not our intention to do general equilibrium analysis, we leave aside this relationship and take money and (spare-) time as exogenous. We believe that the framework and discussion provided by Steedman (2001) is especially suitable for our investigation of the enjoyment of leisure goods because of two reasons. First, leisure activities are only enjoyable at certain rates of consumption. Its no pleasure, although possible, to go for arbitrarily many activities within a limited period of time. Second, once the amount of leisure is chosen, one must decide upon how to spend this time because one cannot ‘not use’ his time.
2.1 The Concept of Time in Consumption: A Simple Model

We now introduce time as an additional resource constraint into a simple model of consumer behavior, illustrated by Steedman (2001, pp. 7). We denote the disposable income for leisure activities by $M$ and consider the amount of available leisure time as $L$. As in the previous section, we assume that there is no other way to spend time than by consumption of leisure activities $x_1$ and $x_2$ at market prices $p_1$ and $p_2$. We assume that the two goods can be consumed at fixed average rates $r_1$ and $r_2$, which denote the amount of time that is necessary to consume one unit of commodity 1 and 2. That is to say, one is able to consume $1/r_1$ units of commodity one per unit of time.\(^1\) Two constraints follow from this setup:

\[
\begin{align*}
  p_1 x_1 + p_2 x_2 & \leq M, \\
  r_1 x_1 + r_2 x_2 & = L,
\end{align*}
\]

where the time constraint (2.2) is just a linear version of the time identity illustrated in figure 2.1(c). In order to receive non trivial results, we have to make assumptions on the relations of $r$ and $p$. The case $r_1/r_2 = p_1/p_2$ is unattractive as the slopes of the constraints are identical. We assume $p_1/p_2 > r_1/r_2$, which causes the expenditure constraint to be steeper than the time identity. The case $L/r_2 > M/p_2$ would mean that the agent cannot afford any consumption bundle which is compatible with the time identity. Since $L/r_1 < M/p_1$ would imply that the agent could afford any bundle on the time identity (and the money budget constraint is therefore irrelevant), we opt for $p_2/r_2 < M/L < p_1/p_2$ which is a special case of our starting point. This situation is depicted in figure 2.2.

![Figure 2.2: Relation of the Time and Budget Constraint](image)

For reasons discussed above, Steedman refuses the use of any utility function and assumes that in the absence of a binding expenditure constraint, our representative agent wants to consume at point $\ast$. This situation is interesting because the preferred consumption bundle lies on the time identity but the budget constraint is binding and does not allow for consumption at the ‘bliss point’ $\ast$. In our case, the solution is given by the intersection of both curves as this is the closest affordable bundle. Consumption will actually be at point $P$.

Now we can consider the common own- and cross price effects or reactions to changes in available income. Given that the consumption bundle is given by the intersection of two downward sloping curves,

\[\text{We know from the time use survey discussed in chapter 4 that the average duration per visitation of a museum is 159 minutes. This means in return that one can only consume } 1/159 \text{ of a museum entry per minute. Later we use this time coefficient in the empirical discussion.}\]
we first note that
\[
\frac{\partial x_2}{\partial M} < 0 < \frac{\partial x_1}{\partial M}.
\]
This means that the second leisure good is inferior, i.e. the amount consumed decreases as income increases. Consumption of the first commodity increases as the disposable income rises. We may further notice that leisure activity two is a Giffen good because the own price effect is positive. The first one is a normal good since an increase in its price leads to a reduction of demand:
\[
\frac{\partial x_1}{\partial p_1} < 0 < \frac{\partial x_2}{\partial p_2}.
\]
The cross price effects of both goods are interesting: a price increase of commodity one leads to a higher demand for commodity two but a price increase of commodity two leads to a lower demand for the first good. This is due to the fact that commodity two is a Giffen good. Therefore the cross price effects are of opposite signs:
\[
\frac{\partial x_1}{\partial p_2} < 0 < \frac{\partial x_2}{\partial p_1}.
\]

We realize that the introduction of a time identity (which is always binding) changes at least parts of the insights of standard consumer theory, since there is always a recreational good that is inferior with respect to income. Most of these changes are a consequence of the time identity and the assumption that time must be spent on activity 1 or 2. In line with later chapters, this seems to be a reasonable approach. The Time Use Survey for example defines leisure as the sum of the time that is spent on all recreational activities. These activities are considered as those that yield direct utility.

2.2 Implications of Time Constraints for Recreational Activities

We now ask for the effects of changes in the time constraint. What will be the effect on consumption of leisure goods 1 and 2 when more time is available? As before, we consider a situation where the first activity is relatively ‘money intensive’, whereas the second activity is relatively ‘time intensive’, i.e. that more money (time) is needed for consumption of the first (second) activity. We have illustrated an increase in the available leisure time in figure 2.3(a).

If total available leisure increases, the consumer decides to consume more of the time intensive and
less of the money intensive activity, i.e. the consumer switches from P to Q given that the preferred bundle is located at \(\ast\). It follows that total time devoted to the second activity \((x_2 \cdot r_2)\) increases, whereas total time devoted to the first activity declines. Unsurprisingly, the share of activity 1 in total leisure decreases when more time is available. We will see in section 6.2 that the available time for leisure activities increases on weekends. Although more time is available, we will observe a reduction of the share of some activities. This is in line with our intuition: if one has available more time for recreational activities, the participation in time intensive activities rises. The converse argument would be that if one has less spare time available, he demands more of the goods that are money intensive but require less time for consumption.

The same is true for an increase in disposable income, illustrated in figure 2.3(b). Again, \(x_1\) is the more expensive activity, whereas \(x_2\) is the more time consuming one. Consumption points switch from \(P'\) to \(Q'\), which means that more of the money intensive leisure good is demanded and less of the time intensive. The outward shift of the budget constraint necessarily leads to a decline in time devoted to consumption of \(x_2\) and a rise of time devoted to \(x_1\), the more expensive good. The increase in disposable income devoted to leisure activities means that leisure gets more expensive in terms of money, i.e. the monetary expenses per minute of recreational activity rise. According to our trivially simple model, one is willing to spend more money per unit of leisure good but dedicates less time to relatively cheap activities. This finding is in line with daily experience: as we observe a rise in income, maybe even accompanied by a shrinking of available spare time, expensive hobbies like golf, sailing, . . . become more attractive.

We can draw two main conclusions from this simple model. First, in the case of two leisure activities where one is time and the other is money intensive, the time intensive one is always inferior. Second, when we relax the time constraint, one spends less time with the expensive activity. Recall that we have made strong assumptions in our model. The amount of recreational activities \(x\) is perfectly divisible and there is no uncertainty, i.e. the example of the golf match with variable length is still beyond the limits of the model. Furthermore, we have treated the consumption rates \(r\) as exogenous and assumed that there is no free disposal of time, i.e. the whole leisure budget \(L\) has to be spent on consumption of two leisure goods and ‘that there is no use of time that does not involve the consumption of commodities’. (Steedman, 2001, p. 13) In the following section we discuss the implications of fixed or varying consumption rates.

### 2.3 Rates of Consumption

We now relax the assumption of fixed consumption rates and briefly discuss the implications of flexible consumption rates, following Steedman (2001, pp. 13). Consumers may basically choose their consumption rates freely but in practice, the range of enjoyable consumption rates is quite limited. We have seen that even the introduction of rates of consumption into consumer theory may change basic findings remarkably. Consider for example the concept of the utility function and the non satiation assumption. Monotonicity implies that larger bundles of goods are always preferred to smaller amounts. Given the fact that the utility function is defined for a given period of time, this assumption is only consistent with infinite rates of consumption. To stick to our earlier example, is an amount of 5 pizzas per hour really preferred to 4 pizzas per hour? Any amount of goods or activities in considered in a limited period are inevitable associated with certain rates of consumption. The consumption rate \(1/r\) must become ever larger, the higher the amount of goods in a given period of time. As \(r\) becomes small, one can certainly have too much of a good thing. Hence, the principle of non satiation is not supportable when we act on the assumption of limited time periods.

Let’s introduce a little formal example for illustration. Suppose we have two leisure goods and treat
the consumption rate of activity 2 as fixed at - for simplicity - one. For commodity 1, the consumption rate may vary within limits. We assume that the utility of consumption of commodity 1 decreases to zero when the consumption rate rises above/below a certain upper/lower level but \( r_1 \) can take on all values within this range. We denote the smallest possible coefficient of time by \( R \) and the lowest consumption rate by 1. Note that \( R \) is the smallest possible number, which means that consumption is as less time consuming as possible, i.e. one consumes at the highest possible rate without loosing utility. On the other hand, it is not possible to consume less than one unit per unit of time. Thus we can write the time identity as

\[
x_1 \cdot r_1 + x_2 = L.
\]

What happens to the set of feasible consumption bundles? Figure 2.4 provides a graphical answer. As the consumption rate for commodity one is allowed to vary between 1 and \( R \), the time identity can be represented as the dotted area \( X \) in the first quadrant. Even this approach may be too simplifying since different rates of consumption imply in any case different levels of utility. We conclude that varying consumption rates at least relaxes the limited range of the time identity. Therefore, the set of possible consumption bundles not only consists of a single line as illustrated in figure 2.2 but could be thought of as the dotted area \( X \) in figure 2.4. The fact that consumption takes time is therefore not totally inconsistent with the definition of a utility function within a certain domain. However, the introduction of time constraints is not without any consequence. Suppose there exists an optimal consumption rate \( r^* \) that lies between 1 and \( R \). Let’s fix the amount of \( x_2 \) and increase consumption of \( x_1 \). The utility level would be zero at high values of \( r \), then rise and later fall back to zero as \( r \) reaches its minimum level \( R \). We can repeat this process for different levels of \( x_2 \) with the same conclusion: the utility first rises and then falls as we go across the consumption set \( X \). Hence, the whole consumption set must be covered by indifference loops, allowing for a ‘bliss point’ of maximum utility at each level of \( x_2 \). Note that these points of maximum utility just arise as a consequence of time constraints and varying consumption rates, not because of the use of a specific utility function and the maximization subject to a budget constraint. Steedman (2001) further remarks that time constraints could well have implications on general equilibrium theory as Walras’ law could be violated.

We have learned that introducing time constraints into utility models causes some difficulties and tends to limit the range of choices for the consumer in different ways. Nonetheless it is worth to deal with time constraints because it provides insights into the way agents allocate their time to certain activities.
or consumption of commodities. Especially for the economics of leisure it is useful to introduce rates of consumption or the time intensity. It demonstrates that consumption has sort of a ‘price of time’ that one has to pay implicitly. Dealing with time constraints allows to discuss opportunity costs with respect to time but limits the domain of feasible consumption bundles considerably.

2.4 Weather Dependent Utility

Up to now we have not revolutionized standard consumer theory but we have at least made it less familiar. We now proceed by modifying a conventional utility function to indicate that leisure activities are not only time consuming but may also be weather dependent.\(^2\) Although Steedman provides good arguments that the concept of utility does not hold when we introduce time, we nonetheless stick to a utility function and leave aside the time identity.

Consider for example the decision on how much time to spend on activities like skiing or swimming within a certain period of time. Of course, this is a highly weather dependent choice, therefore it is straightforward to incorporate a weather component into the decision process. We extend the utility function by a temperature parameter and show how first order conditions are affected by its changes. These theoretical foundations will be used for the models of time allocation in section 3.1 and are incorporated into an example of weather dependent choice behavior for leisure activities in section 5.1.

Consider the utility function \(U = U(x_i; t)\) for two goods \(i = 1, 2\), where \(t\) indicates a temperature parameter. In addition to the desirable properties of positive but declining marginal utility \((U'_i > 0, U''_i < 0)\), we are looking for a temperature dependent substitutability between the two goods. First, we distinguish between the two goods with respect to their ‘optimal consumption temperature’. Suppose the first commodity \(x_1\) is better consumed at high temperatures, whereas consumption of \(x_2\) is preferred at lower levels of temperature. One can think of the two goods as swimming \((x_1)\) and skiing \((x_2)\), for example. A higher temperature should raise the utility of an additional unit of \(x_1\) and lower the utility gained by the consumption of an additional unit of \(x_2\).

When income is the only relevant constraint, it is well known that utility maximization requires the marginal rate of substitution (MRS) to equal the price ratio, i.e.

\[
\text{MRS} = \frac{U'_i}{U'_2} = \frac{p_1}{p_2}.
\]

(2.3)

In order to examine the effect of changes of temperature on consumption patterns, we must allow for the temperature to affect the first order condition in (2.3), respectively the marginal rate of substitution (MRS). Since the MRS consists of the ratio of marginal utilities, we have to assure that temperature not only affects total utility but particularly marginal utility. We should think of the marginal utility of commodity \(i\) as a function of \(x\) and temperature \(t\), i.e. \(U'_i(x_i; t)\). The case of swimming and skiing can therefore be illustrated as follows:

\[
\frac{\partial U'_1}{\partial t} > 0, \quad \frac{\partial U'_2}{\partial t} < 0.
\]

(2.4)

According to (2.4), the marginal utility of 1 (2) increases (decreases) when temperatures rise. This implies further a rising MRS as a consequence of an increasing temperature:

\[
\frac{\partial \text{MRS}}{\partial t} = \frac{\frac{\partial U'_1}{\partial t} \cdot U'_2 - \frac{\partial U'_2}{\partial t} \cdot U'_1}{U'_2^2} > 0.
\]

(2.5)

\(^2\)Inspiration for this section was given by Franz Pretenthaler who suggested to analyze the weather dependence by a utility function.
The interpretation of the change in the MRS is straightforward: as the temperature rises, \( x_1 \) becomes more valuable (in terms of \( x_2 \)). In other words: after a temperature increase, the consumer is willing to give up more units of \( x_2 \) in exchange of one additional unit \( x_1 \). We have depicted the effect of a temperature increase on the first order condition in figure 2.5. It can be seen that for a given consumption bundle \( P \), the ratio of marginal utilities changes as a consequence of an increasing temperature. The price ratio, i.e. the budget constraint is of course constant. \( P \) is not optimal any longer for this price ratio because one could substitute \( x_1 \) for \( x_2 \) and enhance the utility level from \( U' \) to \( U'' \) by consuming at \( P' \) rather than \( P \). At point \( P' \), the agent consumes a higher amount of \( x_1 \) and lowers consumption of \( x_2 \), which is optimal given the new temperature level \( t \). If we assume that one unit of \( x \) needs an amount of time \( r \) for consumption, it follows that the consumer spends more time on activity 1 and less time on activity 2. This is the theoretical background for the time use patterns presented in later chapters. Certain amounts of time are reallocated from one activity to another, which can be interpreted as a consequence of a changing utility due to weather.

Note that in this mini model we have considered leisure activities as \textit{amounts of goods} with certain market prices but ignored the time intensity at consumption. Nonetheless, this model accounts for the fact that the circumstances under which the consumption of leisure takes place are probably more relevant to marginal utility than the amount of goods consumed. We extend this model to a more general case in section 5.1 where we consider time as the only scarce resource and make use of a Cobb-Douglas utility function. After all, the use of this modification only applies to the utility function, the time and money constraints play a subordinate role. However, we unify both constraints as well as the weather dependent utility in the following section.
Chapter 3

Models of Time Allocation

In the empirical application of this work we discuss the time allocation of households in Styria. The literature on time allocation attempts to offer a theoretical explanation for the time use patterns observed in practice. Hence, we prefer to discuss these models first. One of the firsts who addressed the question of how households allocate their time was Becker (1965). He presented a theory of time allocation which claims that households act as small producers that need time and market goods as inputs in the production process. The interest in this field of research was primarily motivated by the insight that individuals spend more than two thirds of their total time on non-work activities. Therefore, non working time could be of great importance to economic welfare. The time allocation approach is especially useful for the evaluation of time spent on education and the welfare effects caused by it through the abandonment of earnings of students for example.

The opportunity cost approach is even valid for the evaluation of the time spent on the consumption of goods or leisure activities. For example, the full costs of visiting a museum consist of its direct costs, i.e. the market prices plus the indirect costs as the time of actually strolling through the exhibition could have been used productively. Furthermore, this time could have been spent on another activity. We argued in the previous section that the marginal utility - and therefore the opportunity cost - of any good could depend on weather. We therefore believe that the theory of time allocation is appropriate for a weather dependent extension. The work of Gronau uses a framework similar to Becker and discusses the interplay of leisure, market work and work at home. We will use the idea of weather dependent consumption to give these models their meaning.

3.1 A Theory of Time Allocation

We assume that households combine time and market goods to produce commodities that are ready for consumption. Indeed, it is pretty obvious that we need time and electronic devices to watch the soccer world cup or to visit the theater. Even sleeping as an activity usually requires a house, bed (pills?) and time as inputs.\footnote{This is an example stressed by Becker (1965, p. 495)} Note that from this point of view, leisure activities can be considered as final goods that need time and market commodities as inputs. We denote these final goods by $Z_i$ and suppose that the goods, to be ready for consumption, need to be produced according to a production function

$$Z_i = f_i(x_i, T_i),$$

(3.1)
where \( x_i \) is a vector of market goods and \( T_i \) denotes the time input required per unit of \( Z_i \). The amount of final goods \( Z \) enters a utility function of the form

\[
U = U(Z_1, \ldots, Z_M) = U(x_1, \ldots, x_M; T_1, \ldots, T_M),
\]

(3.2)

which is maximized subject to two constraints. The goods constraint can be written as

\[
\sum_{i=1}^{M} p_i x_i = I = V + N \cdot w,
\]

(3.3)

where \( I \) denotes the money income which consists of labor income (\( N \) times the wage rate \( w \)) plus other sources of income, for instance capital income, \( V \). The time constraint relates total time \( T \), time dedicated to consumption \( \sum_i T_i = T_c \) and time spent at work via

\[
\sum_{i=1}^{M} T_i = T - N.
\]

(3.4)

Of course, these two constraints are not independent: they are related through the time spent at work \( N \) because more working time implies more market goods but less time for consumption. Therefore, both constraints can be reduced to

\[
\sum_{i=1}^{M} p_i x_i = V + w \cdot (T - \sum_{i=1}^{M} T_i).
\]

(3.5)

Whereas Becker (1965) considers the case of a general production function, we assume a fixed proportions production function of the form

\[
Z_i = \min\left(\frac{T_i}{r_i}, \frac{x_i}{b_i}\right),
\]

(3.6)

where \( r_i \) is the familiar time coefficient and \( b_i \) denotes the material input (e.g. sleeping pills) required per unit of \( Z_i \). By use of coefficients \( r_i \) and \( b_i \), the constraint in equation (3.5) can be written as

\[
\sum_{i=1}^{M} p_i Z_i b_i + w \cdot \sum_{i=1}^{M} Z_i r_i = V + w \cdot N.
\]

(3.7)

From this equation, two conclusions can be drawn. First, consider the RHS of (3.7). This is the money income if the total available time is devoted to work. This total income can either be used directly for the expenditure on market goods, \( \sum_{i=1}^{M} p_i Z_i b_i \) or indirectly on the consumption of goods, \( w \cdot \sum_{i=1}^{M} Z_i r_i \). This is the time spent on non-working activities evaluated at a wage rate \( w \). Second, we can write equation (3.7) as

\[
\sum_{i=1}^{M} Z_i (p_i b_i + w r_i) = V + w \cdot N.
\]

(3.8)

One can see from (3.8) that the price of commodity \( i \) can be divided into two components: the ‘full price’ is determined by the (direct) market price and the (indirect) price that consists of the time spent on production, evaluated at \( w \). Of course, this is also true for any kind of leisure activity: even if the activity is low in costs in terms of market prices, it could be expensive with respect to its full price when it is relatively time consuming. The visitation of a museum, although low in its direct cost, may be expensive in terms of its indirect costs since it is quite time consuming: 159 minutes. We implicitly

\[^{2}\]

Note that we consider \( w \) to be constant for simplicity, which is not necessarily true. However, it simplifies the utility maximization and the equilibrium condition in (3.9).
assume that the time spent on leisure activities could also be used productively. By maximizing utility in (3.2) subject to (3.8), one gets the equilibrium condition

$$\frac{\partial U}{\partial Z_i} \cdot \frac{1}{\pi_i} = \lambda = \frac{\partial U}{\partial Z_j} \cdot \frac{1}{\pi_j},$$

(3.9)

where $\pi_i$ denotes the sum of the direct- and indirect prices ($p_i b_i + \ell_i$) of commodity $i$. This first order condition states that marginal utility from consumption of all goods divided by its full price has to be equal to a value $\lambda$ which can be thought of as the marginal utility of money income.

The presentation of this model by now is based on the ‘total income’ given by $V + w \cdot N$, which critically depends on the assumption of a constant wage rate. Instead, the resource constraint could be expressed via a term called ‘full income’. This is the income that can be achieved if all time resources are dedicated to maximize the money income. Note that dedicating all available time $T$ to work would probably not maximize the money income: eating, sleeping and even leisure may serve to maximize one’s earnings. Imagine that even ‘slaves, for example, might be permitted time off from work only in so far as that maximized their output.’ (Becker, 1965, p. 498) However, utility maximization, not income maximization, leads to a reduction in income which means that income is given up in order to obtain additional utility. Becker (1965) refers to the maximized money income as full income. If we denote full income by $S$ and the loss in earnings due to utility maximization by $\ell$, we can relate these terms via money income $I$ through

$$\ell(Z_1, \ldots, Z_m) \equiv S - I(Z_1, \ldots, Z_m).$$

(3.10)

The loss $\ell$ and the income $I$ are functions of $Z_i$ because they depend on the consumption set that is chosen. We can substitute the goods constraint (3.3) and the production function (3.6) into (3.10) to receive again one basic resource constraint

$$\sum_{i=1}^{m} p_i x_i Z_i + \ell(Z_1, \ldots, Z_m) \equiv S.$$  

(3.11)

‘This basic resource constraint states that full income $S$ is spent either directly on market goods or indirectly through the forgoing of money income.’ (Becker, 1965, p. 499) This is insofar convenient as households maximize their utility subject to a single budget constraint. Again, leisure is evaluated through an opportunity cost approach as $\ell$ denotes the income forgone due to interest in utility. The loss is caused through a ‘waste of time’, not because income is spent on market goods. Utility maximization requires the marginal utility divided by its full price to be equal across all goods, hence

$$\frac{\partial U}{\partial Z_i} \cdot \frac{1}{(p_i b_i + \ell_i)} = \frac{\partial U}{\partial Z_j} \cdot \frac{1}{(p_j b_j + \ell_j)}.$$  

(3.12)

The direct costs are reflected in $p_i b_i$ while $\ell_i = \frac{\partial \ell_i}{\partial Z_i}$ denotes the loss or reduction in full income of one additional unit of $Z_i$. To make this more concrete, we can write the resource constraint for a two commodity world as $S = p_1 b_1 Z_1 + p_2 b_2 Z_2 + \ell(Z_1, Z_2)$. The equilibrium is depicted in figure 3.1 in point $P$. As stated in (3.12), the ratio of the marginal utilities equals the price ratio in the optimum.

This model is characterized by two main features. First, leisure or the time spent on consumption is evaluated through an opportunity cost approach as this time could have been used productively to achieve full income. Consequently, for individuals that face high average wages $w$, the indirect price of consumption (i.e. the time) represents the more significant component of marginal costs. Second, this model adapt the view that time and market goods are complementary inputs in the achievement of
utility. In contrast to the view of Steedman (2001), this framework allows us to evaluate the time used up in consumption by a reduction in earnings. Note that both properties characterize the choice behavior regarding leisure activities. Therefore, we believe that it is appropriate to consider commodities \( Z_i \) as recreational activities, whose utility in consumption is weather related. While Steedman (2001) argued that a utility function cannot be defined for a bundle of goods that involves more than 168 hours per week, this issue is not addressed by Becker (1965) whose model is based on the existence of a utility function.

Consider a world of two activities which can be produced through a combination of time and market goods via the production functions \( Z_i = \min(\frac{T_i}{r_i}, x_i b_i) \). The equilibrium allocation of these two goods has already been shown in figure 3.1. Now, we distinguish between the two activities with respect to their input coefficients \( r_i \) and \( b_i \). Let activity one be the more time intensive, i.e. \( r_1 > r_2 \) and activity two the more goods intensive, i.e. \( b_2 > b_1 \). Recall the weather related utility function in section 2.4. Suppose that the utility function depicted in figure 3.1 is characterized by the feature that temperature has a positive (negative) effect on the marginal utility of activity 1 (2). Then, through an increasing temperature, the preferences would shift such that a higher amount of \( Z_1 \) and a lower amount of \( Z_2 \) is consumed. Depending on the coefficients \( r_i \) and \( b_i \), the mix of direct and indirect costs for the new consumption bundle would change. The new consumption bundle \( P' \) requires more consumption time if \( Z_1 \cdot r_1 + Z_2 \cdot r_2 < Z_1' \cdot r_1 + Z_2' \cdot r_2 \). Although we have assumed that \( r_1 > r_2 \), it is not necessarily true that more time is needed after the shift to a new bundle of activities. The time change of activity one can be denoted by \( r_1 \cdot (Z_1' - Z_1) \) which is positive. The time change of activity two is \( r_2 \cdot (Z_2' - Z_2) \) which is negative. Ex ante, the net effect cannot be determined since it depends on the magnitudes of \( (Z_1' - Z_1) \) and \( (Z_2' - Z_2) \). The bundle will require more time input if \( \frac{Z_1'}{Z_1} > \frac{Z_2'}{Z_2} \cdot \frac{r_2}{r_1} \). Of course, the same argument holds for the market goods that are needed in the new situation, but with opposite sign.

In section 6.5, we provide estimates for the amount of time that is required when the bundle of leisure activities changes due to altering temperatures. It would be interesting to estimate the weather induced consumption of market goods but unfortunately, there is no data available on the 'goods intensiveness' of leisure activities. We will return to this issue in section 5.2.5. From a theoretical point of view, the loss \( \ell \) and the income \( I \) also depend on the consumption bundle that is chosen. Therefore, the opportunity costs of consumption time or leisure could also differ among weather conditions.
3.2 Work, Leisure Time and Home Production

The focus is now on the tradeoff between labor and leisure. While the familiar Robinson Crusoe approach just distinguishes between two uses of time, we will consider two reasonable extensions of the classical example. Gronau (1977) uses a framework similar to that of Becker but considers work at home as an additional non-working use of time. He argues that market work and work at home should be treated separately because 'leisure and work at home are not affected in the same way by changes in socioeconomic variables.' Steedman (2001) however suggests to distinguish between 'consumption time' and 'pure leisure'. He shows that the labor/leisure tradeoff cannot be separated from the act of consumption since the market goods have to be consumed within the remaining leisure. We suppose that the utility gained by the consumption of goods or leisure could be affected by weather conditions which implies that the overall time use changes at different weather conditions.

Let’s assume that goods produced at home are perfect substitutes to market goods. This is probably true for some kinds of activities e.g. cleaning, which is ‘something one would rather have somebody else done if the cost were low enough.’ It must not be true for activities like child care or work in the garden. Precisely these two activities cannot be assigned clearly to leisure or work at home. Let utility be defined as a function of goods \(x\) and leisure \(L\),

\[ U = U(x, L), \]  

where \(x\) consists of market goods \(x_m\) and goods produced at home \(x_H\). Since market or home made goods act as perfect substitutes, we can write \(x = x_m + x_H\). The homemade goods can be produced by dedicating time to work at home \(H\). Production takes place according to a production function \(x_H = f(H)\) which is subject to decreasing marginal utility (\(f' > 0, f'' < 0\)). Note that we have made a simplification in contrast to the previous section: time and market goods are not considered as inputs but enter the utility function directly. We assume implicitly that all goods can be consumed during the time period \(L\).

Maximization of utility in (3.13) is done subject to two budget constraints. First, the goods constraint with prices \(p\), market work \(N\) and other income \(V\)

\[ p \cdot x_m = w \cdot N + V, \]  

and second the time constraint

\[ L + H + N = T. \]

In the optimum, the household allocates its time such that the ratio of the marginal utilities of leisure and goods equals the marginal productivity of work at home. In case the household works in the market, the marginal rate of substitution also equals the real wage rate \(w/p\), which can be thought of as the marginal utility of time.

\[ \frac{U_L}{U_x} = f' = \frac{w}{p}, \]

We have depicted this situation in figure 3.2. The first order condition is satisfied at point \(P\), where the household consumes an amount \(x_0\) of market goods and enjoys an amount \(L_0\) of leisure. Work is usually measured from right to left, hence the amount of work carried out at home is \(T - N_0\). Since the marginal productivity (in terms of goods \(x\)) of work performed in the market is higher than at home when we go further to the left of \(N_0\), the individual decides to work \(N_0 - L_0\) hours in the market. Note that this time split between home and market work is a result of declining marginal productivity and the perfect

\[ ^3\text{Note that this model does not explicitly account for the fact that consumption takes time. If one adopts a goods intensive technology, there may be too little time for the actual consumption of goods. To account for this, we could extend the model by an additional constraint like } x \cdot r = L. \]
substitutability between market goods and home made goods. For sure its true that there are goods that certainly cannot be made at home, which is reflected by the declining marginal productivity and the decision to participate in the labor market.\footnote{Schreyer and Diewert (2013) tie in at this point and investigate the value of household production. They discuss two approaches for evaluation: at market prices of suitable substitutes (replacement cost approach) and the opportunity cost approach, i.e. how the time could have been used productively.}

We have again seen that the real wage rate as opportunity cost of leisure is a major determinant for the decision between work and leisure, at least in the long run. Although we are not in doubt about this conclusion, we believe that there are other factors that affect the labor/leisure decision in the short run. The empirical investigation points out that many recreational activities, and even the sum if it, are highly weather dependent. This implies that the opportunity costs cannot be determined ex ante as they are affected by the weather. We include this finding into our model by assuming that the marginal utility of leisure rises at higher temperatures i.e. $\frac{\partial U}{\partial t} > 0$. One can see from equilibrium condition (3.16) that the MRS increases and the original solution, point $P$ in figure 3.2 is not optimal any longer. However, the point where the individual finds it cheaper to work in the market and replaces work at home by market work is left unchanged. The change in preferences can be interpreted as one towards a time intensive taste, i.e. at higher temperatures, the household prefers to cut back the amount of market work by $L_1 - L_0$ and expands the consumption of leisure by the same distance. At the same time, consumption of goods reduces by $x_0 - x_1$. This must be the case since consumption of goods is inversely related to leisure via the budget constraint. We suppose that this is not necessarily true in the case of leisure goods. At least in the short run, a higher amount of leisure could be positively related to expenditures on leisure goods. Since leisure mostly involves consumption of market goods as well, we believe that a higher amount of it could also be related to a different consumption bundle.

One could however adopt the view of Steedman (2001) and argue that the above theory does not account for the fact that parts of leisure must be devoted to the consumption of goods. In this respect, one has to distinguish between three uses of time: market work, leisure and consumption time, which results in the time constraint

$$N + rx + L \equiv T. \quad (3.17)$$
The budget constraint can again be written as

\[ p \cdot x = V + w \cdot N. \]  

(3.18)

In this setup, Steedman analyzes compensated changes of a rising wage rate \( w \). It turns out that his view adds force to the idea that market work \( N \) decreases as \( w \) rises, since more time must be dedicated to consumption. Note that \( L \) denotes 'pure leisure' i.e. during leisure, no consumption of goods takes place. That one is not allowed to consume during leisure is a strong assumption but points out that one must leave some time for consumption of goods. One might reject this approach as it is no adequate description of reality but it rules out the absurd case where the agents works in order to consume but leaves not time for it. This approach further implies that 'pure leisure' can be consumed without any expenditure. We leave this question open for discussion and conclude by saying that this view is not very appropriate, at least for the description of leisure activities as perceived by the time use survey. These activities are mostly linked to any kind of expenditure.
Chapter 4

Data

The empirical part is based on two types of data: first, Statistics Austria provides data from a time use survey conducted in 2008/2009, published by Ghassemi-Bönisch (2011). From this study we draw average daily time durations of leisure activities, which are established by a year-round investigation. Second, we have access to attendance data of various tourism and recreation facilities in Styria on a daily basis. The primary data is gratefully provided by Joanneum Research for this survey. By blending these two types of data, we are able build a weather based choice model for the recreational behavior in Styria. The aim of the following empirical part is to restate the daily time use of leisure activities as a function of weather. This model allows us to generate short run predictions for the entire province of Styria.

4.1 Secondary Statistics

We briefly discuss the data provided by Statistics Austria and adjust it to be practical for the estimation of the recreational behavior in Styria.\(^1\) We use the data of the time use survey to get an idea about the average time use of leisure activities. In Austria, the magnitude of leisure is estimated to be about 3 hours and 43 minutes on an average day. Of course, the time use survey distinguishes between weekdays and weekends: on Saturday and Sunday, the average Austrian spends about 4 hours and 44 minutes on recreational activities, whereas this amount reduces to 3 hours and 19 minutes on days between Monday and Sunday.

In contrast to the standard approach of microeconomic theory, leisure is not treated as the residual amount between 24 hours and working time. Leisure is considered as ‘real leisure’, which is the time remaining when any kind of work (paid and unpaid) is done.\(^2\) To be precise, in the time use survey there is no time of being idle: total leisure time is the sum of any kind of recreational activity and the sum of all other activities amounts to 24 h. Activities like taking a nap, talking to the child or preparing a meal are excluded from the list of leisure activities and can be found in other classes. Taking a nap or shower are typical activities of the class ‘Personal Care’, while playing with children or preparing a meal are summed up in the classes ‘Household Activities’ or ‘Social Contacts’. Taking a walk for example, as a typical activity of the class ‘Leisure’, consumes exactly 12.4 minutes of an average day, whereas doing the laundry in the class ‘Household Activities’ is done for about 7 minutes per day. A list of all activities and their average time use can be found in the Appendix in table 3, but we illustrate a brief summary of

\(^1\)Participation in this survey is voluntary. Therefore persons older than 10 years were asked to document their daily life in a standardized diary.

\(^2\)In fact, the definition by Statistics Austria follows the narrowest definition of leisure by Aguiar and Hurst (2007), i.e. leisure activities are considered as those that yield direct utility, except child care or work in the garden.
typical leisure activities in table 4.1.3

<table>
<thead>
<tr>
<th>Activity</th>
<th>Time</th>
<th>Examples</th>
<th>Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cultural Activities</td>
<td>3.62</td>
<td>Cinema, Theater, Museum, Concert, . . .</td>
<td>Cultural Activities</td>
</tr>
<tr>
<td>Visitation of Entertainment Events</td>
<td>4.77</td>
<td>Zoo, Disco, Sport Events, Theme Parks, . . .</td>
<td>Cultural Activities</td>
</tr>
<tr>
<td>Walks</td>
<td>1.00</td>
<td>Stroll in the Town</td>
<td>Outdoor Sports</td>
</tr>
<tr>
<td>Running, Hiking</td>
<td>3.53</td>
<td>Mountain Climbing, Nordic Walking, . . .</td>
<td>Outdoor Sports</td>
</tr>
<tr>
<td>Cycling (as sports)</td>
<td>2.30</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gymnastics, Fitness</td>
<td>3.08</td>
<td>incl. Courses e.g. Back Gym</td>
<td>Indoor Sports</td>
</tr>
<tr>
<td>Other Sporting Activities</td>
<td>11.00</td>
<td>Winter-, Water-, Ballgames, Dancing, . . .</td>
<td>Indoor Sports</td>
</tr>
<tr>
<td>Watching TV</td>
<td>120.33</td>
<td></td>
<td>Watching TV</td>
</tr>
</tbody>
</table>

Table 4.1: Selected Parts of the Time Use Survey 08/09. Source: Statistics Austria.

The second column illustrates the average daily time use in minutes.4 We list some examples in the third column to convey an idea about the activity in question. The assignment to own created categories is illustrated in the fourth column and is further discussed in the following section. Of course, all these values differ from men to women, from young adults to retired persons, from unemployed to employed persons and from people living in the city to people living in rural areas. The time use survey distinguishes between all these categories but we will not consider this division here as this is beyond the scope of this text.

How is the average daily time use calculated? As many other time use surveys, Statistics Austria uses two values to calculate the average time per activity: the Participation Rate and the Average Time per Participants (both not illustrated in table 4.1). The participation rate reflects the share of total population that carries out the activity in discussion, whereas the average time per participants is the average time duration. Then, the average for the total population is calculated as the product of the participation rate and the average time per participants. Let’s take for example the activity running/hiking, a part of leisure activities in table 4.1: This activity is performed by only 3.29 % of the population but is relatively time consuming when its done, namely 107.25 minutes per run/hike. Therefore, everyone in the population performs this activity for 3.53 minutes per day. Running/Hiking is done rarely but is quite time intensive, which results in a medium average time. Note that the average time per participant is perfectly compatible to the time intensity or the rate of consumption in chapters 2 and 3; its the average time duration when a certain activity is effectively executed.5

As already mentioned, the survey differentiates whether the activity is done on weekdays or weekends. Therefore, all three indicators are calculated individually for weekdays, (-ends). We take the activity ‘reading books’ to illustrate the computation: this activity has a time intensity of 62 minutes during weekdays and is executed by 7.25 % of the population. Hence we get an average time of 4.5 minutes per day. The calculation is entirely different for weekends. There, reading books requires 77 minutes and is

3The time dedicated to leisure activities is calculated without commuting times. For example, travel time to a concert is included in the sum of leisure activities but is itemized as an extra activity and will not be considered for further calculations.

4The survey distinguishes between activities that are carried out as ‘secondary activities’ and ‘core activities’. During the survey, the participants were asked to document whether the activity was done as a secondary activity besides other activities like eating, having a conversation, etc. or as a core activity, i.e. as the only relevant one. All values presented in table 4.1 represent time values for core activities. For example, watching TV is done for 120 minutes per week as a core activity and for 61 minutes as secondary activity.

5This empirical method adds force to the view that consumption rates are exogenous and cannot be chosen freely. Each activity has its price in terms of time.
done by only 6.89 %, which gives us an average of 5.3 minutes. We conclude that on weekends, reading
books is done by fewer people, whereas those who read dedicate more time to it. These effects do not
balance each other: average reading time rises by 0.8 minutes on weekends. How is the average time
use from Mon – Sun calculated? The average time use comes as a weighted average of the time use on
weekends, (-days). Therefore, average time of reading books is given by \( \frac{3}{7} \cdot 5.3 + \frac{4}{7} \cdot 4.5 = 4.73 \). The
same procedure is done for the participation rate: 7.15% is the weighted average of 7.25% and 6.89%.
Consequently, the time intensity is calculated as the division of the average time use by the participation
rate.

4.1.1 Adjustment and Blend of Leisure Activities

Our goal is to restate the average time use as a function of calendrical factors and weather conditions.
We suppose that the time spent on most of these activities is subject to huge fluctuations. Therefore,
we group the leisure activities itemized by Statistics Austria in five disjoint categories: Watching TV,
Outdoor Sports, Indoor Sports, Culture and Swimming. The main reason for this is that we expect the
activities within one category to exhibit similar weather dependencies.

Cultural activities, for example, is an itemized activity itself. Therefore, it is straightforward to create
an own category from it. For Outdoor Sports, the classification by Statistics Austria does not allow for
such an easy arrangement. Besides the activities walks and running/hiking, we consider the time spent
in theme parks or zoos to be a kind of outdoor sports. Unfortunately, this activity is not itemized by
Statistics Austria but is included in the activity ‘visitation of entertainment events’, which also covers
activities like the visitation of ball, clubs and sports events. The imagination that the visitation of balls,
clubs and sports events exhibits similar reactions to weather conditions like the visitation of a zoo sounds
strange. Therefore, we seek to extract the amount of time dedicated to the visitation of zoo and add it
to the category outdoor sports. Fortunately, the time use survey 2005 from Belgium\textsuperscript{6} provides a reliable
time duration for the visitation of zoos: one minute per day. We accept this value as a rule of thumb
for Austria and deduct one minute from the visitation of entertainment events and add it to the outdoor
sports category. This arrangement is also shown in table 4.1. Since the category outdoor sports consists
of three different activities (running/hiking, walks and theme parks), the time intensity for the category
was calculated as a weighted average of the activity specific time intensities. The visitation of theme
parks consumes on average 164 minutes, walks last for about 75 minutes and running/hiking is done for
about 107 minutes effectively. As weights, we use the popularity of the activity, i.e. the participation
rate which is 0.6 %, 16.5 % and 3.3 %. This results in an average time intensity of 83 minutes.

A similar problem arises in the category swimming. This activity is included in other sporting activities
and is not itemized separately by Statistics Austria, hence we cannot filter out the average time dedicated
to swimming. Again, data from the time use survey of Belgium provides an average value for swimming:
one minute per day. We use data of the attendance of five swimming facilities in Graz to check whether this
value is a reasonable proxy for Styria. By taking the annual attendance sums of some swimming facilities
in Graz from 2005–2012 and relating it to the number of inhabitants, we find that every inhabitant attends a
swimming facility 1.06 times per year.\textsuperscript{7} This is the average from 2005 to 2012, the exact values
can be found in figure 4.1(a). Assuming that one visit consumes 210 minutes, which is a heuristics for
the time intensity, we get an average value of 0.61 minutes per day and inhabitant of Graz. Figure 4.1(b)
shows the development from 2005 to 2012. Given the fact that not all locations for swimming in Graz
\textsuperscript{6}The Head Office of Statistics and Economics of Belgium conducts a survey similar to the Austrian design. Data can be
accessed on http://www.time-use.be

\textsuperscript{7}According to UN data, the inhabitants of Graz from 2005 to 2012 are 240,278 244,604 247,698 250,653 253,994 257,328

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are considered in this sample, let alone the private swimming pools in Graz, we claim that the average time duration of 0.61 is slightly undervalued. Thus we can accept one minute per day as a good rule of thumb for Styria.

Similarly, we found a reasonable proxy for the participation rate and the time intensity of swimming. By building annual sums of five swimming facilities in Graz, we found that on average 715 persons visit a swimming facility per day. This means that every day, 715 persons out of 250,653 inhabitants (2008) attend a swimming facility, which gives us a mean participation rate of 0.3 % and therefore a time intensity of 333 minutes, given the average time use of one minute.

To simplify the empirical work, we substituted the time use for watching TV established by the time use survey by the time use estimated by the teletest of the ORF.\(^8\) The sum of TV consumption as core and secondary activity (120 + 60 minutes) differs slightly from the average time use of teletest which is 166 minutes. Due to this exchange, total leisure enlarges artificially from 223 minutes to 267 minutes on average.\(^9\)

Any other recreational activity that is itemized in the time use survey, for example playing computer games, technical hobbies or reading were assigned to a residual category ‘Unexplained’, as there are no weather dependent observations available for these activities. The arrangement described here is illustrated in table 4.1 as well.

### 4.1.2 The Average Time Allocation

We depict the average time values of the time use survey, blended with the new categories in table 4.2. It is striking that activities of the category culture are very time intensive (more than 2 and half hours) but are carried out by very few people (2 %), which results in a low average time use. Unsurprisingly, watching TV is the most popular leisure activity and is carried out by 64 %, followed by outdoor sports with 20 %.\(^{10}\) Swimming is the least common activity in our arrangement but with 333 minutes, it is the

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\(^8\)To analyze the weather dependency of TV consumption in Styria, we use official data of the so called Teletest. Parts of the data are available on http://mediaresearch.orf.at/fernsehen.htm. This test provides i.a. exact data of the daily time use on television on a daily basis.

\(^9\)The inclusion of TV consumption was made possible by the ORF and enables us to study the weather dependent reaction of about 3/4 of total leisure time.

\(^{10}\)A high participation rate in this case could be caused by the weighted average of the time intensity, which is relatively low.
most time intensive.

<table>
<thead>
<tr>
<th>Category</th>
<th>Average Time</th>
<th>Participation Rate</th>
<th>Average Time per Participants</th>
</tr>
</thead>
<tbody>
<tr>
<td>Culture</td>
<td>3.62</td>
<td>2.28 %</td>
<td>158.96</td>
</tr>
<tr>
<td>Outdoor Sports</td>
<td>16.93</td>
<td>20.41 %</td>
<td>82.94</td>
</tr>
<tr>
<td>Indoor Sports</td>
<td>10.00</td>
<td>5.55 %</td>
<td>127.91</td>
</tr>
<tr>
<td>Watching TV</td>
<td>166.07</td>
<td>63.62 %</td>
<td>261.03</td>
</tr>
<tr>
<td>Swimming</td>
<td>1.00</td>
<td>0.30 %</td>
<td>333.33</td>
</tr>
</tbody>
</table>

*Sum Explained: 197.62 Sum Unexplained: 69.78, Total: 267.40*

Table 4.2: Average Time Use per Category, Mon-Sun

The average daily time use of table 4.2 is illustrated by the pie chart in figure 4.2 and is worth a brief discussion. It is striking that the category TV represents the largest part of recreational activities: 166 minutes, given a total amount of leisure time of 267 minutes. About two thirds of one’s total leisure is spent on watching TV. The large share of TV is followed by the small part of outdoor sports with 6 %, indoor sports with 4 %, cultural activities with 1.4 % and swimming with 0.4 % of total leisure. Compared to TV consumption, all other activities seem to be negligible.11

The average division of daily leisure may itself be astonishing. We suppose that this recreational time allocation is strongly affected by weather conditions and could look entirely different on a Tuesday in June than on a rainy Saturday in November. In section 5.2, we illustrate the empirical framework for the weather dependent change of the daily time use and present the results in section 6.3. We further build a utility model to look for a weather induced changes of this ‘static’ time allocation. The empirical strategy for the utility model is presented in section 5.3.2 and the results are illustrated in section 6.6 where we show a ‘dynamic version’ of figure 4.2. Through the estimation of a utility model, we are able to discuss substitution effects between leisure activities and consider dynamic flows between the categories.

11 An interpretation of Franz Prettenthaler suggests to consider TV consumption as a residual value, maybe because TV is often turned on, although one does not always pay its full attention to it. The fact that watching TV is the only activity that is done at home supports this idea. Recall that the time use for watching TV calculated by Statistics Austria only considers the core activities separately and obtains 120 as core activity and 60 minutes as side activity. These values come with some uncertainty. Therefore, we believe that about 1/3 of TV consumption estimated by the teletest can be thought of as side activity or residual value, not pure leisure.
4.2 Primary Statistics

In this section, we summarize the data gratefully provided by Joanneum Research for this research. We use attendance data on a daily basis of 50 recreational facilities in the region of Styria, mainly swimming facilities, museums, castles, indoor sports facilities, hiking trails, zoos and aerial passenger lines. The data are basically time series data, i.e. every firm in our sample provides data from minimum one year to maximum ten years on a daily basis. In order to analyze the dependency of visitors on weather conditions, we use three important weather parameters for every location in our sample: daily maximum temperature, air pressure and precipitation. In particular, we use E-OBS weather data.\textsuperscript{12}

4.2.1 Data Aggregation

Given the fact that we have plenty of observations of visitors in leisure facilities of different points in time and different locations, we need a mechanism to aggregate the data. It is easy to sum up attendance data on each day of a given year. But two problems arise: first, the data from leisure facilities differ with respect to their time horizon, i.e. for some sites we have ten years but only one year for others. Second, the leisure facilities differ with respect to their locations and weather conditions. At any day, we observe a different number of visitors per leisure facility combined with different temperatures or precipitation. To counter the time horizon problem, we choose one representative year in which the data provision by leisure facilities is reasonably high. The categories cultural activities, indoor and outdoor sports consist of 366 observations of the year 2012. For category swimming, we use the years 2011 and 2012, from May to September, i.e. we have 306 observations. Furthermore, it is important that the number of firms in our sample is constant during the period under observation, i.e. that each facility provides data for a complete year, not only for a fraction.

The analysis of the behavior of visitors in leisure facilities for different weather conditions is tricky since the sum of visitors originate from different locations with different weather conditions which can be fundamentally different across the province. Which weather should be considered most? We resolve this problem by an index for temperature, air pressure and precipitation: for each day, the weather in Styria comes as a weighted average of the weather at the locations where the visitors were observed. The weight of a location constitutes of its relative share in total visitors on a particular day. Therefore, a more frequented place get’s a higher weight in the temperature, precipitation and air pressure index. If, for example, we observe 781 visitors in a swimming facility in Murau, while the total sum of bathers in Styria is 8043, the weather of Murau is weighted by 781/8043. In fact, this approach is not ready for the prognosis of attendance levels, since we do not know the weights in advance. However, it is more appropriate to explain the current behavior of visitors. When a certain place does not experience any visitors, its weight is zero in the sample.\textsuperscript{13}

For watching TV, the variable we use is the time use, which is on average 166 minutes per day for persons above the age of 12. The data we use consist of years 2010–2012, i.e. we use three years to characterize TV consumption. People watch TV in the entire province, but what kind of weather should be considered? Concerning weather conditions, we basically face the same challenge as described above. To resolve this problem, we build a population-weighted average of all weather parameters. We therefore use the population figures for all 539 communities in Styria of the year under consideration to give the

\textsuperscript{12}Consider Haylock et al. (2008). The data are available on http://www.ecad.eu/, free of charge. The main reason for using E-OBS data is that data is available for each arbitrary location in Europe. The easy availability comes with the caveat that the resolution is rather crude.

\textsuperscript{13}The fact that the model is appropriate for an ex post explanation, but not for prognosis was remarked by Franz Pretenthaler.
weather of each community its weight. Hence, the weather index for TV data is a population-weighted average for the entire of Styria and could actually be interpreted as the average weather on a particular day. Since Graz is the biggest community in Styria, the weather of Graz has the greatest influence.

Data of the category outdoor sports contain attendance data of 2 zoos, 2 parks, 4 theme parks, 1 cable car, 1 pit and 2 hiking trails in Styria. Data of the category culture include the attendance data of 13 museums and one monastery. Data of category swimming contain attendance data of 25 swimming facilities (pools and lakes). Data of the category indoor sports contain the visitors of one indoor climbing wall. The graphical investigation of histograms in figure 4.3 suggests that the data is applicable for modeling. However, there are a few outliers in the aggregated visitors in outdoor sports facilities and museums, which are probably caused by special events, e.g. open house, special exhibitions, etc. which are not known from our point of view.

4.2.2 Testing for Normality and Model Choice

In the following, we show histogram plots of the aggregated visitors or the time use on TV and conduct a test for normality. For this purpose, the Shapiro and Wilk (1965) test seems appropriate. It indicates whether the population (not the sample) of a variable can be considered as normally distributed. Investigation of the histograms in figure 4.3 suggests that, with the exception of category indoor sports, the attendance data differ significantly from normal distribution (illustrated by the blue line) and often exhibit positive skewness. This presumption is confirmed by the p-values of the Shapiro-Wilk test in table 4.3. As all p-values are highly significant, we must reject the normality assumption almost with certainty.

<table>
<thead>
<tr>
<th>Category</th>
<th>Culture</th>
<th>Indoor Sports</th>
<th>Outdoor Sports</th>
<th>Watching TV</th>
<th>Swimming</th>
</tr>
</thead>
<tbody>
<tr>
<td>P-Value</td>
<td>0.0000</td>
<td>0.0035</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

Table 4.3: Results of the Shapiro-Wilk Test

Of course, this has implications for our modeling strategy. Since the common OLS model requires a normally distributed response variable to carry out inference on a sample, this model seems inappropriate. One can see from figure 4.3 that our data exhibit two main characteristics. First, we are faced with count data, i.e. our response variable (visitors) take on integer values 0, 1, 2, . . . . Second, the histograms show that high values seem to occur rarely, while we frequently observe low values close to zero. In other words, the density function exhibits positive skewness. A distribution that is characterized by these features is the poisson distribution. Therefore, we choose the poisson regression model - which we will describe in more detail in section 5.3.1 - to estimate dependencies of visitors on weather conditions. Even if the assumption of a poisson distributed response variable is not entirely true for the population, the poisson regression is a model that provides consistent estimates of beta coefficients. However, it is possible that standard errors of beta coefficients are systematically underestimated through the poisson assumption. This problem is called overdispersion and is discussed in section 6.2.2.

4.2.3 Multicollinearity

In table 4.4, we illustrate the correlation coefficients between three weather variables: maximum temperature ($tx$), air pressure ($pp$) and precipitation ($rr$). Note that weather variables of all categories may differ substantially since they originate from various locations and different points in time. All
Figure 4.3: Histograms of Aggregated Visitors

(a) Swimming Facilities

(b) Viewers on Television

(c) Museums

(d) Indoor Sports Facilities

(e) Outdoor Sports Facilities
three variables represent a weighted average of the weather conditions at the various leisure facilities. In the category swimming, we only consider the months May to September. This may explain why the correlation coefficient between tx and pp of swimming differs from all others.

<table>
<thead>
<tr>
<th>Category</th>
<th>Culture</th>
<th>Indoor Sports</th>
<th>Outdoor Sports</th>
<th>Watching TV</th>
<th>Swimming</th>
</tr>
</thead>
<tbody>
<tr>
<td>tx/pp</td>
<td>-0.247</td>
<td>-0.26</td>
<td>-0.224</td>
<td>-0.134</td>
<td>-0.057</td>
</tr>
<tr>
<td>tx/rr</td>
<td>0.107</td>
<td>0.115</td>
<td>0.162</td>
<td>0.048</td>
<td>-0.176</td>
</tr>
<tr>
<td>rr/pp</td>
<td>-0.271</td>
<td>-0.271</td>
<td>-0.311</td>
<td>-0.346</td>
<td>-0.292</td>
</tr>
</tbody>
</table>

Table 4.4: Correlation Among Explanatory Weather Variables

We observe the highest correlation coefficient of -0.346 in the category TV between precipitation and maximum temperature, which is even quite moderate. There is no mutual consensus about a startling value for correlation between explanatory variables but as a rule of thumb, the correlation could be problematic when it exceeds 0.5. Since we do not observe values greater than 0.35 in table 4.4, we suppose that multicollinearity does not constitute any problem in our data.

### 4.2.4 Correlation of Weather and Visitors

As a first step in analyzing the weather dependency of visitors and therefore the recreational behavior, we investigate the correlation of visitors and daily maximum temperature. In figures 4.4 - 4.6, we show scatter plots of visitors or minutes spent on television and the temperature index. The smooth blue line indicates the reaction of visitors on temperature and is calculated as a simple poisson regression of visitors/minutes on tx and tx². This simple regression on temperature points out the typical reaction pattern of visitors and viewers on temperature.

Figure 4.4(a) clearly points out that visitors in swimming facilities increase exponentially as the temperature rises: the leisure good swimming simply offers a higher utility when its consumed at higher temperatures. This results in a correlation coefficient of 0.695. On the contrary, viewers on television depicted in figure 4.4(b) tend to turn off their devices when temperatures rise. This is reflected in a correlation coefficient of -0.544 with the temperature index. In the presence of higher temperatures,
predictable) as one could wish. Therefore, cultural activities are not as weather dependent (and particularly in urban areas, are mainly frequented by tourists, which may not organize their program hardly any influence of it on visitors. This is confirmed by a correlation coefficient of 0.139. Does this -0.718.

Figure 4.6: Scatterplot of Temperature and Visitors in Outdoor Sport Facilities

Figure 4.6: Scatterplot of Temperature and Visitors in Outdoor Sport Facilities

watching TV faces big competitors: outdoor activities, which exhibit a positive correlation coefficient of 0.679, are depicted in figure 4.6. As weather conditions improve, people seem to substitute outdoor for indoor activities: indoor sports activities are negatively correlated with temperature to an extend of -0.718.

The dependency on temperature is not necessarily true for cultural activities: figure 4.5(a) shows hardly any influence of it on visitors. This is confirmed by a correlation coefficient of 0.139. Does this mean that culture is not sensitive to weather at all? Not necessarily, since attendance data of the category culture consist exclusively of visitors in styrian museums, which seem to have a special feature: museums, particularly in urban areas, are mainly frequented by tourists, which may not organize their program with regard to weather conditions. Therefore, cultural activities are not as weather dependent (and predictable) as one could wish.

Outdoor sports and indoor sports seem to act as close substitutes. For a simple reason, outdoor sports activities increase as weather conditions get better: utility of hiking or walking is certainly higher at warm temperatures. Furthermore, we observe an ‘optimal temperature’ for both activities. Since most outdoor
sports activities require a minimum level of physical effort, running or hiking is not very enjoyable at very high temperatures. Therefore, in figure 4.6, we observe a slight reduction of visitors at temperatures beyond 30°C. In contrast, indoor sports activities in figure 4.5(b) exhibit a mirror inverted relationship. As temperatures decline, sportive activities tend to be relocated to sports facilities such as indoor swimming pools or indoor climbing walls. As before, we observe an optimal temperature for indoor sports activities. This could be explained by the fact that commuting to the sports facility may be less comfortable at very bad weather conditions. In section 6.6, we focus on the substitutability of leisure activities. We are able to point out the movements people make from activity A to activity B.

From this brief investigation, we conclude that the data is ready for modeling. At the first glance, visitors in all leisure facilities, except museums, seem to show considerable reactions to weather variables. However, a high correlation between visitors and temperature does not necessarily imply a reliable dependency. In fact, we don’t know whether the dependence arises from different months or actually from a varying temperature. For estimation, we are going to include the day of the week, month, official holiday and school holiday to control for calendrical factors.
Chapter 5

Empirical Strategy and Methods

In the previous section, we presented average daily values for many different time uses. The motivation for what follows is that we believe the above reported daily values to be true on average. But is it plausible that the daily time use does not depend on weather conditions? Surely not. The answer to the question ‘how will I spend my day?’ certainly depends on it. In this chapter we build a framework to show how the attendance data of the recreational sites can be linked to the data of the time use survey. Furthermore, we illustrate the econometric background for the Poisson regression and a random utility model.

5.1 Cobb-Douglas Utility and Weather Dependent Time Use

We start by building a theoretical model for the organization of recreational activities and tie in with the weather dependent utility illustrated in section 2.4: the utility level gained from recreational activities not only arises from the amount consumed, but also depends on the weather conditions at which it is consumed. We are going to use a Cobb-Douglas utility function as it has convenient properties to calculate the exact weather related time use. Although Steedman argued that the concept of utility is critical when we introduce time constraints, we believe that a utility function is useful to represent preferences and their changes, even beyond the time identity. Although one cannot achieve bundles that blow up the time frame, one can assign a utility level. We suppose that time is the fundamental scarce resource for the choice of leisure activities. Therefore, we leave aside the money budget constraint which allows us to ignore the market prices for leisure activities and state demand as a function of the available leisure time $L$. We can think of $L$ as the ‘budget of leisure’ available in Styria, i.e. 223 minutes per day.\footnote{It is not obvious that the daily leisure budget is constant. We expect the time spent working to reduce and leisure to increase in the summertime. How the daily budget of leisure is subject to changes will be analyzed in section 5.2.4.}

We take advantage of a convenient property of the Cobb-Douglas case: if parameters in the exponents sum up to one, they usually represent the income shares spent on the respective commodity. In our framework, this means that the agent spends a share $\alpha$ of his available time on consumption of the first good. This share of time is very likely to depend not only on weather parameters, but also on the calendrical situation like weekend, month, ... We summarize these parameters by a vector $v$, one of which is temperature $t$ and write $\alpha$ as a function of these parameters: $\alpha = \alpha(v)$. We restrict $\alpha$ to values between zero and one for any values of $v$: the time dedicated to any activity is always smaller or equal to the total time available, i.e. $0 \leq \alpha \leq 1$. As before, we assume the first activity to be one that offers a higher utility at higher temperatures which means that $\alpha(v)$ is upward sloping with regard to
temperature, $\frac{\partial \alpha}{\partial t} > 0$.

This model provides a theoretical explanation for the mix of leisure activities illustrated by the pie chart in figure 4.2 and its changes; the coefficient $\alpha \in [0, 1]$ can be interpreted as the share of total time spent on a certain activity. Thus we get a utility based interpretation for a weather dependent version of this pie chart and the willingness to substitute between two activities.

We know that the marginal rate of substitution for the familiar Cobb-Douglas utility function in the two goods case is

$$\text{MRS} = \frac{U'_1}{U'_2} = \frac{\alpha x_2}{(1 - \alpha)x_1}. \quad (5.1)$$

Given the assumption $\frac{\partial \alpha}{\partial t} > 0$, one can see that the utility function has the same properties regarding temperature reactions as discussed in the theoretical section 2.4. The MRS rises as the temperature increases. Let’s now extend the utility function to $M$ different leisure activities. Then, the Cobb-Douglas utility of leisure activities is given by

$$U = \prod_{i=1}^{M} x_i^{\alpha_i(v)}, \quad (5.2)$$

where $\alpha$ is again a function of parameters $v$ and is characterized by the feature $\sum \alpha_i(v) = 1$. Hence, the shares of time dedicated to activity $i$ sum up to one for each value of $v$. As discussed above, we introduce a time budget constraint and leave aside the money expenses of leisure goods. When consumption of one unit of activity $i$ requires $r_i$ units of time, the time constraint can be written as

$$\sum_{i=1}^{M} x_i \cdot r_i = L. \quad (5.3)$$

Utility maximization points out that demand for activity $i$ is a function of available leisure, the time intensity and parameters $v$:

$$x_i^* = \frac{\alpha_i(v) \cdot L}{r_i}. \quad (5.4)$$

Furthermore, the substitutability of two goods $i$ and $j$ is given by

$$\text{MRS}_{i,j} = \frac{\alpha_i(v) \cdot x_j}{\alpha_j(v) \cdot x_i}. \quad (5.5)$$

Suppose that good $i$ is better consumed at high temperatures, i.e. $\alpha'_i(v) > 0$ and good $j$ is one which is better consumed at low temperatures, i.e. $\alpha'_j(v) < 0$. Then, the MRS has the familiar feature of higher values at higher temperatures. This means that one is ready to give up more units of $x_j$ in order to receive one additional unit of $x_i$. In section 6.6, we provide estimates for the share of total leisure $\alpha(v)$ spent on activity $i$ and its sensitivity to weather. A multinomial logit model even allows us to estimate marginal rates of substitution between to leisure activities. Unfortunately, the estimated MRS can only be interpreted in an impractical way. We return to this issue when we describe the multinomial logit model in section 5.3.2.

### 5.2 Empirical Relations

From the review of the time use survey in section 4.1, we know that every inhabitant of Styria of age 10–99 spends certain amounts of time on all kinds of leisure activities.\footnote{Styria had 1,205,514, 1,207,202 and 1,209,466 inhabitants from 2010–2012. The time use survey represents average time use values for the population of Austria of age 10–99. Thus, we deduct the population of age 0–9 to obtain 1,099,464.} Let’s call this amount of time $a_i$,
where $i$ denotes a index for the five categories specified in section 4.1.1. Then, we are able to determine the total amount of time spent on this activity for the entire province: in 2012 for example, the population of Styria spent $1,103,731 \cdot 365.25 \cdot a_i$ minutes on activities of category $i$. Let’s denote this amount of time by $A_i$.

The discussion in chapters 2 and 3 pointed out that the time intensity of activities plays a central role for the allocation of time. Even the demand for leisure activities in equation (5.4) confirms its importance as an implicit ‘price of time’. Then, its appearance in the time use survey shows that $r_i$ is not only valuable for a theoretical discussion, but is relevant in practice. Now we use this coefficient of time to relate the attendance data to quantities of time spent with certain recreational activities.

### 5.2.1 The Observed Share $\delta_i$

We denote the time series of daily visitors during the year $\tau$ of a recreational facility $j$ of category $i$ by the vector $x_{ij\tau} = (\ldots)$. As we are interested in the behavior of visitors on an aggregate level, we pass on the index $j$ and sum up the daily attendance data for all facilities to receive a vector $\sum_j x_{ij\tau} = x_{i\tau}$. This is a vector with maximum length of 366, containing the daily visitors for category $i$ on each position. Furthermore, we denote the annual sum of visitors by $x_{i\tau}$. We know that in a representative year, the total amount of time spent on activities of category $i$ is given by $A_i$. As parts of these activities were observed through the attendance data, we are able to calculate the observed share of total time in each category. We assume implicitly that our (weather based) observations picture a representative part $\delta_i$ of the basic population. Hence, we can illustrate this relation as

$$\delta_i \cdot A_i = x_{i\tau} \cdot r_i. \quad (5.6)$$

The RHS of (5.6) sums up the observed amount of time that is spent in category $i$. As $A_i$ denotes the total amount of time of category $i$, these two values must be related through $\delta_i$.

Now, we are able to do a projection for the behavior of visitors in Styria: whenever we observe $x_i$ visitors in category $i$, we conclude that $x_i/\delta_i$ people engage in a leisure activity of category $i$. But we should be cautious in interpreting this relationship. We only observe a small part of all spare time activities but we have implicitly assumed that each observation in our sample mimics the behavior of the entire population in a suitable way. Of course, this is not entirely correct since our sample may not be representative for Styria and could be biased in many ways, for example with respect to age, sex, income or employment status. In fact, $\delta$ varies from day to day. What we observe is the average annual value, which means that the prediction models incur additional uncertainty. But the point is that, even we are aware of the bias in our sample, we cannot correct for it or even quantify the uncertainty. Table 5.1 illustrates the observed share $\delta$ as well as the values of equation (5.6) for $\tau = 2012$.

It is obvious that the observed share for swimming is surprisingly high. Private swimming pools are a good reason to believe that $\delta$ is overestimated in this case. In other words, this would mean that the average time use of swimming, one minute per day, is underestimated systematically, which would cause a high value for $\delta$. All other values are unsurprisingly low. This means that we have only observed very small parts of total recreational behavior. In spite of these low values, it is critical to do projections and derive conclusions for the whole population, especially because $\delta$ varies from day to day. Nonetheless, we believe that this method constitutes a reasonable approach for a crude analysis. After all, $\delta$ allows at
least to derive any conclusion on an aggregate level. Empirical models could always be improved through a better provision of data.

5.2.2 Variation of Minutes per Day and the Participation Rate

Given the time series of observed visitors \( x_i \) and the parameters like weather, weekday, holiday, month, . . . , we are able to estimate a functional relationship between the daily sum of visitors and its explanatory variables \( v \). Therefore, \( y \) becomes a function of independent variables, \( y(v) \). Then, we can use the coefficient \( \delta \) to project the observed visitors for the entire province. Furthermore, the time intensity \( r_i \) allows to derive the total amount of time spent with activities of category \( i \). Let \( M_i \) denote the total time use in Styria spent on category \( i \) in minutes, this relation can be written as

\[
M_i = \frac{y_i(v)}{\delta_i} \cdot r_i. \tag{5.7}
\]

Now we arrived at the aggregate relation between the recreational time use and its explanatory variables \( v \). Note that the dependent variable \( M_i \) is driven by a weighted average of temperature, air pressure and rain. Thus, the estimation is based on heterogeneous weather conditions across Styria.

In order to get a weather dependent estimation of the daily time use \( a_i \), we divide \( M_i \) by the inhabitants of Styria of age 10–99 in the year 2012 to obtain

\[
m_i = \frac{M_i}{1,103,731}. \tag{5.8}
\]

A main advantage of this approach is that this value can be interpreted in the same way as \( a_i \): a representative person spends \( m_i \) minutes per day on activities of category \( i \). The extension we have made is that \( m_i \) is a function of variables \( v \) and is close to \( a_i \) only in the long run or at ‘average weather conditions’.

The interested reader will notice that we ignored the participation rate in the previous analysis. But if we leave the time intensity \( r \) constant and seek to obtain a change in the average daily minutes, the participation rate implicitly changes too. Recall that the participation rate is defined as the share of total population that carries out a certain activity. We can do a simple computation to let the participation rate float according to weather conditions: as \( y_i/\delta_i \) denotes the projected visitors in every category, we obtain the participation rate via

\[
k_i = \frac{y_i}{\delta_i \cdot 1,103,731}. \tag{5.9}
\]

Illustrations of the participation rate are useful to get an idea of how popular certain recreational activities are. Since minutes per day do not offer information about how widespread certain activities are done, we include the participation rate in our analysis. Of course, on could opt for the converse case in which...
the participation rate is fixed but the time intensity changes. This would leave the result for the minutes per day unchanged. But we decide to leave the time intensity fixed, as the imagination that one could choose the time intensity arbitrarily is a bit strange, having in mind that time intensities can basically be interpreted as exogenous values or prices of time.

5.2.3 Composition of Leisure Activities

A static analysis of the time split was already provided in figure 4.2. Now, we are interested in the weather dependency of this timing. How does the time division of time, illustrated in the pie chart in figure 4.2, change with regard to weather conditions? Speaking differently, what will be the shifts between the different categories, i.e. how many people are, respectively how much time is expected to move from activity 1 to activity 2 when we observe a marginal temperature increase?

In chapter 4, we consider total leisure as the sum of all activities, i.e. \( \sum a_i = 267 \) minutes and denote the share of any category by \( a_i/267 \). We could use the estimation of daily minutes \( m_i \) and denote the daily minutes as a share of total leisure: \( m_i/267 \). But this could lead to formal difficulties, since the shares may not always sum up to one at certain weather conditions. We could also express the share of leisure spent in one category as \( m_i/\sum m_i \) to solve the formal difficulty. However, we think it is even more adequate to interpret the share of total leisure as the probability that one engages in the respective activity. Imagine that the population of Styria chooses among 5 different leisure activities every day. We are convinced that this decision is strongly affected by weather conditions since the utility gained from the activities differs among temperature levels. We now build the framework to estimate a probability model and discuss the adjustments of our data.

Recall that \( x_{i\tau} = (\ldots) \) denotes a vector of aggregated visitors during the year \( \tau \) in category \( i \). Before we can use these observations for a probability model, we have to make some adjustments of our sample. The observed share \( \delta \) allows us to project the time series of visitors in this category for the entire of Styria: \( \tilde{x}_{i\tau} = x_{i\tau}/\delta_{i\tau} \). Now, we suppose to know how many people engage in activity \( i \) on a specific day. We denote by \( N \) the sum of all people that engage in any of our 5 activities, \( N = \sum_i \tilde{x}_{i\tau} \). Then, the share of the population in Styria that goes for activity \( i \) is \( P_i = \tilde{x}_{i\tau}/N \). Of course, \( N \) is not the true population of Styria but the sum of all people that undertake any leisure activity, which varies from day to day. However, it is best to think of \( N \) as the total demand for leisure activities in Styria. We are going to estimate the probability \( P_i \) as a function of \( \nu \), where this choice is probabilistic from our point of view. Probabilities \( P_i \) therefore explain how the ‘leisure budget’ \( L \) divides and have the convenient property that they always sum up to one.

We provide a brief illustration of the econometric background for the MNL in section 5.3.2. Note that the probability model implicitly assumes that total leisure \( L \) is constant, although \( N \) varies from day to day. However, we tie in with the theoretical discussion on the weather dependent leisure/work decision in the next section. As suggested in the theoretical section 3.2, the decision on the amount of leisure could depend on weather conditions, at least in the short run.

Since multinomial logit models require a large sample size, we need more than one year for the estimation and therefore calculate \( \delta_{i\tau} \) for all categories, except TV consumption, and four years separately. The values are shown in table 5.2. These values reflect the availability of data which differs substantially throughout the years.

Except for the category indoor sports, the availability of data significantly drops in the year 2009, whereas in 2012 we observe the highest coefficient in all categories. For indoor sports we only have one leisure facility in our sample. The exact number of recreational sites in the sample are depicted in table 5.3. We only use months from May to Sep, since there is no data available for swimming from Oct to
Table 5.2: Deltas Used for the MNL Model

<table>
<thead>
<tr>
<th>Category</th>
<th>Culture</th>
<th>Indoor Sports</th>
<th>Outdoor Sports</th>
<th>Swimming</th>
</tr>
</thead>
<tbody>
<tr>
<td>2009</td>
<td>0.006061844</td>
<td>0.002315476</td>
<td>0.006438437</td>
<td>0.3732674</td>
</tr>
<tr>
<td>2010</td>
<td>0.02947664</td>
<td>0.002131806</td>
<td>0.01124142</td>
<td>0.4592614</td>
</tr>
<tr>
<td>2011</td>
<td>0.02197509</td>
<td>0.00194733</td>
<td>0.01165178</td>
<td>0.5547883</td>
</tr>
<tr>
<td>2012</td>
<td>0.03003246</td>
<td>0.002157514</td>
<td>0.01962547</td>
<td>0.57185</td>
</tr>
</tbody>
</table>

Table 5.3: Number of Leisure Facilities Used for Estimation of MNL

<table>
<thead>
<tr>
<th></th>
<th>2009</th>
<th>2010</th>
<th>2011</th>
<th>2012</th>
</tr>
</thead>
<tbody>
<tr>
<td>Culture</td>
<td>3</td>
<td>10</td>
<td>11</td>
<td>14</td>
</tr>
<tr>
<td>Outdoor Sports</td>
<td>2</td>
<td>5</td>
<td>5</td>
<td>13</td>
</tr>
<tr>
<td>Swimming</td>
<td>17</td>
<td>22</td>
<td>25</td>
<td>25</td>
</tr>
</tbody>
</table>

5.2.4 The Sum of Leisure Activities

Each bundle of leisure activities needs time inputs to be ready for consumption. We now analyze the reaction of the time input not only for a single activity but for the whole bundle of activities. In terms of the theory for time allocation, we are looking for change in \( \sum_i Z_i \cdot r_i \). The sum of \( a_i \) denotes virtually the average time input for leisure activities, respectively total leisure itself. The weather related time input or ‘daily total leisure’ can be denoted by \( \hat{L} = \sum m_i \). This is the sum of daily leisure activities as function of weather and calendrical factors. As all single leisure activities like swimming, hiking or watching TV react on weather conditions, the sum of all these activities should be weather sensitive too. This means that \( \hat{L} \) is a function of \( v \). Recall that some spare time activities may act as substitutes, thus we are interested in whether the decrease in one activity is balanced by an increase in another or which kind of weather causes the total leisure to reach its maximum. Note that we have to be cautious by interpreting this amount as ‘total leisure’ since we only observed 3/4 of all activities. Hence, it is better to think of this amount as ‘time inputs’ for activity consumption.

We are not able to observe all kinds of leisure activities. In other words, we are able to observe the weather dependency of \( M - 1 \) out of \( M \) categories, whereas the last one is completely unobserved. More precisely, we have estimates for \( m_i \) out of five categories, but not for the category ‘unexplained’. Of course, we know the average value \( \omega = 69.8 \) of this category, but we cannot observe any weather dependency of this time use. Although we have no problem in analyzing the behavior of the other categories, it could be hard to determine the total sum of leisure activities when one category is unexplained. In order to get estimates for the total leisure time \( L \), two options remain.

First, we could assume that the time use of the unobserved category, \( \omega \), is constant for all weather conditions. This is certainly not true but this approach has the advantage that total leisure \( \hat{L} \) reacts as a function of \( v \). Second, we could assume that daily total leisure \( L \) is constant for each day and the unobserved category varies as a residual. Therefore, we obtain a weather dependent behavior of this category via \( \omega(v) = L - \sum m_i \), which is weather sensitive following the inverse of all other categories. Both approaches have their benefits and drawbacks. The first one provides an idea about the behavior of total

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leisure, whereas the second one is attractive as we observe the weather dependence of the unexplained recreational activities. Note that the second approach could lead to a formal inconvenience: at certain temperatures we might observe negative values of \( \omega \) because the sum of the observed categories might be greater than \( L \), which is virtually impossible. But even this can be interpreted as a consequence of a certain weather dependence: negative time values can be seen as a postponement of the unobserved activities, i.e. they are better done at other temperatures.\(^4\) We will consider both of them and depict the results in section 6.5.

5.2.5 Market Goods as Inputs for Leisure Activities

The theory on time allocation pointed out that leisure activities do not only require time as inputs, but also market goods. Consider \( Z \) as a bundle of leisure activities that is consumed. Then, the money needed in order to consume is \( \sum_i M_i \cdot Z_i \cdot b_i \cdot p_i \). Suppose that each visitor in category \( i \) spends an amount of \( p_i \) for access to the leisure site, i.e. that \( b_i = 1 \). Then, given the fact that we can estimate the number of visitors per category, we can illustrate the total expenditures per category by

\[
E_i = \frac{y_i(v) \cdot b_i \cdot p_i}{\delta_i}.
\]

Hence, the expenditures for leisure activities follow the variables \( v \). Of course, we are able to build the total expenditures on leisure activities of all categories, \( E = \sum E_i \), which is a function of variables \( v \). This relation gives rise to further questions. For example, can we think of weather conditions, months or days that maximize (minimize) the total expenditures for leisure activities or can we expect \( E \) to be constant? Which substitution effects between activities would occur?

Furthermore, we could estimate the elasticity with respect to temperature. The expenditures would react according to

\[
\frac{\Delta E_i}{E_i} \cdot \frac{t}{t} = \frac{\partial E_i}{\partial t} \cdot \frac{t}{E_i}
\]

(5.11)
to a one percent increase in temperature. Simplification yields

\[
\frac{\partial y_i}{\partial t} \cdot \frac{t}{y_i},
\]

(5.12)

which is nothing else but the percentage reaction of visitors on temperature. We can sum up equation (5.12) to get the reactions of total expenditure \( E \). In fact, problems could arise with respect to elasticities. Since temperature is ordinal, reactions in terms of percentage are problematic, but for theoretical purposes the discussion is fine. When we consider more than one activity, elasticity of expenditure with respect to temperature could be interpreted in the following way: a one percent increase of temperature could result in a 5% reduction of expenditures on cultural activities but raise the expenditures for outdoor sports activities by only 3%. Similar to the reactions of the time input, the total expenditures are determined by the interplay of many activities. Total budget for leisure activities should approximately change by the sum of all single effects.

Having observed the attendance of many leisure facilities in Styria, we could assume \( p_i \) to be the cost per leisure activity \( i \). Unfortunately, we have no data for market prices \( p_i \). To get a rough proxy of expenditures, one could use a weighted average of admission fees. Given that any recreational site charges a fee for entry of \( p_j \), the average cost per category could be estimated by \( \sum p_j \cdot g_j \), where \( g_j \) denotes the weight of the site \( j \) in our sample. We will not implement this strategy but leave the question

\(^4\)This interpretation was given by Franz Prettenthaler.
of monetary inputs open to future research.

5.3 Methods

In this section we illustrate the econometric background that enables the analysis of weather dependent time use. We employ a Poisson regression to estimate the weather dependence of visitors and therefore the weather induced change of \(a_t\). Furthermore, we use a multinomial logit model to consider the weather related changes of the mix of leisure activities. The multinomial logit model further points out the substitution effects between certain activities.

5.3.1 Poisson Regression

In order to model a relationship between the total sum of visitors in one category \(y_i\) and its influence factors \(v_i\) we apply a Poisson regression model. This type of regression model belongs to the family of the Generalized Linear Models, (GLM) (see e.g. Nelder and Wedderburn (1972)) which is characterized by the feature that the response variable \(y\) differs from the normal distribution. In our case, the response is a count variable which only takes on integer values and high values can be thought of as relatively rare events whereas low values occur frequently. We are interested in modeling the relationship between the observed number of visitors and useful predictor variables such as weather. In our illustration, we closely follow the chapters on the Poisson regression in Myers et al. (2010) and Wooldridge (2008).

In our situation, the number of visitors \(y_i\) can be modeled by a Poisson distribution in a reasonable way which is given by

\[
f(y_i) = \frac{e^{-\mu_i} \mu_i^{y_i}}{y_i!}, \quad y_i = 0, 1, 2, \ldots \quad (5.13)
\]

Recall that the Poisson distribution is characterized by a single parameter \(\mu\), which represents the mean and the variance. Hence for a Poisson distributed variable one can show that

\[
E(y) = \mu, \quad Var(y) = \mu. \quad (5.14)
\]

We will figure out later that this is a quite restrictive assumption which is often violated in the empirical practice.\(^5\) In a Poisson regression model (as in any other GLM), the mean \(\mu\) of the response variable \(y\) is related to its predictor variables \(x_i\) via a link function \(g(.)\). When \(\eta\) denotes the linear predictor, we can write the relation as

\[
g(\mu_i) = \eta_i = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k = x'_i \beta. \quad (5.15)
\]

By inverting this relationship, we find that the mean of the response variable is related to its linear predictor via

\[
\mu_i = g^{-1}(\eta_i) = g^{-1}(x'_i \beta). \quad (5.16)
\]

The classical linear model assumes that the response variable can be modeled by a normal distribution, renounces the link function and therefore uses the identity link \(g(\mu_i) = \mu_i = x'_i \beta\). With this link function, \(E(y_i) = \mu_i = x'_i \beta\). For the Poisson regression model, we decide to use the popular log link. We therefore assume that the logarithm of the mean is given by the linear predictor:

\[
g(\mu_i) = ln(\mu_i) = x'_i \beta. \quad (5.17)
\]

\(^5\)This problem is known as over-, underdispersion and is briefly discussed in section 6.2.2.
As the mean of the response variable is given by the inverse of the link function, the relationship for the log link is

$$
\mu_i = g^{-1}(x_i'\beta) = e^{x_i'\beta}.
$$

(5.18)

The usage of the log link for Poisson regression models is especially attractive as it ensures that the predicted values will be nonnegative. To estimate the parameters $\beta$, the method of maximum likelihood is used. We receive predicted values for our sample data via

$$
\hat{y}_i = g^{-1}(x_i'\beta) = e^{x_i'\beta}.
$$

(5.19)

### 5.3.2 A Random Utility Model: Multinomial Logit

What will happen to the share of available leisure dedicated to watching TV as temperatures increase? Put differently, what will be the probability of visiting a swimming facility on a particular day? To answer these questions, we employ a Multinomial Logit model (MNL). This type of model is an extension to the standard binomial logit model and enables us to predict probabilities for the choices of $n > 2$ nominal distinctive outcomes. We closely follow Croissant (2012), Wooldridge (2001) and Long (1997) for brief illustration of the formal model structure.

A common application of the MNL is the choice of transportation modes.\(^6\) The probability that a certain outcome occurs is $P(y = k) \in [0, 1]$ and is supposed to be a function of explanatory variables $x$, where these variables may be individual- or alternative specific. The individual specific variables can be attributed to individuals, e.g. age or income. The alternative specific ones can be assigned to the choice that is made, e.g. travel time or cost of transportation modes. Furthermore, alternative specific variables may have generic or alternative specific coefficients. This distinction can be illustrated for the variables travel costs and travel time at different transportation modes. For example, one additional minute of travel time in car may affect the utility differently than one additional minute in train. Hence, the variable travel time can be assigned an alternative specific coefficient. However, one additional euro should affect the utility equally, whatever it is spent in car or public transport. Therefore, we can assign the alternative specific variable money a generic coefficient. The data presented in chapter 4 only allow for the existence of alternative specific variables with alternative specific coefficients, since weather or calendrical variables should affect the utility of swimming or watching TV differently.

Suppose that the satisfaction level for individual $i$ derived from the choice of option $j$ from $J$ different and exclusive alternatives can be denoted by

$$
V_{ij} = \alpha_j + \beta x_{ij} + \gamma_j z_i + \delta_j w_{ij}.
$$

(5.20)

The coefficient $\alpha_j$ represents the intercept assigned to alternative $j$. Furthermore, utility in (5.20) is a linear combination of all three kinds of variables:

- alternative specific variables $x_{ij}$ with a generic coefficient $\beta$,
- individual specific variables $z_i$ with an alternative specific coefficient $\gamma_j$,
- alternative specific variables $w_{ij}$ with an alternative specific coefficient $\delta_j$.

Models with only alternative specific variables are usually called the conditional logit model, whereas models with only individual specific variables are sometimes referred to as the multinomial logit model.

\(^6\)This is the classic example analyzed by McFadden (1974). He estimates the probabilities that individuals choose certain travel modes for commuting.
In fact, the conditional logit turns out to be a special case of the model stated in (5.20). For notational simplicity, we will now omit the individual specific index $i$ and denote the utility level from choice of alternative $j$ by

$$U_j = V_j + \epsilon_j,$$  

(5.21)

where $\epsilon_j$ represents an unobserved component. From the researcher’s point of view, this component can be considered as an error term. It is important to understand that the utility and therefore the choice is purely deterministic from the decision maker’s point of view.\(^7\) As some variables are unobserved, the choice can be analyzed in terms of probabilities. (Croissant, 2012, p. 10) We consider utility to be ordinal, hence we only take care of differences in utility. Alternative $l$ will be chosen if and only if $\forall j \neq l, U_l > U_j$. Therefore, the difference in utilities can be denoted by

$$U_l - U_j = (V_l - V_j) + (\epsilon_l - \epsilon_j) > 0,$$  

(5.22)

$$\epsilon_j < (V_l - V_j) + \epsilon_l.$$  

(5.23)

The probability that alternative $l$ is preferred to any alternative $j$ can be computed as

$$P(\epsilon_j < V_l - V_j + \epsilon_l) = e^{-e^{-(V_l - V_j + \epsilon_l)}}.$$  

It follows that the conditional probability that alternative $l$ is chosen, i.e. preferred to all alternatives $j$, is given by the product

$$P(y = l|\epsilon) = \prod_{j \neq l} e^{-e^{-(V_l - V_j + \epsilon_l)}}.$$  

(5.24)

The expected value of (5.24) with respect to $\epsilon_l$ yields the unconditional probability that $l$ is chosen:

$$P(y = l|x) = \frac{e^{V_l}}{\sum_j e^{V_j}}.$$  

(5.25)

The model as stated above has the convenient property that probabilities sum up to one but is unidentified since more than one set of parameters could generate the same probabilities of the observed outcomes.\(^8\) This issue can be resolved by the definition a ‘base category’. When we define the first category as the base outcome, we set $\beta_1 = 0$. Then, for $J$ choices, we get $J - 1$ coefficients which can be interpreted as the relative changes to the base category.

Interpretation of the coefficients is difficult for the multinomial logit model. For $J$ outcomes and $K$ variables, one obtains $(J - 1)K$ coefficients, only from comparison with the base category. When we denote all explanatory variables and their coefficients by $x\beta_j$, we can put the probabilities as odds ratios (= relative risk ratios) equal to

$$\frac{P(y = l|x)}{P(y = k|x)} = \frac{exp(\beta_l x)}{exp(\beta_k x)} = e^{(\beta_l - \beta_k) x}.$$  

(5.26)

The difference $(\beta_l - \beta_k)$ is called contrast and is the effect of $x$ on the logit of outcome $l$ versus outcome $k$. Comparison with outcome 1 simplifies to

$$\frac{P(y = k|x)}{P(y = 1|x)} = e^{\beta_k x},$$  

(5.27)

\(^7\)This is because in the original model (5.20), $V_j$ is simply a linear function of explanatory variables.

\(^8\)(Long, 1997, p. 153) provides a more detailed discussion on this issue.
because $\beta_1$ equals zero. We can therefore interpret $\beta_k$ as the factor by which the odds ratio of outcome $k$ versus outcome 1 changes when $x$ increases by one unit. We will investigate the odds ratios in section 6.6, to point out which activities compete. Furthermore, since we have considered the multinomial model as a utility model, $\beta$ coefficients can be interpreted as marginal utilities with respect to alternative/individual specific variables. This means that the change of an alternative specific variable increases the utility of choice $j$ by $\beta_j$. But utility is ordinal, therefore marginal utilities cannot be interpreted in a reasonable way. However, the ratio of marginal utilities can be interpreted as marginal rates of substitution between explanatory variables. Interpretation of the MRS would give the Cobb-Douglas model in section 5.1 its meaning. If, for example, $\beta_2$ denotes the marginal utility of rain, $\beta_1$ the marginal utility of temperature and $\frac{\beta_1}{\beta_2} = 10$, then, one additional degree of temperature has to be compensated by 10 mm of rain, given that the utility $V$ of choice $j$ is constant. This interpretation is not very useful for our analysis. The case of transport modes is easier, since the MRS could be interpreted as the money one is willing to give up to reduce travel time by one minute. (Croissant, 2012, p. 19)

McFadden (1974) shows that this model relies on three hypothesis. It is assumed that the error terms $\epsilon$ are identically, independently distributed following a Gumbel distribution. From the hypothesis of independence of error terms, the assumption of Independence from Irrelevant Alternatives (IIA) follows. One can see from (5.25) that the relative probabilities $\frac{p_l}{p_k}$ only depend on $V_l$ and $V_k$, which means that the odds ratio of two outcomes is independent of any other alternative. This assumption may be violated in practice if some important variables are unobserved. Consider the following example. The utilities from two alternatives are

$$
U_{i1} = \alpha_1 + \beta_1 z_i + \gamma x_{i1} + \epsilon_{i1}, \\
U_{i2} = \alpha_2 + \beta_2 z_i + \gamma x_{i2} + \epsilon_{i2}.
$$

We implicitly assumed that $\epsilon_{i1}$ and $\epsilon_{i2}$ are uncorrelated. Suppose now the individual specific variable $z$ is unobserved. The utility level is now

$$
U_{i1} = \alpha_1 + \gamma x_{i1} + \eta_{i1} \quad \text{with} \quad \eta_{i1} = \beta_1 z_i + \epsilon_{i1}, \\
U_{i2} = \alpha_2 + \gamma x_{i2} + \eta_{i1} \quad \text{with} \quad \eta_{i2} = \beta_2 z_i + \epsilon_{i2}.
$$

(5.28)

It follows from (5.28) that the error terms are now correlated because of the common influence of $z$. In our model, the choices, i.e. the leisure activities, could share certain characteristics which are unobserved from our point of view.

**Goodness of Fit.** For models of choice behavior with categorical or limited dependent variables, the computation of goodness of fit measures is not as straightforward as in the linear model. We will rely on two measures for evaluating the estimated model: the percentage correctly predicted, discussed in Wooldridge, (2008, p. 536) and Long, (1997, p. 107) and the McFadden pseudo $R$-squared presented in McFadden (1977). The percentage correctly predicted is calculated as

$$
R_{\text{Count}} = \frac{1}{N} \sum_{ij} n_{ij},
$$

where the $n_{ij}$'s are the number of correct predictions for outcome $j$ and $N$ is the number of total observations. According to (Wooldridge, 2008, p. 536), this measure is useful but its possible to get high values for the percentage correctly predicted without the model being of much use. The second measure
is proposed by McFadden (1977), sometimes called the ‘likelihood ratio index’ and is constructed as

$$R^2_{McF} = 1 - \frac{L}{L_0},$$

where $L$ denotes the log likelihood for the estimated model at convergence and $L_0$ the log likelihood for a simple constant shares model (with an intercept only). The log likelihood $L$ is defined as

$$L = \sum_{n=1}^{N} \sum_{j=1}^{J} s_{nj} \ln p(y_n = j),$$

where $s_{nj}$ is equal to 1 if individual $n$ chooses alternative $j$ and zero otherwise. $L_0$ is computed as

$$L_0 = \sum_{n=1}^{N} \sum_{j=1}^{J} s_{nj} ln Q_j,$$

where $Q_j$ is the sample aggregate share of alternative $j$. Some authors suggest to adjust this measure for the positive effect on $L$ if new variables are added to the model by subtracting the degrees of freedom in the numerator.

A likelihood ratio test compares the values of the log likelihood function of the unrestricted model and an restricted model (where some variables are dropped). According to Wooldridge, (2008, p. 535), the value of the log-likelihood cannot decrease when additional values are added to the model, therefore the test statistics

$$LR = 2(L_{ur} - L_{re})$$

is strictly positive and follows a chi square distribution. If $LR$ is significantly high, the variables dropped have explanatory power.
Chapter 6

Results

We begin by a brief investigation of the ‘market for leisure’ in Styria on a macro level: how much leisure is available in total and is ready be filled with activities? We proceed by analyzing the time split between weekends and weekdays and show that the attendance data seem to confirm the results of the time use survey. In sections 6.3 and 6.4, we arrive at the core of our work and illustrate the daily time use as a function of weather. Section 6.5 points out that the total amount of leisure we consume every day is strongly weather related. This chapter concludes with the results of the random utility model and illustrates the weather dependent variation of $\alpha(v)$.

6.1 Demand for Leisure in Styria

Before we look at the weather sensitivity of leisure activities, we briefly specify the total amount of leisure that is available in the entire province. We think that this amount of time can also be considered as the ‘demand for leisure activities’, since time is the raw material for recreational activities. Given that every inhabitant has about 223 minutes at his disposal, we find that in 2012, where Styria had 1,209,466 inhabitants, total leisure amounts to about 270 million minutes per day in the entire province. Of course, not only inhabitants spend their leisure in Styria. We must also consider the demand for leisure that comes from outside, i.e. the tourists that spend recreational time here. Assuming that tourists visit Styria only for recreational purposes, we conclude that tourists have 802 minutes of leisure per day at their disposal and decide upon how to spend it.¹ The number of tourists (overnight stays from non-styrians) fluctuates from month to month. Whereas in August 2012, Statistics Austria registered on average 41,248 stays per day - which is the maximum - we find the smallest number of stays in November: 12,532.² By the use of 802 minutes, we find that about 20 million minutes of leisure demand per day comes from abroad, every day. This amount adds to the amount of time that is involved by inhabitants. In figure 6.1, we show how the total amount varies throughout the year.

¹We use a specific leisure profile for tourists and assume that apart from activities like eating, sleeping, . . . , tourists spend the rest of the day on leisure activities, i.e. we deduct 638 minutes per day spent on activities of personal care of 1440 minutes to arrive at 802 minutes of leisure.
tourism sector into the proceeding analysis, i.e. we assume that all observations made originate from the styrian population of years 10–99. On the other hand, leisure of styrian inhabitants is sometimes spent abroad. Since this amount is probably included in the average value of 223 minutes, it is not perfectly correct to analyze its division by a sample taken in Styria. Nonetheless, one could argue that the effects of imports and exports of leisure balance each other. Though our theoretical concept it not spotlessly clean, we believe that this approach is legitimate for a good rule-of-thumb analysis.

6.2 Time Allocation on Weekends

At the beginning, we are interested in differences of the time use between Monday/Friday and Saturday/Sunday and the composition of recreational activities. First of all, we observe an increase in the total amount of leisure on weekends: whereas we only enjoy 199 minutes of leisure during weekdays, this sum increases by nearly one and half hour to 284 minutes on Saturday or Sunday.\(^3\) Recall that this is the net sum of leisure activities, that is, net of any housework, naps or talks to friends etc. This means that any minute of total leisure can be assigned to any activity. In table 6.1 we show the data provided by Statistics Austria, blended with our categories. Note that for the category Swimming, we only have an average value of 1 minute per day, but we do not know how this one minute behaves on Weekends and Weekdays. For this purpose, we apply a Poisson regression to estimate the division of one minute of swimming to into a weekend and weekday specific time use. We will do the same for all other categories to check whether the primary data and our model mimic the results of the time use survey of Statistics Austria.\(^4\)

\(^3\)Recall that we have substituted the time use for watching TV by the ORF data. Therefore, the sum of all activities during weekdays and weekends amounts to 245 and 329 minutes. The participation rate is calculated as the share of TV population that watches TV for at least 60 seconds per day, i.e. the average viewing rate. The average time per participant is then calculated as the time use on TV divided by the participation rate. This is done for weekends and weekdays separately.

\(^4\)Note that for the category Swimming, we assume that the participation rate on weekends (and weekdays) is equal to the average participation rate of 0.3 % but the time intensity varies. Of course, one can opt for the other way, without considerable changes.
### Table 6.1: Average Time Use per Category, Mon–Fri

<table>
<thead>
<tr>
<th>Category</th>
<th>Average Time</th>
<th>Participation Rate</th>
<th>Average Time per Participants</th>
</tr>
</thead>
<tbody>
<tr>
<td>Culture</td>
<td>2.57</td>
<td>1.73 %</td>
<td>148</td>
</tr>
<tr>
<td>Outdoor Sports</td>
<td>13.09</td>
<td>16.3 %</td>
<td>80</td>
</tr>
<tr>
<td>Indoor Sports</td>
<td>9.79</td>
<td>7.42 %</td>
<td>132</td>
</tr>
<tr>
<td>Watching TV</td>
<td>157.01</td>
<td>63.20 %</td>
<td>248</td>
</tr>
<tr>
<td>Swimming</td>
<td>0.91</td>
<td>0.30 %</td>
<td>304</td>
</tr>
<tr>
<td><strong>Sum Explained</strong></td>
<td><strong>183.37</strong></td>
<td></td>
<td><strong>61.93</strong></td>
</tr>
</tbody>
</table>

### Table 6.2: Average Time Use per Category, Sat–Sun

<table>
<thead>
<tr>
<th>Category</th>
<th>Average Time</th>
<th>Participation Rate</th>
<th>Average Time per Participants</th>
</tr>
</thead>
<tbody>
<tr>
<td>Culture</td>
<td>6.27</td>
<td>3.64 %</td>
<td>172</td>
</tr>
<tr>
<td>Outdoor Sports</td>
<td>26.53</td>
<td>24.02 %</td>
<td>110</td>
</tr>
<tr>
<td>Indoor Sports</td>
<td>14.02</td>
<td>8.82 %</td>
<td>159</td>
</tr>
<tr>
<td>Watching TV</td>
<td>188.64</td>
<td>64.66 %</td>
<td>292</td>
</tr>
<tr>
<td>Swimming</td>
<td>1.22</td>
<td>0.30 %</td>
<td>407</td>
</tr>
<tr>
<td><strong>Sum Explained</strong></td>
<td><strong>236.68</strong></td>
<td></td>
<td><strong>92.91</strong></td>
</tr>
</tbody>
</table>

Similarly, the same is true for the participation rate and the time per participant. The time per participant for cultural activities for example increases from 148 to 172 minutes on weekends and the participation rate more than doubles. The absolute time for TV consumption increases but is under proportional: on weekends, the share of time dedicated to watching TV decreases slightly. As both, the participation rate and the time use per participant increases for indoor sports, the average time use increases from 9.8 to 14 minutes. For better illustration we plot the time use depicted in tables 6.1 and 6.2 in figure 6.2. As already mentioned, on weekends all leisure activities increase with respect to their absolute numbers. But one can see from figure 6.2 that the variation of the share is not as straight forward. The share of TV consumption declines slightly and allows for an increase in other activities, mainly cultural activities.
and outdoor sports. While the share of indoor sports and swimming is approximately constant, it follows from figure 6.2 that on weekends, people dedicate a higher share of their leisure to cultural activities and outdoor sports.

Recall that we used the framework of Steedman in section 2.2 to argue that when more time is available, individuals tend to enlarge the share of activities that are relatively time consuming. Unfortunately, this idea does not seem to be supported by the observations made here. The share of TV consumption declines, even it is relatively time intensive. The share of outdoor sports increases, although it is the least time intensive. However, we do not have any observations with regard to their goods intensity, hence we only observe parts of the requirements that are needed to check the theory. The same is actually true for time shares in the pie chart. This is only an extract of total leisure, shifts of the time shares are therefore difficult to observe at all.

6.2.1 Estimation of the Time Split

In order to calculate the time use for swimming on weekends and weekdays, we estimate the model

$$y = we + pp + tx + rr + month + \epsilon \quad (6.1)$$

via a Poisson regression, where $we$ denotes a dummy variable for weekend, $pp$ for air pressure, $tx$ for daily maximum temperature, $rr$ is precipitation in liters per hour and $month$ is a factor variable for month.\(^5\) The dependent variable $y$ denotes the aggregated visitors per category. In fact, we are fitting a visitor forecast model using seasonal or calendrical effects as predictors and controls for weather variables. We choose a log link function, i.e. exponentiated coefficients represent factor changes for one unit increases of the predictor variables. In other words, the beta coefficients can approximately be interpreted as percentage changes. In table 6.3, we illustrate the beta coefficients with standard errors in brackets, goodness of fit and the number of observations.\(^6\)

<table>
<thead>
<tr>
<th>Category</th>
<th>$we$</th>
<th>$pp$</th>
<th>$tx$</th>
<th>$rr$</th>
<th>$R^2$</th>
<th>$N$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Culture</td>
<td>0.439***</td>
<td>-0.004</td>
<td>-0.02***</td>
<td>0.001</td>
<td>0.507</td>
<td>364</td>
</tr>
<tr>
<td></td>
<td>(0.049)</td>
<td>(0.004)</td>
<td>(0.005)</td>
<td>(0.003)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Outdoor Sports</td>
<td>0.467***</td>
<td>0.003</td>
<td>0.04***</td>
<td>-0.026***</td>
<td>0.725</td>
<td>366</td>
</tr>
<tr>
<td></td>
<td>(0.049)</td>
<td>(0.005)</td>
<td>(0.006)</td>
<td>(0.005)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Indoor Sports</td>
<td>-0.054*</td>
<td>-0.005*</td>
<td>-0.026***</td>
<td>0.009***</td>
<td>0.611</td>
<td>355</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.002)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Watching TV</td>
<td>0.182***</td>
<td>0.001</td>
<td>-0.006***</td>
<td>0.002***</td>
<td>0.622</td>
<td>1096</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0)</td>
<td>(0.001)</td>
<td>(0)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Swimming</td>
<td>0.291***</td>
<td>0.008</td>
<td>0.265***</td>
<td>-0.012*</td>
<td>0.829</td>
<td>306</td>
</tr>
<tr>
<td></td>
<td>(0.058)</td>
<td>(0.008)</td>
<td>(0.01)</td>
<td>(0.005)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Significance levels: (***) 0.1 % (**): 1 % (*): 5 % ('): 10 %

Table 6.3: Regression of Visitors on Calendrical Factors and Weather Controls

Note first of all that coefficients on the daily maximum temperature $tx$ are highly significant at the 0.1 % level in all categories. This is strong evidence that the visitors in all kinds of leisure facilities react

\(^5\)Note that the data provided by Statistics Austria does not distinguish between a day of official holiday and an ordinary weekday. Hence we do not control for official holidays in the model (6.1).

\(^6\)We follow Wooldridge (2008, p. 551) and calculate the R squared as the squared correlation coefficient between the predicted values $\hat{y}_i$ and $y_i$. 

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on the daily maximum temperature. The magnitude however differs substantially between categories. In swimming facilities, visitors increase by 27 % per degree, whereas in indoor sports facilities loose 2.6 % of visitors by a one degree increase. This is the only category where air pressure is weakly significant. Note that in chapter 4, visitors in cultural facilities even had a slight positive correlation coefficient. Now, controlling for calendrical effects, the effect of temperature turns negative, although weakly. Precipitation has no significant effect for cultural activities and swimming but is highly significant for all other categories. However, our primary interest is on the time allocation between weekends and weekdays in this section. We therefore find that, except for the category indoor sports, visitors seem to react significantly positive on the weekend dummy variable. This coefficient is significant at the 10 % level for indoor sports and at the 0.1 % level for all other types. Obviously, visitors seem to alter their behavior in a positive direction on weekends, i.e. more visitors can be observed everywhere. This is strong evidence that more time is spent on each leisure activity. We illustrate the exponentiated coefficients of the variable weekend and their implications on the time allocation in the second column of table 6.4. The

<table>
<thead>
<tr>
<th>Category</th>
<th>Average Time</th>
<th>Weekend Factor</th>
<th>Weekdays</th>
<th>Weekends</th>
</tr>
</thead>
<tbody>
<tr>
<td>Culture</td>
<td>3.62</td>
<td>1.552</td>
<td>3.13</td>
<td>4.86</td>
</tr>
<tr>
<td>Outdoor Sports</td>
<td>16.93</td>
<td>1.595</td>
<td>14.47</td>
<td>23.08</td>
</tr>
<tr>
<td>Indoor Sports</td>
<td>10.00</td>
<td>0.947</td>
<td>10.15</td>
<td>9.61</td>
</tr>
<tr>
<td>Watching TV</td>
<td>166.07</td>
<td>1.199</td>
<td>157.14</td>
<td>188.41</td>
</tr>
<tr>
<td>Swimming</td>
<td>1.00</td>
<td>1.340</td>
<td>0.91</td>
<td>1.22</td>
</tr>
</tbody>
</table>

Table 6.4: Estimation of the Time Split

last two columns of table 6.4 are the result of two equations: first, the minutes on weekends are given by the minutes on weekdays multiplied by the weekend factor. Second, 2/7 times the minutes on weekends plus 5/7 times the minutes during weekdays must give us the average value in the second column of table 6.4.

From comparison of table 6.4 and the actual time allocation in tables 6.1 and 6.2, we conclude that our empirical model seems to mimic the data of the time use survey quite well. The estimated time split does not differ considerably from the official data. The category indoor sports seems to be an exception since it is the only category where the weekend factor is smaller than unity, which means that we expect 5.3 % more visitors on weekdays. This is not in line with the findings of the time use survey: their data suggest that one spends 9.8 minutes with indoor sports activities on weekdays and 14.0 on weekends instead of 10.2 and 9.6. This could be caused by a lack of primary data: remember that visitors of the category indoor sports originate from only one indoor sports facility in Styria. Our model suggests that the 3.6 minutes spent on cultural activities split into 3.1 minutes on weekdays and 5.1 minutes on weekends. Compared to the time use survey, we seem to underestimate the weekend factor slightly: they suggest an even stronger split of 6.3 and 2.6. The same is true for outdoor sports. According to secondary statistics, we seem to underestimate the gap for the time split. For the category TV, the time split estimated by the Poisson model is pretty much the same as calculated from the original data.

As the overall assessment of our model is good, we can accept the estimated time split for swimming: on weekends, average time for swimming increases to 1.22 minutes, whereas it declines to 0.91 minutes on weekdays. What follows from the estimated average time use is a varying time intensity when we leave the participation rate constant. Of course, leaving the participation rate constant is a strong assumption given the fact that all other activities in tables 6.1 and 6.2 depict a varying participation rate as well as a varying time intensity. But in light of the minor availability for swimming data, we realize this option.
6.2.2 Overdispersion in Poisson Regressions

Recall that in section 5.3, we stated in equation (5.14) that the mean and all higher moments of the Poisson distribution are characterized by a single parameter $\mu$. According to Wooldridge (2008, p. 548), this assumption is very often too restrictive in practice and violated in many applications. The restrictive assumption often leads to the phenomenon called (under-) overdispersion, which means that in a Poisson regression model, the standard errors of the beta coefficients are underestimated. The good news is that we still get ‘consistent, asymptotically normal estimators of the $\beta_i$', whether or not the variance assumption holds. In case of over- or underdispersion there is help since we can adjust for the standard errors by assuming that the variance is proportional to the mean:

$$Var(y|x) = \sigma^2 E(y|x).$$

Here, $\sigma^2$ is the unknown parameter for dispersion. The case of $\sigma^2 > 1$ is known as overdispersion, whereas the case $\sigma^2 < 1$ is called underdispersion which is less common but also valid. According to Wooldridge (2008), a consistent estimator for $\sigma^2$ is $(n-k-1)^{-1} \sum_{i=1}^{n} \hat{u}_i^2 / \hat{y}_i$. To correct the standard errors, we can take the square root of $\sigma^2$ and multiply the Poisson standard errors by this factor $\sigma$.

Zeileis et al. (2008) suggest two ways to implement this adjustment in practice: first, one can use the sandwich() function in R to estimate $\sigma^2$ or second, one could estimate a quasi-Poisson model instead of a Poisson model. For our applications, we go for the second way, which corrects the standard errors and reports the estimate of $\sigma^2$ automatically in R. We have already shown the corrected standard errors of our first regression in table 6.3 and illustrate now in addition the dispersion parameters in table 6.5.

<table>
<thead>
<tr>
<th>Culture</th>
<th>Outdoor Sports</th>
<th>Indoor Sports</th>
<th>Watching TV</th>
<th>Swimming</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma^2$</td>
<td>154.62</td>
<td>446.34</td>
<td>12.32</td>
<td>1.84</td>
</tr>
</tbody>
</table>

Table 6.5: Dispersion Parameter: Adjustment of the Standard Errors

These values are clearly larger than one, which indicates that overdispersion is present in the data. Once we are aware of this problem, we can encounter it by using the quasi-Poisson family for GLMs in R. In all Poisson regression models that follow, we detect indicators of overdispersion and correct it by the use of the quasi-Poisson family. As described above, this leads to the same beta coefficients but corrects for the standard errors which would be underestimated massively in the presence of overdispersion.

6.3 Reactions of Minutes per Day on Temperature

In this section, we illustrate the full empirical model, project the visitors via $\delta_i$ for the entire of Styria and finally calculate the time use in minutes $m_i$ according to equation (5.7) to address the question of the weather dependent time use. We think of the average time use as $a_i$, but have in mind that this is actually a function $m_i(v)$, which is close to $a_i$ only in the long run. In order to get a relationship $y(v)$, we estimate the specification

$$y = tx + tx^2 + rr + pp + month + weekday + ohday + shday + \epsilon$$  \hspace{1cm} (6.2)

in a quasi-Poisson regression model, where $ohday$ and $shday$ denote dummy variables for official and school holidays. We show the most interesting results in table 6.6, the detailed results as well as plots of
residuals can be found in the appendix in table 2. From the analysis of the residual plots in the appendix in figure 1, we conclude that equation (6.2) is an appropriate formulation of the model.\(^7\)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Culture</th>
<th>Outdoor Sports</th>
<th>Indoor Sports</th>
<th>Watching TV</th>
<th>Swimming</th>
</tr>
</thead>
<tbody>
<tr>
<td>(tx^2)</td>
<td>0</td>
<td>-0.003***</td>
<td>-0.001***</td>
<td>0***</td>
<td>-0.005*</td>
</tr>
<tr>
<td>(rr)</td>
<td>0.004</td>
<td>-0.024***</td>
<td>0.009***</td>
<td>0.002***</td>
<td>-0.012*</td>
</tr>
<tr>
<td>Official Holiday</td>
<td>0.17</td>
<td>0.904***</td>
<td>0.04</td>
<td>0.192***</td>
<td>0.219</td>
</tr>
<tr>
<td>September</td>
<td>-0.176'</td>
<td>0.699***</td>
<td>-0.088</td>
<td>0.035*</td>
<td>-1.114***</td>
</tr>
<tr>
<td>Friday</td>
<td>0.743***</td>
<td>-0.096</td>
<td>-0.187***</td>
<td>0.003</td>
<td>-0.217*</td>
</tr>
</tbody>
</table>

\(R^2\) = 0.738 0.823 0.712 0.743 0.873

\(Dev.\ \text{reduced}\) = 0.191 0.607 0.645 0.336 0.811

| Significance levels: (***): 0.1 % (**): 1 % (*) : 5 % ('): 10 % |

Table 6.6: Main Results for the Full Model of Aggregated Visitors

First of all, it is striking that weather variables seem to have a significant influence on visitors of leisure facilities, except the category cultural activities. Especially for swimming this is unsurprising, since we expect temperature to be the most important factor for swimming activities. The last row of table 6.6 illustrates the reduction of total deviance in the model that is achieved through the addition of weather variables.\(^8\) The higher the reduction in total deviance achieved through the variables, the higher is their explanatory power. Obviously, for swimming, nearly all of the model’s explanatory power is caused by the addition of weather variables. For outdoor and indoor sports, weather succeeds to explain at least very large parts of total variance of the model. This contradicts existing results. Recall that Arnberger and Brandenburg (2001) find that recreational outdoor activities can best be explained via the calendrical effects, whereas weather variables have less explanatory power. For TV consumption, weather reduces unexplained deviance by about 34 %, whereas cultural activities seem to be strongly influenced by calendrical effects. Although the entire model is useful for crude predictions \(R^2 = 0.74\), total deviance can be reduced by only 19 % through the addition of weather variables.

The coefficients can again be interpreted approximately as percentage changes. Hence we expect a 18 % decrease of visitors in museums and a 70 % increase in outdoor sports activities in September compared to April. As before, precipitation has significant impact on four activities but not for culture and only weak significant impact on swimming. One liter of rain per \(m^2\) seems to reduce visitors in outdoor sports and swimming facilities by about 1-2 % but to increase the visitors in all other categories by less than 1 %. This is an unsurprising result since any outdoor activity is more enjoyable on rainless days. Note that on official holidays, activities of all categories increase by minimum 4 % (indoor sports) to maximum 90 % (outdoor sports). In general, outdoor sports activities seem to have a strong calendrical component. The weekend factor as well as the coefficient on official holidays have a significant impact, which is even high in magnitude. After all, we find that visitors in all kinds of leisure facilities exhibit good predictability as the \(R^2\) is beyond 0.7 for all categories. This is suitable for practical purposes. Activities in categories swimming and outdoor sports are particularly well predictable which is caused by a high weather dependency.\(^9\)

\(^7\)Note that one could opt for the strategy to estimate separate models for each month since month and temperature are not as independent as suggested by the model in (6.2). Furthermore, many recreational activities require scheduling the day before. This means, many activities presumably depend on the expected weather, i.e. the weather forecast for the next day, rather than on the actual weather. Therefore, one should include weather forecasts into (6.2). But the weather forecast and the actual weather exhibit strong correlation, which could cause multicollinearity.

\(^8\)Usually, the pseudo \(R^2\) is calculated as \(1 - \frac{\text{residual deviance}}{\text{total deviance}}\) and provides a goodness of fit measure for an empirical model.

\(^9\)At this point we have to remark that it is easier to predict visitors on an aggregate level than on the firm specific level.
That the $R^2$ is quite robust, encourages us to go for predictions of the changes of the daily minutes at any weather conditions. Via $y(v)$, we estimate the aggregate visitors. According to equation (5.7), we project the visitors for all facilities through the coefficient $\delta$. The result is the supposed true number of visitors in one category. We multiply this sum by the time intensity $r_i$ to get the total amount of time spent in this category. At this point it should be said that we distinguish between the time intensity on weekends and weekdays: for predictions on weekdays, we use the time intensity depicted in table 6.1, whereas on weekends we use the values of table 6.2. What we get is the sum of total minutes in Styria, $M_i$. As these large numbers aren’t really informative, we divide this amount by the inhabitants of age 10–99 in 2012 to get the average minutes per person, $m_i$. The results are illustrated in figures 6.3 - 6.5 and correspond to a rainless Wednesday in May with average air pressure. The actual minutes per day exhibit a reaction on temperature that is already familiar from the scatter plots in figures 4.4 - 4.6. The dotted lines around the solid blue one depict the 95 % confidence interval for our estimation. From figure 6.3(a), it turns out that the average value for swimming, 0.9 minutes on a Wednesday, is unsurprisingly subject to huge changes due to maximum temperature. Below a maximum temperature of 20°C, the amount of swimming activities in Styria is virtually zero, whereas it rises to about 15 minutes at temperatures around 32°C. Its average value seems to be reached at about 22°C. Note that the confidence interval diverges at higher temperatures. This could be due to the fact that we have very few observations beyond 30°C. After all, through the formation of a temperature index, temperatures become less extreme as well, i.e. temperatures higher than 30°C on average occur quite rarely.

We illustrate the daily time spent on watching TV in figure 6.3(b). As watching TV displays an average value of 157 minutes on this day, we find that the daily use is always below its average value in May and decreases further at higher temperatures. Note that the estimation gets more reliable around moderate temperatures and increases as temperatures rise towards 30°C or fall below 5°C. This is probably caused by the fact that we have fewer observations at extreme weather conditions. However, the time use for watching TV are subject to strong fluctuations as well. On hot summer days, TV

For small recreational sites, prediction is difficult because the decision of a single visitor has a greater impact on the total number of visitors.

Note that this does not include the uncertainty caused by $\delta$ but only the uncertainty detected by the Poisson model.
consumption tends to decline to about 100 minutes, which is a reduction of an hour compared to its average value. The reduction per degree gets higher at higher temperatures, which could be due to the fact that there exists a trade-off for leisure activities: we hardly find alternatives to watching TV at very low temperatures since commuting to cultural or indoor sports facilities may be uncomfortable. But on warm days, we are faced with the availability of other activities: swimming or outdoor sports.

![Graph showing the relationship between temperature and outdoor sport activities](image)

(a) Minutes per Day spent with Outdoor Sport Activities

Figure 6.4: Minutes per Day

Outdoor activities represent the second largest part of all leisure activities, namely about 7% or 13 minutes on weekdays. From figure 6.4, one can see that this daily value decreases to about 5 minutes on days with maximum temperature below 0°C, which is of course a hypothetical value for May. On warm days however, the average time spent on outdoor activities reaches its peak of 25 minutes at temperatures of about 25°C. Outdoor activities like hiking, walking or running require a minimum level of physical activity, therefore this seems to be the optimal temperature for these activities. This kind of leisure activity is unpleasant at high temperatures, and is probably substituted for watching TV at low temperatures because taking a walk is not very enjoyable at zero degrees. Again, our model achieves good predictability for temperatures below 20°C, which can again be explained by a bad availability of data at high temperatures.\footnote{High temperatures in this category occur even more seldom since the data include the weather of hiking trails and air passenger lines where temperatures are usually lower.} Between 15°C and 20°C, outdoor sports activities seem to compete with indoor sports activities.

Indoor sports activities add up to about 10 minutes on weekdays but exhibit considerable reactions to temperature as can be seen from figure 6.5(a). Indoor sports activities are done most often when temperatures are slightly above zero degrees, namely around 14 minutes per day but are predictable with moderate quality around this value: the 95% confidence interval narrows not until the temperature rises beyond 15°C. Again, in this range of temperature, indoor sports activities are faced with good alternatives of leisure activities outside enclosed rooms and individuals are facing a trade-off in the presence of time constraints.

The reaction of 2.6 minutes per day of cultural activities is depicted in figure 6.5(b). Its value decreases as well, which is not too surprising since cultural activities are a kind of indoor activity. Therefore, we expect it to decline at higher temperatures. We already found in section 4.2.4 that this kind of activity...
does not exhibit a strong weather dependency, which is confirmed by a broad confidence interval for our prediction. In general, cultural activities are characterized by visitors that do not seem to act very spontaneously on weather conditions. However, we find that cultural activities do not reach their average value until the temperature rises beyond 30°C on Wednesdays. One may find it disturbing that the average value is reached at pretty warm days. But recall that cultural activities are mostly explained through calendrical effects. Well, according to our regression coefficients, the months of June, July and May seem to be very attractive for visitors of cultural facilities. In May, we expect about 12% more visitors than in April. The above average value is rather caused by the month of May, not the weather.

6.4 Variation of the Participation Rate

As we treat the time intensity as constant in our analysis, the participation rate has to vary. The participation rate is defined as the share of total population that participates in a certain activity. Recall that this measure gives useful insights regarding the popularity of leisure activities. In figures 6.8 - 6.6 we illustrate the prediction for a Sunday in May and indicate the effect of 10 mm of rain, which is equivalent to 10 liters per m², on the participation rate by the green schedule.

First of all, it is noticeable that the popularity of the categories varies substantially. Unsurprisingly, watching TV is the most widespread one, independent of weather. Its participation rate decreases from maximum 60% to minimum 50% on very hot days in May and is always below its average value of 65% at this time.\footnote{To get estimates for the participation rate, we run a regression of the variable Viewing Rate on the same explanatory variables as in (6.2).} This means that at least half of the inhabitants in Styria watch TV, at minimum for 60 seconds.\footnote{This is the definition of the teletest: A person is considered to watch TV when the TV was turned on for at least 60 seconds.} However, the participation increases slightly on rainy days. The lowest participation rate can be observed for cultural activities, which is at its maximum at 1.6% at about zero degrees and decreases steadily. Average temperatures in May lie between 15°C and 25°C, which implies that about 4 - 5% undertake activities such as visiting monasteries, museums and the cinema on Sundays in May. Again,
this is above its expected value of 3.6 %. Below 20°C, the participation rate of swimming is irrelevant but later it experiences a sharp increase: beyond 25°C, the share of the styrian population that spends its time at lakes or swimming pools rises from 0.5 % to 7 %. This is a very sharp increase, given an average value of 0.3 %.

We find outdoor sports among the most popular recreational activities, following TV. On rainless weekends in May, approximately 50 % (!) carry out activities like walking through parks, hiking or running when the temperature is optimal around 25°C. This constitutes a doubling to the average rate of 24 %. The high participation rate of outdoor sports is, amongst other things, a result of the low time intensity, which is a weighted average and actually calculated arbitrarily. On could certainly choose different weights. When the participation rate for outdoor sports is at its maximum, it will be reduced by about 10 percentage points when rain sets in. This is not very surprising since rain affects the enjoyment of outdoor activities in a considerable way. We observe the opposite effect of rain on indoor sports activities, although much lower in magnitude. For average temperatures in May, about 4 % - 6 % in Styria engage in any indoor sports activity, which is nearly half of its average of 9 %. However, this rate is expected to rise by about 1 percentage point when a rain shower is passing.

It is obvious that the effect of rain lowers the participation rate of open-air activities, but increases the rate for indoor sports and cultural activities. Participation in swimming activities decreases minimally by 10 mm of rain. At this point it should be mentioned that even on hot summer days we might observe huge amounts of rain due to thunder storms. Thus, we do not observe rain to have large effects. The effect of rain on visitors in cultural facilities is positive but is negligible in magnitude. We conclude that recreational activities open air and indoor act as substitutes with respect to rain: more people shift their leisure activities outside when they experience a rainless day.

6.5 Total Leisure and the Unexplained Rest

We now address the question whether the decision between work and leisure is affected by weather conditions. In section 3.2, we argued that the marginal utility of leisure or consumption of goods may change with respect to the weather. Intuitively, given the fact that in summer most people go on holiday
Figure 6.7: The Effect of 10 mm of Rain on the Participation Rate on Weekends in May

Figure 6.8: The Effect of 10 mm of Rain on the Participation Rate on Weekends in May
and spend it on all their favorite activities, we suppose that this is caused by appropriate weather conditions. Furthermore, we often have in mind that working is harder on hot summer days because of high opportunity costs at work. What do we expect, which temperatures allow for the highest amount of leisure? In the light of our data, we are not able to observe the sum of all leisure activities and their weather dependent reaction, but parts of it. Furthermore, our empirical model does not provide the ideal framework for a detailed labor-leisure analysis, but we may at least observe a change in the consumption bundle of leisure activities and its associated time input, i.e. $Z \cdot r$. We implement the strategy described in section 5.2.4 and apply two different approaches. First, we analyze the behavior of ‘total leisure’ when the (supposedly weather independent) unexplained rest, which adds up to about 62 minutes during weekdays and to 93 minutes on weekends, is constant. Second, we analyze the reaction of the unexplained rest by assuming that total leisure is constant.

We already know that the sum of $a_i$ is about 245 minutes on weekdays and approximately 329 minutes on weekends. But what will be the behavior of the sum of $a_i$ on a rainy Tuesday in September? To answer this question, we build the sum of minutes per day for all activities and call it $\tilde{L}(v) = \sum m_i(v) + \omega$, where $\omega$ denotes the unexplained rest on weekends/weekdays. We illustrate the value of $L(v)$ for several situations in figure 6.9. The blue line indicates the sum of leisure activities on a rainless Thursday in the month of May and the red one a Sunday in January, with 10 mm of precipitation. The green curve represents a Tuesday in September which is a day of official and school holidays with 10 mm of rain.

It is obvious that a Sunday in January offers the highest amount of leisure, at least for average temperatures in January. The schedule is declining at higher temperatures which is probably due to the negatively inclined TV schedule. After all, in January, total leisure does not change a lot: it seems to stay close to its average value of 329 minutes at average weather conditions. Furthermore, figure 6.9 indicates that total leisure always first increases and then decreases with respect to temperature, i.e. has an inverted U-shape. Where does this shape come from? Probably this is due to the fact that the time input to all categories declines sooner or later (except the one for swimming). Watching TV, as biggest part of leisure is decreasing in temperature anyway, so it is not surprising that the sum of all activities is decreasing as well. The only resort to retrieve the concept of an increasing amount of leisure is through the category swimming. Although activities in swimming facilities grow exponentially, they do not seem to compensate the shrinking of TV, cultural activities, indoor sports and even outdoor sports at high levels.

\[14\text{Recall that the total amount of leisure enlarges due to the substitution of the time spent watching TV estimated by the time use survey by the data provided by the Teletest.} \]
A Tuesday of official holiday in September (the green line) is close to this value as well, although we consider a weekday. Total leisure peaks at 20 °C, which is probably due to outdoor activities. The reduction of outdoor sports and TV explain why this schedule reduces again at higher temperatures. Swimming is not able to compensate the reduction in September. This is probably caused by the use of the weekday specific time intensity for calculation. That is to say, the time use survey does not distinguish between official holiday and ordinary weekdays: they are equally considered as weekdays. Nonetheless, this day of official holiday offers approximately the same amount of leisure as the Sunday in January. The dummy variable for official holiday is strictly positive in every category, which is probably the reason for the huge increase of total leisure compared to another weekday like the blue line.

Total leisure on a Thursday in May is slightly below its average value of 245 minutes and approximately unchanged up to 15°C. As temperatures increase further, total leisure tends to decline. This is probably caused by the same reasons as discussed above, i.e. that swimming is not able to compensate the reduction caused by all other categories, especially watching TV.

Next, we implement the second approach and define the unexplained rest $\omega$ as total leisure (62 or 93 minutes) minus the sum of all observed activities, $\sum m_i(w)$. What we get is the weather dependent reaction of the unobserved leisure activities like reading, playing computer games or listening to the radio. The result is depicted in figure 6.10, where the blue line indicates the prediction for a rainless Saturday in April, the green for a Wednesday in November with 15 mm of rain and the red one a rainless Friday in August, a day of school holidays.

Unsurprisingly, the unexplained rest is U-shaped as it is defined as the inverse of $\tilde{L}$. The blue schedule, a Saturday in April, is permanently above the average value of 93 minutes for weekends and reaches its minimum at about 10°C with a value of about 130 minutes. As temperatures get hot (although this is not common for April), unobserved activities grow beyond 150 minutes per day. We conclude that activities like reading, technical or artistic hobbies are done with above average frequency on warm weekends in April, pushing back the explained activities.

The contrary is true for the green schedule, a weekday in November. It suggests that unexplained activities are cut back by about 15 minutes at average temperatures in November, i.e. between -5°C and 10°C. This is probably caused by a high magnitude of TV consumption which is expected to be large on cold November days. The red schedule for August fluctuates around its average value of 62 minutes but increases slightly beyond it on hot days. This is kind of surprising since we expect activities as swimming and outdoor sports to replace unexplained activities on hot days in summer. The red schedule suggests that this is only the case at mid-range temperatures.
Recall that both of the above described approaches have their drawbacks and are systematically incorrect, as an additional equation is missing. The first approach is more suitable to explain the reaction of total leisure but commits the mistake to treat the unexplained activities as constant, which is most certainly untrue. The second approach assumes total leisure to be constant, which is most certainly incorrect as well. As already mentioned, our framework is not perfectly suitable for an analysis like this because too many activities are unobserved to draw concrete conclusions out of it. The model itself incorporates a lot of aggregation and certain amounts of the available leisure may disappear to activities that cannot be observed empirically. After all, the strong dependency of nearly all recreational activities on weather provides at least evidence that the total time input that is needed for these activities is weather related as well.

6.6 Division of Leisure and Substitution Effects

How does weather affect the composition of leisure activities? We suppose that the choice of leisure activities is associated with different levels of utility at different weather conditions. By applying the multinomial logit model described in section 5.3.2, we explain the choice of leisure activities in Styria by weather conditions. As we analyze the division of total leisure, we implicitly assume that the available ‘budget’ of leisure, \( L \), is fixed and ask for its breakdown into single activities. We first extend the pie charts shown in section 6.2 to a dynamic version. In the resulting bar chart, we plot the share of total time that is spent on any activity. This is the familiar coefficient \( \alpha_i \) from the Cobb-Douglas utility model. It turns out that \( \alpha_i \) is indeed a function of \( v \). Furthermore, the MNL allows to analyze the substitution effects between leisure activities. Since the time budget is fixed, the increase of time use in one activity must reduce the time use of another one. The contrast uncovers the actual time shifts.

The following specification was estimated in a multinomial logit model:

\[
\ln \left( \frac{P(y = k|x)}{P(y = 1|x)} \right) = tx + rr + pp + year + month + weekday + ohday + shday + \epsilon,
\]

which gives the relative probability of choosing activity \( k \) versus the base category, watching TV. The most important results are shown in table 6.7, which depicts exponentiated beta coefficients to simplify the interpretation.\(^{15}\) These coefficients can be interpreted as increases in the odds of doing activity \( k \) versus watching tv, when the explanatory variable increases by one unit. We find that a one unit increase in temperature highers the odds of participating in outdoor sports instead of watching TV by about 5%. On the other hand, a one unit increase in temperature lowers the odds of participating in indoor sports compared to watching TV. In other words, increasing temperatures cause people to shift from indoor sports to TV. On the contrary, indoor sports gains from rain and draws time from TV to indoor sports facilities. Therefore, the increase of the odds of indoor sports from rain can be interpreted as a slight loss of minutes spent watching TV. It is unsurprising that TV draws time use from outdoor activities on rainy days, but we would not expect people to shift from TV to swimming facilities. The positive coefficient of 1.003 is probably a result of the sample we have chosen: the sample includes observations from May to September. Thus, it is reasonable to believe that people have spent time in swimming facilities during summer, although a thunderstorm occurred in the evening.

On official holidays, the chance for outdoor activities doubles compared to watching TV. As all coefficients on official holiday are positive, we conclude that it gets likelier to do anything else than

\(^{15}\) The full results are illustrated in table 3 of the appendix. Investigation of the residual plots in figure 2 points out that the model specification is appropriate for most categories. The category swimming however seems to be problematic, as the residuals differ from normal distribution.
Odds Ratios

<table>
<thead>
<tr>
<th>Variable</th>
<th>Culture</th>
<th>Outdoor Sports</th>
<th>Indoor Sports</th>
<th>Swimming</th>
</tr>
</thead>
<tbody>
<tr>
<td>tz</td>
<td>0.965</td>
<td>1.054</td>
<td>0.936</td>
<td>1.338</td>
</tr>
<tr>
<td>rr</td>
<td>1.003</td>
<td>0.987</td>
<td>1.004</td>
<td>1.003</td>
</tr>
<tr>
<td>Official Holiday</td>
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<td>2.011</td>
<td>1.055</td>
<td>1.561</td>
</tr>
<tr>
<td>September</td>
<td>0.64</td>
<td>0.965</td>
<td>1.637</td>
<td>0.314</td>
</tr>
<tr>
<td>Monday</td>
<td>0.761</td>
<td>0.747</td>
<td>0.746</td>
<td>0.952</td>
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</table>

<table>
<thead>
<tr>
<th>N</th>
<th>612</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_{McF}$</td>
<td>0.042</td>
</tr>
<tr>
<td>$R_{Count}$</td>
<td>0.855</td>
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</tbody>
</table>

Table 6.7: Exponentiated Coefficients of Multinomial Logit

watching TV on official holidays. Interpretation of month and weekday coefficients is somehow tedious since they denote the effect on the odds compared to August and Tuesday. A crude interpretation would be that in September, the odds of doing indoor sports compared to watching TV is much higher (63 %) than in August. The contrary is true for swimming (0.31) and cultural activities (0.64). On Monday, the odds for watching TV are usually greater than on Tuesdays.

Although the percentage correctly predicted is about 85 %, we obtain a low pseudo R-squared of 0.042. Following McFadden (1977), values from 0.2 to 0.4 represent an excellent fit. Therefore, our result does not seem to predict the choice of leisure activities perfectly. Multinomial logit models usually require a very large sample size, which forces us to use several years for estimation. We have chosen years from 2009 to 2012 for months May–Sep, since there is no data available for swimming from Oct–Apr. As weather index, we use the population weighted index described in section 4.2.1. In general, it is difficult to use a single weather index for the whole region and all activities. The different location of the sites causes additional sources for errors since the actual heterogeneous weather conditions could differ substantially. One option to improve the R-squared would be to boost the availability of data. The observed share δ varies substantially across the years, which creates additional uncertainty for our model. In fact, δ varies from day to day and assuming it constant throughout the year implies great uncertainty itself. Enlarging its value should help to improve the MNL as well as the overall uncertainty of the Poisson model. However, ‘goodness of fit is not usually as important as statistical or economical significance of the explanatory variables.’ (Wooldridge, 2008, p. 536) As all variables are significant at the 5 % level, we can conclude that weather conditions have at least an important impact on the recreational behavior. The significant impact of weather variables on the recreational behavior is further confirmed by a likelihood ratio test. The result is highly significant, which means that dropping the weather variables reduces the explanatory power of the model. In other words, this means that weather variables affect the utility gained by the choice of leisure activities. The results of the likelihood ratio test is presented in table 4 in the appendix.

We show a dynamic version of the pie chart in figure 6.11 where we plot a prediction for a rainless Wednesday in August of average air pressure which is a day of school holiday. Total leisure amounts to about 245 minutes minus its unexplained share, i.e. 183 minutes on this day. We treat this amount as constant and plot its composition. On the y-axis, we find the share of total time that is spent on any activity, which is the estimated value for $\alpha$. The development from left to right shows its functional form with respect to temperature.

It is striking that indoor activities like the visitation of museums and indoor sports make up for about 10 percent each at - 4°C and nearly disappear at temperatures above 30°C. On hot days, swimming accounts for about 10 % of total time. In fact, these shares constitute probabilities, i.e. the probability
that one goes swimming is in fact 10 % on a hot summer day. TV consumption makes up for about 60 % on cold days but finds its substitutes in outdoor activities and swimming. On the other hand, the probability for watching TV is still huge: even on hot summer days, we spend about 40 % of our total leisure on TV consumption. Furthermore, we must not disregard outdoor activities. Its share is huge as well, as it reaches its maximum around 25°C at about 50 %. When temperatures get even warmer, we suppose that the time spent on outdoor activities is substituted for swimming.

In table 6.8, we reveal the substitution effects between leisure activities via the contrast, i.e. \( \exp(\beta_l - \beta_k) \). The exponentiated coefficients can be understood as the change in the odds of doing activity \( l \) versus doing activity \( k \). In general, results are not very surprising. A one unit increase of maximum temperature for example changes the odds of going swimming versus cultural activities by about 39 %. Unsurprisingly, swimming attracts people from every other activity as the temperature increases, even from outdoor sports. The chance of doing indoor sports vs. going swimming reduces for example by 30 % per unit of \( tx \). Indoor sports suffers most from nice weather since even the chance for cultural activities increases relative to indoor sports. Unsurprisingly, one mm of rain attracts visitors from outdoor sports towards indoor activities such as sports facilities and museums.

### Contrast

<table>
<thead>
<tr>
<th></th>
<th>Swimming - Culture</th>
<th>Swimming - Outdoor</th>
<th>Outdoor - Culture</th>
<th>Outdoor - Indoor</th>
<th>Indoor - Swimming</th>
<th>Culture - Indoor</th>
</tr>
</thead>
<tbody>
<tr>
<td>( tx )</td>
<td>1.386</td>
<td>1.269</td>
<td>1.126</td>
<td>1.092</td>
<td>0.7</td>
<td>1.031</td>
</tr>
<tr>
<td>( rr )</td>
<td>1</td>
<td>1.016</td>
<td>0.983</td>
<td>0.984</td>
<td>1.002</td>
<td>0.998</td>
</tr>
<tr>
<td>Sunday</td>
<td>1.022</td>
<td>1.038</td>
<td>1.95</td>
<td>0.985</td>
<td>0.494</td>
<td>1.98</td>
</tr>
<tr>
<td>September</td>
<td>0.491</td>
<td>0.326</td>
<td>0.589</td>
<td>1.507</td>
<td>5.209</td>
<td>0.391</td>
</tr>
</tbody>
</table>

Table 6.8: Changes in Odds

Swimming and outdoor sports compete for visitors on days with nice weather since swimming even attracts visitors on rainy days (probably due to thunder storms). On Sundays, it is more attractive to participate in cultural activities than in outdoor sports; the relative chance of outdoor sports is reduced by about 1.5 %. Furthermore, Sundays cause people to shift from indoor sports towards cultural activities, the odds change by 98 %. In September, outdoor and indoor sports get much more attractive than
swimming or cultural activities: the odds for indoor vs. swimming increases by about 420%. The chance for outdoor sports relative to culture increases by 50% and the chance for cultural activities declines by 60% relative to indoor sports.

Although our model is not brilliant in terms of goodness of fit, we believe that we have learned a lot with regard to substitution effects and the weather dependent time split. Through the underlying utility models, we assumed that the utility gained by the time spent on activities differs from day to day. The pie chart for the division of leisure is indeed subject to substantial variation with respect to temperature and the overall recreational behavior in Styria is strongly influenced by calendrical and weather related factors.
Chapter 7

Conclusion and Discussion

The objective of the present work was to quantify the weather dependency of the recreational behavior in Styria. We find that weather variables achieve to explain very large parts of the recreation time, at least for outdoor activities like sports or bathing. Even for indoor sports activities or TV consumption, weather variables succeed to explain substantial parts. However, cultural activities are not as weather sensitive as one would expect, although we achieve good predictability on the aggregate level. Whereas the effects of weather on the time use are unsurprising with regard to sign, they are sometimes surprising with respect to their magnitude. The amount of precipitation for example has significant effects on most activities, but is harmless in its size. Analysis of the substitution effects pointed out that indoor sports suffers most from nice weather conditions but is the only winner from precipitation.

Predicting the time use could be of relevant to the social sciences in general as well as for particular branches of leisure industry. Undoubtedly, the time spent watching TV should be of interest for TV stations. First, predictions could be relevant since the price one is willing to pay for one minute of advertising is strongly related to the number of viewers. Knowing the number of viewers in advance could help to adjust the frequency of repetition of advertising spots. Second, ex post analysis could provide explanations for the time spent on TV, when it is corrected for weather. However, other forms of TV consumption gain in popularity and replace traditional forms. Therefore, predictions of the time spent on watching TV could become more difficult to estimate.

Through the forecast of the recreational behavior, human behavior becomes more predictable, which enables a more efficient planning in many respects. On the one hand, public transport could adjust according to the predicted number of visitors at any location. Since housing areas sometimes differ from areas where leisure activities take place, weather based demand forecasts have implications on the scheduling of public transport. Though, if public transport starts to adjust to its weather based predictions, we would observe kind of feedback effects as the weather dependency for some sites would even intensify. Some regions could gain or lose in accessibility because of flexible public transport scheduling. After all, leisure sites could gain substantially from a good predictability of their customers. Therefore, the prognosis of attendance levels has economic value per se, either with respect to the staff which could be deployed in an improved way or by a more efficient utilization of means of production. Estimation of these savings on an aggregate level can be subject to future research. In any case, our study offers a deeper understanding of how weather affects recreational behavior, which may be relevant to policy makers or single economic units such as firms.

Considering climate change, our model could be useful in capturing adaptations of human behavior

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1 This interpretation was given by Dominik Kortschak.
to changing weather conditions. Given certain scenarios of global warming, our model is prepared to do at least short run predictions on the change of preferences. Of course, the present thesis is not comparable to sectoral impact studies of climate change on tourism a la Hamilton and Tol (2004), but is useful for predictions on the microeconomic level. Because of climate change, we expect the occurrence of days of adverse weather to increase. Therefore, demand predictions for recreational sites could gain importance. Under a scenario of global warming, we expect an enlargement of the outdoor activity sector and a reduction of days spent with indoor activities or maybe a temporal relocation of activities among different months of the year.

The monetary implications of weather dependent time allocation could be analyzed in more detail. One could for example analyze the pecuniary consequences for certain recreational branches in a short term perspective. On the basis of the dynamic pie charts of the time use, the monetary expenses could be illustrated in a similar way. In recent years, shopping starts to emerge as an additional sort of leisure activity. It should be uncontroversial that shopping behavior in the city center (outdoor) or in shopping malls (indoor) could exhibit different reactions to weather conditions. The investigation of this issue could point out monetary implications that are even more relevant.

The accuracy of our model is in general reduced through the use of E-OBS data, which is gridded rather crude. One could certainly achieve better results via the use of exact meteorological data obtained by a nearby weather station. The models for the prediction of attendance levels could be enriched by parameters such as the cloud coverage or sunshine duration. Furthermore, the duration of a rain shower on a specific day could be a better proxy for the recreational behavior than precipitation in \textit{mm}. Thus, thunderstorms which only last for some hours on a day in summer, would not have such a huge impact.

Many leisure activities require some travel time or scheduling the day before. Therefore, they are less weather dependent but rather weather-forecast dependent. The reliability of a forecast model is of course strongly dependent on the reliability of weather forecasts. But the insight that leisure activities are affected by the weather \textit{forecasts} instead of the actual weather reduces the uncertainty of prediction models. Generally, since most activities require scheduling, the types of leisure activities that are chosen could become self fulfilling, as predicted by the weather man or woman.

Finally, we might not forget that the prediction model for the time use incurs great uncertainty through a variety of factors. First, the results of the time use survey should be interpreted cautiously because of their experimental design. In the end, participation in the time use survey is voluntary. Furthermore, one minute of swimming and the time intensity that results from it are better viewed as a heuristic. Next, the model incurs especially uncertainty with respect to the observed share $\delta$. This value is calculated on an annual basis but is in fact used for predictions on a daily basis, i.e. we have to expect massive deviations from day to day. Private swimming pools are a good reason to believe that the observed share $\delta$ for swimming is overestimated, which means that the average time use of swimming is underestimated. It is basically reasonable to believe that the unobserved share exhibits similar reactions to weather as we observed. However, all activities in our sample arise from commercial recreational sites, i.e. the visitors are required to pay for admission. The fact that we only observe behavior linked to any costs, eventually leads to a biased sample since weather dependent behavior may change. Consider a private swimming pool or outdoor activities free of charge. The threshold value of temperature is certainly lower for the decision to go swimming at home than it is for public swimming pools, since they are not linked to admission fee. In this respect, data for watching TV should point out its true reaction.

Nonetheless, we believe that with this work, we make a valuable contribution to the existing literature. At least, this is the first attempt to extend the existing literature on time allocation by predictions and to analyze the weather dependence of human recreational behavior.


## Appendix

### Summary Statistics

<table>
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<tr>
<th>Variable</th>
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<th>Std. Dev.</th>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
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<td><strong>Culture</strong></td>
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Table 1: Means and Standard Deviations of Variables

*Weekend* is a dummy variable indicating if a specific day was Sat/Sun or a weekday. *School holiday* indicates whether the day fall into the time of school holiday. *Precipitation or pp* measures the amount of precipitation per day in liters per square meter (equivalent to liter per square meter). *Visitors* is the average daily attendance level observed in this category. *Official holiday* is a dummy indicating whether the day was a day of official holiday. *Max temperature or tx* is the weighted average of the daily maximum temperature. *Air pressure or pp* measures the atmospheric pressure. *Average Use* denotes the average time use on Tv per inhabitant of Styria, detected by the teletest. *Tv population* is the population in Styria above age 12 that has access to any kind of Tv set. *Viewing Rate* is the share of the Tv population that watches Tv for at least 60 seconds per day. All weather variables originate from the E-OBS data set, available on http://www.ecad.eu, free of charge.
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| \( R^2 \) | 0.738 | 0.823 | 0.712 | 0.743 | 0.873 |
| \( N \) | 364  | 366  | 355  | 1096 | 306  |

Significance levels: (***): 0.1 % (**): 1 % (*): 5 % ('): 10 %

Table 2: Full Regression Model of Aggregated Visitors
Figure 1: Q-Q Plots of Residuals for the Full Poisson Model
### Multinomial Logit

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<td>(0.00048)</td>
<td>(0.00025)</td>
<td>(0.00042)</td>
<td>(0.00001)</td>
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<td>Mai</td>
<td>-0.330*</td>
<td>-0.454*</td>
<td>0.358*</td>
<td>-0.277*</td>
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<td>(0.00043)</td>
<td>(0.00037)</td>
<td>(0.00032)</td>
<td>(0)</td>
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<tr>
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<td>-0.021*</td>
<td>-0.189*</td>
<td>0.382*</td>
<td>0.336*</td>
</tr>
<tr>
<td></td>
<td>(0.00041)</td>
<td>(0.00035)</td>
<td>(0.00032)</td>
<td>(0.00001)</td>
</tr>
<tr>
<td>Juli</td>
<td>-0.055*</td>
<td>-0.147*</td>
<td>0.349*</td>
<td>0.367*</td>
</tr>
<tr>
<td></td>
<td>(0.00055)</td>
<td>(0.00025)</td>
<td>(0.00045)</td>
<td>(0.00003)</td>
</tr>
<tr>
<td>September</td>
<td>-0.446*</td>
<td>-0.036*</td>
<td>0.493*</td>
<td>-1.157*</td>
</tr>
<tr>
<td></td>
<td>(0.0005)</td>
<td>(0.00031)</td>
<td>(0.00033)</td>
<td>(0)</td>
</tr>
</tbody>
</table>

$N = 612$ \quad $R_{McF} = 0.04159$ \quad $R_{Count} = 0.855$

Significance levels: (*): 5 %

Table 3: Multinomial Logit

<table>
<thead>
<tr>
<th>Df</th>
<th>LogLik Df</th>
<th>Chisq</th>
<th>Pr ( &gt; Chisq)</th>
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</thead>
<tbody>
<tr>
<td>80</td>
<td>-635562167</td>
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<td></td>
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<tr>
<td>85</td>
<td>-1583916824</td>
<td>1896709314</td>
<td>&lt; 0.000000000000000022 * **</td>
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Table 4: Likelihood Ratio Test
Figure 2: Q-Q Plots of Residuals for the MNL
### Average time spent per day (Monday - Sunday) of all persons aged 10

<table>
<thead>
<tr>
<th>Main Activities</th>
<th>All</th>
<th>Participation Rate</th>
<th>% in</th>
<th>All</th>
<th>Participation Rate</th>
<th>% in</th>
</tr>
</thead>
<tbody>
<tr>
<td>Personal care</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sleeping</td>
<td>08:05</td>
<td>99.8</td>
<td>98:06</td>
<td>08:06</td>
<td>99.8</td>
<td>98:06</td>
</tr>
<tr>
<td>Taking a Nap</td>
<td>00:11</td>
<td>77.1</td>
<td>01:05</td>
<td>Phone</td>
<td>00:05</td>
<td>14:8</td>
</tr>
<tr>
<td>Relaxing</td>
<td>00:10</td>
<td>18.9</td>
<td>00:54</td>
<td>Writing e-mails</td>
<td>00:03</td>
<td>6.9</td>
</tr>
<tr>
<td>In bed because of illness</td>
<td>00:06</td>
<td>1.5</td>
<td>06:06</td>
<td>White letters</td>
<td>00:01</td>
<td>6.1</td>
</tr>
<tr>
<td>Eating</td>
<td>01:16</td>
<td>96.9</td>
<td>01:19</td>
<td>Conversations outside the family</td>
<td>00:36</td>
<td>6.9</td>
</tr>
<tr>
<td>Body care</td>
<td>00:47</td>
<td>94.3</td>
<td>00:50</td>
<td>Visits to, from friends or relatives</td>
<td>00:23</td>
<td>24.2</td>
</tr>
<tr>
<td>Personal medical care</td>
<td>00:01</td>
<td>3.4</td>
<td>00:35</td>
<td>Going out in bars, private parties</td>
<td>00:15</td>
<td>11.6</td>
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<tr>
<td>Ways - Personal</td>
<td>00:21</td>
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<td>00:47</td>
<td>Personal care of the child</td>
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<td>12.8</td>
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<td>Workrelated activities</td>
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<td></td>
</tr>
<tr>
<td>Feeding the child breastfed</td>
<td>00:02</td>
<td>3.2</td>
<td>01:15</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Principal Employment</td>
<td>03:34</td>
<td>45.4</td>
<td>07:52</td>
<td></td>
<td>00:01</td>
<td>2.2</td>
</tr>
<tr>
<td>Lunch break during working hours</td>
<td>00:09</td>
<td>22.4</td>
<td>00:40</td>
<td></td>
<td>00:01</td>
<td>2.6</td>
</tr>
<tr>
<td>Other breaks during working</td>
<td>00:03</td>
<td>12.7</td>
<td>00:26</td>
<td></td>
<td>00:02</td>
<td>4.6</td>
</tr>
<tr>
<td>Secondary occupation</td>
<td>00:05</td>
<td>2.3</td>
<td>03:49</td>
<td>Talk to the child</td>
<td>00:01</td>
<td>3.9</td>
</tr>
<tr>
<td>Other professional activities</td>
<td>00:06</td>
<td>3.8</td>
<td>02:38</td>
<td>Storytelling</td>
<td>00:01</td>
<td>2.9</td>
</tr>
<tr>
<td>Ways - Employment</td>
<td>00:25</td>
<td>42.4</td>
<td>00:59</td>
<td>Playing with the child, playground visit</td>
<td>00:09</td>
<td>11.2</td>
</tr>
<tr>
<td>School and further education</td>
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<td>2.8</td>
<td>01:09</td>
<td>Accompaniment of the child</td>
<td>00:01</td>
<td>2.8</td>
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<tr>
<td>Teaching, Lecture</td>
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<td>9.2</td>
<td>05:20</td>
<td>Care of sick adults</td>
<td>00:01</td>
<td>1.1</td>
</tr>
<tr>
<td>Teaching breaks</td>
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<td>3.7</td>
<td>00:43</td>
<td>Help for 'healthy adults' in the household</td>
<td>00:00</td>
<td>0.7</td>
</tr>
<tr>
<td>Lesson preparation</td>
<td>00:12</td>
<td>9.3</td>
<td>02:11</td>
<td>Formal volunteering</td>
<td>00:04</td>
<td>2.5</td>
</tr>
<tr>
<td>Career development</td>
<td>00:02</td>
<td>0.7</td>
<td>03:33</td>
<td>Informal help, volunteering</td>
<td>00:02</td>
<td>1.9</td>
</tr>
<tr>
<td>Non-professional development</td>
<td>00:02</td>
<td>1.9</td>
<td>02:03</td>
<td>Participation in religious, political events</td>
<td>00:02</td>
<td>2.0</td>
</tr>
<tr>
<td>Ways - School, education</td>
<td>00:06</td>
<td>8.7</td>
<td>01:08</td>
<td>Ways - Social contacts</td>
<td>00:09</td>
<td>19.3</td>
</tr>
<tr>
<td>Ways - Education</td>
<td>00:01</td>
<td>2.4</td>
<td>00:45</td>
<td>Ways - Child care</td>
<td>00:04</td>
<td>9.7</td>
</tr>
<tr>
<td>Household activities</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ways - Care of adults</td>
<td>00:01</td>
<td>2.1</td>
<td>00:40</td>
<td>Ways - Volunteering</td>
<td>00:01</td>
<td>3.0</td>
</tr>
<tr>
<td>Preparing Meal</td>
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<td>54.5</td>
<td>00:56</td>
<td>Leisure activities</td>
<td>00:02</td>
<td>3.9</td>
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<tr>
<td>Baking, Preserving food</td>
<td>00:02</td>
<td>3.9</td>
<td>01:00</td>
<td>Cultural activities</td>
<td>00:03</td>
<td>1.7</td>
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<tr>
<td>Washing dishes, kitchen work</td>
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<td>32.7</td>
<td>00:31</td>
<td>Validation of entertainment events</td>
<td>00:02</td>
<td>1.1</td>
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<tr>
<td>Tidying up, cleaning the apartment</td>
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<td>42.3</td>
<td>00:59</td>
<td></td>
<td>00:02</td>
<td>1.1</td>
</tr>
<tr>
<td>Waste disposal</td>
<td>00:01</td>
<td>4.1</td>
<td>00:22</td>
<td>Taking a walk</td>
<td>00:09</td>
<td>12.9</td>
</tr>
<tr>
<td>Chopping wood, heat</td>
<td>00:04</td>
<td>5.6</td>
<td>01:13</td>
<td>Hiking, running</td>
<td>00:03</td>
<td>3.2</td>
</tr>
<tr>
<td>Garbage, patio cleaning</td>
<td>00:02</td>
<td>4.5</td>
<td>00:52</td>
<td>Cycling</td>
<td>00:05</td>
<td>2.4</td>
</tr>
<tr>
<td>Sorting, searching in the household</td>
<td>00:04</td>
<td>15.1</td>
<td>01:28</td>
<td>Fitness, gymnastics</td>
<td>00:03</td>
<td>6.0</td>
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<tr>
<td>Laundry</td>
<td>00:07</td>
<td>18.3</td>
<td>00:36</td>
<td>Other sporting activities</td>
<td>00:10</td>
<td>7.4</td>
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<tr>
<td>Ironing laundry</td>
<td>00:08</td>
<td>15.1</td>
<td>00:51</td>
<td>Hunting, fishing, gathering in the nature</td>
<td>00:03</td>
<td>1.0</td>
</tr>
<tr>
<td>Cleaning shoes</td>
<td>00:00</td>
<td>1.0</td>
<td>02:20</td>
<td>Artistic hobbies</td>
<td>00:03</td>
<td>3.1</td>
</tr>
<tr>
<td>Handicrafts, repair of clothing</td>
<td>00:03</td>
<td>2.9</td>
<td>01:27</td>
<td>Music</td>
<td>00:02</td>
<td>2.6</td>
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<tr>
<td>Gardening, Plant care</td>
<td>00:14</td>
<td>16.0</td>
<td>01:20</td>
<td>Technical hobbies</td>
<td>00:03</td>
<td>3.2</td>
</tr>
<tr>
<td>Animal care, feeding</td>
<td>00:04</td>
<td>10.1</td>
<td>00:44</td>
<td>Corporate, kids games</td>
<td>00:07</td>
<td>8.5</td>
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<tr>
<td>Walking the dog</td>
<td>00:04</td>
<td>5.4</td>
<td>01:15</td>
<td>Computer games</td>
<td>00:05</td>
<td>5.1</td>
</tr>
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<td>Housing to build</td>
<td>00:03</td>
<td>1.3</td>
<td>03:35</td>
<td>Reading newspapers, magazines</td>
<td>00:10</td>
<td>23.6</td>
</tr>
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<td>Household repair</td>
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<td>3.6</td>
<td>01:41</td>
<td>Reading books</td>
<td>00:04</td>
<td>7.3</td>
</tr>
<tr>
<td>Vehicle maintenance, repair</td>
<td>00:01</td>
<td>2.4</td>
<td>00:58</td>
<td>Reading programs, catalogues, manuals</td>
<td>00:08</td>
<td>14.1</td>
</tr>
<tr>
<td>Shopping</td>
<td>00:21</td>
<td>41.9</td>
<td>00:50</td>
<td>Watching TV</td>
<td>01:51</td>
<td>79.3</td>
</tr>
<tr>
<td>The authorities, banking, postal service</td>
<td>00:01</td>
<td>4.4</td>
<td>00:27</td>
<td>Listening to radio, music</td>
<td>00:02</td>
<td>4.7</td>
</tr>
<tr>
<td>Medical, therapy visits</td>
<td>00:05</td>
<td>6.3</td>
<td>01:13</td>
<td>Information gathering with computer</td>
<td>00:04</td>
<td>7.8</td>
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<td>Hairdressing</td>
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<td>2.2</td>
<td>01:24</td>
<td>Ways - Culture</td>
<td>00:02</td>
<td>2.3</td>
</tr>
<tr>
<td>Use of other services</td>
<td>00:01</td>
<td>3.2</td>
<td>00:38</td>
<td>Ways - Sports</td>
<td>00:04</td>
<td>8.1</td>
</tr>
<tr>
<td>Budget planning and organisation</td>
<td>00:03</td>
<td>6.4</td>
<td>00:45</td>
<td>Ways - Hobbies</td>
<td>00:00</td>
<td>0.7</td>
</tr>
<tr>
<td>Ways - Housework</td>
<td>00:01</td>
<td>2.6</td>
<td>00:35</td>
<td>Activities, not specified</td>
<td>00:02</td>
<td>3.0</td>
</tr>
<tr>
<td>Ways - Shopping</td>
<td>00:12</td>
<td>29.0</td>
<td>00:40</td>
<td>Fill-in diary</td>
<td>00:03</td>
<td>9.0</td>
</tr>
</tbody>
</table>

Figure 3: Results of the Time Use Survey 2008/09