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The effect of exercise on mental health: causal analysis in the face of reverse causality

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Abstract

Much recent literature aimed to find interventions to improve mental wellbeing, including physical exercise. However, such a benefit for exercise has not been well established, with especially trials having inconsistent findings in contrast with the positive correlation between exercise and mental wellbeing that is consistently found in observational studies. The present study aims to find a causal benefit in observational data through careful analysis of data from the LISS panel, a yearly panel in the Netherlands with 7500 participants. It is hypothesised that the discrepancy between trials and observational analysis can be attributed to the reverse action of poor mental wellbeing making one less likely to engage in exercise. To this end, only the effect of previous exercise on present wellbeing is considered, which could not be compromised by such reverse causality. The main finding is that there is no significant effect of previous exercise on mental wellbeing ($p = 0.095$). This does not preclude an appreciable short-term benefit of exercising, warranting further research on the topic. Such research should emphasise controlling for reverse causality in the experimental design, as that appears the only feasible way to differentiate the short-term effect from the reverse action.

Contents

Chapter 1

Introduction

The relationship between physical exercise and mental wellbeing has been the topic of much recent literature, both in empirical studies (Noetel et al., 2024; Mahindru, Patil & Agrawal, 2023), and through mechanistic research (P. J. Smith & Merwin, 2021; Lubans et al., 2016). The latter suggest various mechanisms for the positive influence of exercise on mental wellbeing. Proposed mechanisms include neurobiological ones like structural changes to the brain and endorphin release (e.g. dopamine), as well as psychosocial mechanisms like relatedness, improved body image and self-efficacy (confidence in own ability to perform activities), and behavioural mechanisms like improved sleep, self-regulation and coping skills (Lubans et al., 2016). Note that these mechanisms can be categorised into short-term effects like endorphin release, and long-term effects like improved body image; this distinction will be crucial for the present analysis.

However, while cross-sectional studies consistently find a strong association between the two, Chekroud et al. (2018) note that the causal effect of exercise on mental health as studied in randomised controlled trials (RCT) has been inconsistent. Chalder et al. (2012) for instance find an insignificant change in the Beck's Depression Inventory score ($p = 0.68$), while Philippot et al. (2022) find a significant decrease in the Hospital Anxiety and Depression Scale ($p = 0.016$). Due to this inconsistency, review articles only draw tentative conclusions, for example that exercise "is probably [beneficial] for psychiatric diseases" (Peluso & De Andrade, 2005), "hold(s) promise in the treatment [...] of mental health conditions" (P. J. Smith & Merwin, 2021), et cetera. Strikingly, the review of reviews on the topic by Biddle and Asare (2011) concludes there is a distinct lack of good quality research.

I posit that observational studies to date have not been powered to draw conclusions about the causal effect of exercise on mental health, in part because they have not explicitly modelled the reverse effect, namely that individuals with poor mental health are less likely to engage in exercise. If this is true, estimation of the effect of exercise on mental health is plagued by endogeneity, leading to inconsistent estimation of the causal effect, a fact that Leszczensky and Wolbring (2022) note is often neglected in longitudinal research. In a discussion on causal analysis, Imbens (2024) also claims "using variables affected by the treatment or the outcome is the most common mistake [...] in estimating average treatment effects". There is a decided lack of literature on this reverse action, as is apparent in the review article by Fossati et al. (2021), whose discussion of the forward effect is much more extensive than that of the reverse effect. Nevertheless, they establish a consistent finding that poor mental health is associated with increased injury risk, which may hinder one's ability to engage in exercise. Additionally, other research has found low mood and stress to be common barriers for engaging in exercise (Firth et al., 2016). Azevedo Da Silva et al. (2012) and Jerstad, Boutelle, Ness and Stice (2010) also find empirical evidence for this reverse relationship, though other work is inconclusive (Birkeland, Torsheim & Wold, 2009; Ku, Fox, Chen & Chou, 2012). Altogether, the assumption that engagement in exercise is not influenced by mental health seems tenuous at best.

The aim of this work is then to remedy the discrepancy between on the one hand the consistent association found in cross-sectional studies, and the inconsistent findings of trials on the other hand, by making sure the reverse effect is accounted for. Specifically, the research question is as follows:

Is physical exercise an effective intervention for improving mental wellbeing?

The emphasis is thus on the within-person effect of exercise, not simply the between-person correlation between the two. Additionally, the forward causal effect is of interest, whereas the reverse effect is considered a nuisance parameter. That is, it is an effect that must be considered in the statistical modelling, but no effort is made to quantify the effect.

Panel data provides the means through which the reciprocal relationship can be modelled. Specifically, the simple fact that cause must precede effect can be exploited with panel data. Leszczensky and Wolbring (2022) find excellent statistical properties of Structural Equation Modelling (SEM) when using panel data to model reciprocal action, namely lower bias and significantly greater efficiency than Arellano-Bond (GMM) estimation if the model is correctly specified. Inspired by these findings, the present study follows the procedure outlined by Allison, Williams and Moral-Benito (2017) for modelling reciprocal causation. In SEM, arbitrary (linear) interactions amongst variables can be modelled, which gives a lot of freedom in model specification. SEM thus lends itself well to studying a complex and nuanced topic like human psychology, where manifold model assumptions might have to be made or relaxed.

The data studied is from the LISS panel, which is a representative (invite-only) panel of 7500 Dutch individuals of all ages (Scherpenzeel & Das, 2010). The panel comprises a broad range of questions, including the topics of exercise and mental wellbeing, but also other variables like sociodemographics that can therefore be controlled for in the analysis.

The present study aims to guide further research by contributing to a better understanding of the potentially complicated interdependence between mental health and exercise. The structure of the study is as follows. Chapter 2 elaborates on the studied dataset, followed by a discussion of the general methodology used in Chapter 3, which includes SEM. Then, all the choices made in formulating the model are explained in Chapter 4. The main findings are given and discussed in Chapter 5, and lastly concluding remarks can be found in Chapter 6.

Chapter 2

Data

The LISS panel (Scherpenzeel & Das, 2010) started in 2007 in the Netherlands. It takes the form of an online questionnaire which is held yearly among 7500 participants, on various topics such as health, religion, leisure, family, work and so on. Its data is freely available for the purposes of research and policymaking. Besides these studies, background variables are collected on a monthly basis, like age, household composition, income and primary occupation. Recruitment is done to make the panel representative of the Netherlands as a whole in terms of sociodemographics. Only adults are recruited, but they are asked to respond on behalf of themselves and all other household members, so the data includes people of all ages. The panel is invite-only to limit self-selection, although it cannot be wholly prevented as participation is still voluntary and motivated by a financial incentive. Additionally, some self-selection might occur in the roughly 80% response rate, despite efforts to contact inactive panel members. Due to a yearly attrition of 12%, refreshment samples were occasionally introduced, selected such as to balance representativeness of household type, age and ethnicity (Centerdata, 2024). This also effectively introduces missing data. The nature and impact of this missing data is further discussed in Section 2.3.

The focus of this study is on two of the core studies, namely the Social Integration and Leisure study and the Health study. The prior directly measures engagement in physical exercise by question 104, "Do you practice sports?". This question has been included since 2012. Mental health is queried in the latter, though not as directly. Questions 11 through 15 are the five-item Mental Health Inventory (MHI5), a standard screening questionnaire for mental health (Berwick et al., 1991). These questions have been included since 2008. Respondents are asked how often, over the past four weeks, they felt very anxious; so down that nothing could cheer them up; calm and peaceful; depressed and gloomy; and happy. Responses are measured on a 6-point Likert scale ranging from "never" to "continuously", and the scores are combined linearly to create the MHI5 score from 0 to 100 with increments of 4, where a higher score indicates superior mental health.

The exact set of variables used will be determined in Section 4.1. For the variables that are ultimately selected, the official descriptions can be found in Appendix A, along with descriptive statistics.

2.1 Quality Issues

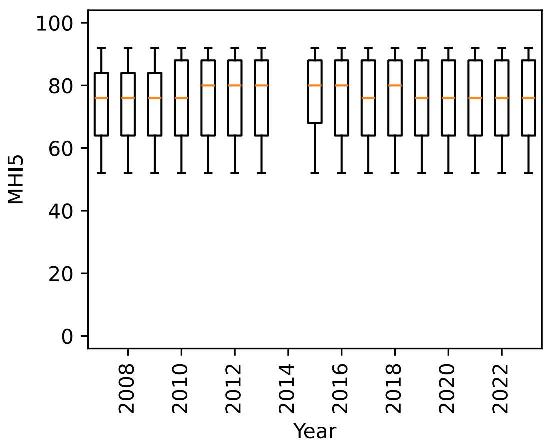
Beyond the problem of self-selection as already discussed, there are more issues that plague the studied data. Naturally, all the information is self-reported. This can lead to noise in the data, as for instance the difference between "sometimes" and "often" in the MHI5 screening can be subjective. Furthermore, Brown, Harris, Srivastava and Taylor (2018) find that mental health is typically overreported, leading to a bias towards zero when estimating the effect of an intervention. Self-reporting bias in general is a well-established phenomenon (Rosenman, Tennekoon & Hill, 2011), but in practice it is a necessary price to pay when gathering data at such a large scale. The large sample size of the LISS panel might help to preserve statistical power in the face of the increased variance, but the resulting bias cannot be overcome without explicitly modelling the bias-inducing effect, which is a psychological phenomenon that is beyond the scope of the present study.

Another risk factor for poor data quality is the extensiveness of the questionnaire. The total yearly LISS study comprises multiple thousands of questions, and it is likely that this causes respondents to not answer each question with as much care as they would on a shorter questionnaire, and perhaps even more significantly, it might lead to failure to respond in the first place. To combat this, the core studies are held at different times of year. The Health study is (almost) always held in November through December, whereas the Leisure study was held in February through March before 2015, and October through November since. The effect of questionnaire length has been studied in the literature, with somewhat conflicting results. Galesic and Bosnjak (2009) for instance find worse response quality for questions later in the survey as compared to earlier. On the other hand, Andreadis and Kartsounidou (2020); Subar et al. (2001) do not find significant evidence for improved response rate and data quality with shorter questionnaires. The latter also note ease of administration may compensate for length, in which regard the online nature and typically multiple-choice questions of the panel do well. The impact of the length of the panel is thus likely not a major concern.

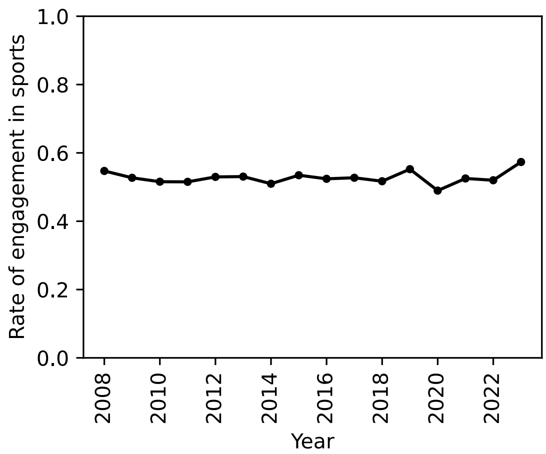
Because of the fact that the Leisure and Health study are not held at the same time of year, it has to be chosen whether a wave of the panel is considered to be a Health study with the most recent Leisure study, or with the first upcoming Leisure study. Sports has only been included in the panel since 2012, whereas the MHI5 score has been recorded since earlier. Noting this, the choice is made to consider a Health study with the previous Leisure study as one wave, so as to have as many available waves as possible. This effectively introduces the assumption that exercise status in March is a good predictor of exercise status in November of the same year, and in so far as it is not ($R^2 < 1$), noise is introduced into the data, reducing the power of the study. Since the background variables are recorded on a monthly basis, they are chosen to align with the Health study, namely November each year.

A curious general finding is that the correlation between MHI5 score and sports is very low in the data, between $\rho = 0.042$ and $\rho = 0.095$, even before controlling for covariates. This is very different from for instance Endrawan et al. (2023) who find $\rho = 0.893$ between physical activity and mental health. Such a small correlation leaves very little statistical power to find a causal effect, and may be a result of the very general phrasing of the question for sports which may cause noisy data. The correlation coefficient is however strikingly small even considering this general phrasing.

A worthwhile consideration is the impact of the Covid-19 pandemic on the data. The negative effect of the pandemic on public mental health has been the topic of much discussion (Cullen, Gulati & Kelly, 2020; Kumar & Nayar, 2021) and has been empirically verified (Kupcova, Danisovic, Klein & Harsanyi, 2023). Additionally, due to closing of public facilities, people engaged in exercise significantly less (Amini et al., 2021). The pandemic thus seems a priori to be a significant risk factor for endogeneity in the present analysis. However, curiously, neither the effect of the pandemic on mental health nor its effect on rates of physical exercise seem to be present in the data. As Figure 2.1 shows, sample statistics of both variables vary little over time with no appreciably change after the onset of the Covid pandemic in 2020. This puts the validity of the data into question, as these findings conflict with the literature on this topic. The constance in sports engagement may be explained by the fact that while sports facilities closed, people had more spare time as for instance social events and commuting were no longer possible, which appears to compensate for the effect of closing sports facilities. However, the lack of decrease in mental health is quite remarkable. It is perhaps an artefact of biases introduced due to self-reported data, as people may have measured their state relative that of people around them, rather than relative to themselves previously. Regardless, based on the lack of impact on the sample statistics, the Covid pandemic will not be of further consideration for this work.



(a) Boxplot of the MHI5 score. Whiskers are 10th and 90th percentiles. Note the appreciable varability in the median is simply because the MHI5 score has an interval of 4



(b) Rate of engagement in exercise

Figure 2.1: Distributions of the MHI5 score and sports engagement across years

2.2 Preprocessing

MHI5

As said, the MHI5 score is derived linearly from the responses to the five relevant questions. It was found that there is no partial missingness, in the sense that either all five questions were answered or none of them were answered. The score is then simply calculated when all responses are given, and missing otherwise. Listwise deletion is performed for those individuals for whom the MHI5 score is always missing, as they provide no information towards the relationship being studied.

Sports

The variable is used as-is, but as with MHI5, those individuals for whom sports is always missing are deleted from the data. A consideration is to also remove individuals for whom sports is constant in time, i.e. either always "no" or always "yes", as for such individuals there is no within-person variability to be studied. Such subjects are likely to be subject to unmeasured individual-specific confounders, causing endogeneity. However, upon further consideration this appears to imply a rather arbitrary threshold. For example, if one individual has a probability of 1 to engage in exercise yet another has a probability of 0.9, it is not unlikely that during their panel participation, both always engaged in exercise, yet these are clearly different individuals. A threshold of 90% engagement in sports may then be used, but this choice quickly becomes arbitrary. Additionally, opposed to endogeneity caused by unmeasured confounders is endogeneity caused by the selection bias that would occur if such individuals were left out. The choice is thus made to include such observations.

Dummy Encoding

Many questions in the study are measured on a categorical or ordinal scale (f.i. a Likert scale), which cannot be meaningfully included directly as regressors, for example primary occupation, ethnicity and education level. Naturally, such variables are expanded to dummy variables, with one dummy variable for each level of the original variable (also known as one-hot encoding).

Additionally, even for variables that are measured on an ordinal scale, for instance age, income and bmi, the effect on mental wellbeing is very unlikely to be linear. Without expert knowledge on the exact relationship between each variable and mental health and in order to avoid model complexity, these variables are stratified into categories and then also included as dummy variables. While this involves some loss of information, it also simultaneously provides robustness against outliers, such as individuals whose reported height and weight imply an infeasible body mass index (BMI) of over 100. Refer to Table 2.1 for the exact stratification. For age, the stratification is chosen as to align roughly with different phases of life, as the strata roughly represent children, students, young adults, middle adults and retirees. For income, the strata represent no income, minimal income, regular income and high income. For BMI, the strata reflect underweight, normal weight, overweight and obese, as derived from World Health Organization (2010). Additionally, for BMI, individuals who reported a weight or height that was excessively high or low were assigned NA as their BMI. Lower cutoffs were 5 cm and 1 kg and upper cutoffs were 270 cm (the height of the tallest man ever) and 635 kg (the weight of the heaviest man ever). These are conservative bounds so as to eliminate outliers due to for instance mistyping, but with minimal subjective judgment to avoid researches biases. Technically, this introduces MNAR missingness with respect to BMI, even though only about 0.14% of the observations are assigned to be NA by this. However, these extreme outliers are likely due to mistyping and are thus only weakly related to the true values, which means the impact of the MNAR data should be very minimal.

Table 2.1: Stratification applied to variables whose effect is unlikely to be linear. All bounds are left-inclusive

Variable	Stratum Bounds	Number of Strata
Age	0 - 18 - 25 - 40 - 67 - ∞	5
Income (€)	0 - 1 - 15000 - 50000 - ∞	4
BMI	0 - 18.5 - 25.0 - 30 - ∞	4

If such a dummy-encoded variable was missing, that observation is assigned NA for each dummy level, and this missing data will then be naturally handled by the method explained in Section 3.2.6. An alternative would be to assign 0 to each dummy level. However, that would imply that on average, mental wellbeing of non-respondents is equal to the mental wellbeing in the dummy level that is left out for identification, which is an assumption that clearly need not hold in general.

Employment status

Employment status is the only covariate for which noteworthy preprocessing is done. Namely, it is derived from a multiple-choice question on primary occupation with 14 different possible answers, which would entail a lot of dummy variables. For the sake of parsimony, these answers are grouped into Employed, Unemployed, Student, Homemaker, Retired and Unable to work. This captures the most major forms of employment, while losing the nuance of for instance the difference between general employment versus employment in a family business or voluntary work, a nuance which is assumed to be of lesser relevance.

2.3 Missingness

After removing individuals for which MHI5 or sports are always unavailable, we are left with data for 12 920 individuals for the years 2008 through 2023. However, a significant portion of all data is missing. For some variables in specific years, all data is available, but for others upwards of 70% is missing. Across all variables considered in this study, after preprocessing, the average percentage of missing variables is 48.8%. This missing data is due to multiple factors. Firstly, due to attrition or due to joining the panel in one of the later recruitment waves, data for a certain individual might not be available for all waves. Additionally, the Leisure study only started in 2008, so no data from it is available for 2007. In 2014, the decision was made to postpone the Health study until May 2015, as a result of which the study was not held that year, leaving a gap in the data. From 2016 onwards, the study was held in November again (Marchand, 2025). In addition to the missing information in 2014, the different time of year might be a cause of anomalies in the data for that year, in the sense that seasonal effects may now perturb the data. However, it was found that regression estimates for the 2015 wave were not appreciably different from those of other waves, so this seasonality is not of further consideration. Lastly, an individual may give a partial response, either in the form of not answering some of the questions in a study, or in the form of not responding to an entire study for a year (even if they did respond to other studies).

A noteworthy quantity is the coverage between sports and the MHI5 score, defined as the percentage of observations (for each year) for which both sports and the MHI5 score is available. This can be found in Table 2.2. It is still somewhat low even after removing individuals for whom MHI5 or sports are always missing, around 40% each year. As a result, out of the almost 13 000 individuals each year, only about 5 000 contribute direct information to the relationship of interest in this study.

Table 2.2: Coverage of sports and MHI5 score each year, i.e. percentage of observations for which both are available. This is after removing individuals for whom MHI5 or sports is always missing

Year	Coverage
2012	40.4%
2013	38.6%
2014	-
2015	42.8%
2016	40.0%
2017	44.2%
2018	40.6%
2019	37.3%
2020	42.6%
2021	37.2%
2022	42.8%
2023	43.9%

When dealing with missing data, it is important to consider why the data is missing, as different reasons for the missingness have differing impacts on the outcomes. In general, we differentiate between three different forms of missingness, namely missing completely at random (MCAR), missing at random (MAR) and missing not at random (MNAR). MCAR is the least problematic as it entails the absence of the data is utterly random and not related to any of the variables used in the study. In this case, we simply lose statistical power due to the missing information, but no biases are introduced. The other extreme, MNAR, entails that whether the data is missing for some variable depends on the value of the variable itself. Imagine for instance an online survey sent out to a chosen group of people that asks how much one uses the internet. Clearly, there would be a selection bias, as no respondents would say “never”. As such, in the face of MNAR data, serious biases may be introduced into the analysis. No general solutions exist for handling MNAR missingness. It might be possible to handle it via a case-specific model of the exact mechanism leading to missing data, but this would at least require extensive expert knowledge of the data being studied. Note that listwise deletion, that is simply removing observations for which some data is missing, does not prevent these biases from occurring, as the remaining studied data is not representative of the population as a whole. Lastly, there is MAR. MAR data is data for which the missingness depends on the values of other variables in the dataset, but not the variable itself. In this case, general solutions exist, which preserve as much information as possible without introducing biases.

SEM has a natural solution to MCAR or MAR data which will be explained in Section 3.2. However, it cannot naturally deal with MNAR data, so a discussion of which mechanisms are present in the LISS data is prudent. First, consider missingness due to late recruitment. As explained earlier, selection for late recruitment is done based on household type, age and ethnicity, so as to make the panel representative of the general population. For cases of missing data due to late recruitment, it is thus MAR in general, but MNAR with respect to those free background variables. Since those variables are only used as controls in this work, the impact of the MNAR data is likely minimal. Second, consider attrition. Centerdata has studied attrition (de Vos, 2009), and it was found the only significant predictors of attrition were age, whether internet was provided and whether there was a disabled person in the household (Table 4 of the report). The latter two variables are not variables studied in this work, so through the same argument as for late recruitment, attrition is only of minor concern. The missing information for the Leisure panel in 2007 can be considered MCAR, and while it cannot be said for certain as the reason for its absence is not known, the same the missing Health panel wave of 2014. Lastly, there is missingness due to incomplete responses, which poses a more significant problem, as poor mental wellbeing is known to be associated with worse self-efficacy. Grøtan, Sund and Bjerkeset (2019) found students with mental distress were four times more likely to experience low self-efficacy, and the association is corroborated in other literature, f.i. Schönfeld, Brailovskaia, Bieda, Zhang and Margraf (2016); Najafi and Foladjang (2007). Lower self-efficacy would almost by definition decrease the probability of responding to the survey, thus providing a significant mechanism for MNAR missingness of mental health. To study this, I examine what percentage of MHI5 scores is missing in between each individual's first and last available MHI5 score, which is just over 9%. This slightly underestimates the true number, as nonresponse in the first or last year of panel participation would not be measured. Nevertheless, it should be a reasonable estimate. Some proportion of this will be just MCAR or MAR missingness, but it cannot be known what proportion. Since self-efficacy is not directly measured in the panel and due to a lack of expert knowledge on this association, the MNAR missingness is not handled explicitly in this work and thus remains as a limitation of the study. In a more strictly controlled environment than online web surveys, such missingness might be avoided, but it is likely a necessary price to pay when studying mental health in large samples.

Chapter 3

Methods

3.1 Causal analysis

3.1.1 Potential Outcome Framework

In order to credibly make the claim that the estimated effect is a causal one, some a priori considerations are in order. To this end, the review on causal analysis by Imbens (2024) is considered.

Firstly, there is the stable unit treatment value assumption (SUTVA), which is the assumption that the outcome for one individual is not influenced by treatment exposure (in this case, engagement in exercise) of another. Since the subjects of the LISS panel are selected to be representative of the Netherlands as a whole, the subjects live all over the country and are not likely to know each other, let alone influence each other. However, it is typical for multiple individuals to partake within a single household. On average, it is found that about 1.6 individuals participate per household. Within one household, we cannot rule out that individuals influence each other. In fact, Maltby, Wood, Vlaev, Taylor and Brown (2012) find that one's perception of the benefit of exercise is influenced by social norms, clearly violating the SUTVA. However, because these violations are local to small groups in the dataset, the assumption is taken to hold at large for the studied data.

Next, we formalise the effect of interest, namely the causal effect of exercise on mental wellbeing, using the potential outcome. For each individual i, $Y_i(T)$ is the potential outcome if they engage in exercise (treatment), and $Y_i(C)$ is the potential outcome if they do not (control). The variable of interest then is the sample average treatment effect

$$\tau_{\text{sample}} = \sum_{i=1}^{N} (Y_i(T) - Y_i(C)), \tag{3.1}$$

which thanks to the representativeness of the sample is assumed to estimate the population average treatment. This is where SUTVA is crucial, as without it the potential outcomes are not simply a function of individual i's treatment, but also of individual j's treatment (where $j \neq i$), and so we could not meaningfully interpret the average treatment effect calculated as in Equation (3.1). For any one individual the treatment effect may deviate from the average effect, in the sense that it may be moderated by for instance personal circumstances or genetics, but such analysis is left to further research.

Denote X_i as the treatment assignment for individual i, $X_i \in \{C, T\}$. The crucial assumption is that the *potential* outcomes are not influenced by the treatment assignment, or formally, given some set of controls W_i,

$$(Y_i(T), Y_i(C)) \perp\!\!\!\perp X_i \mid W_i. \tag{3.2}$$

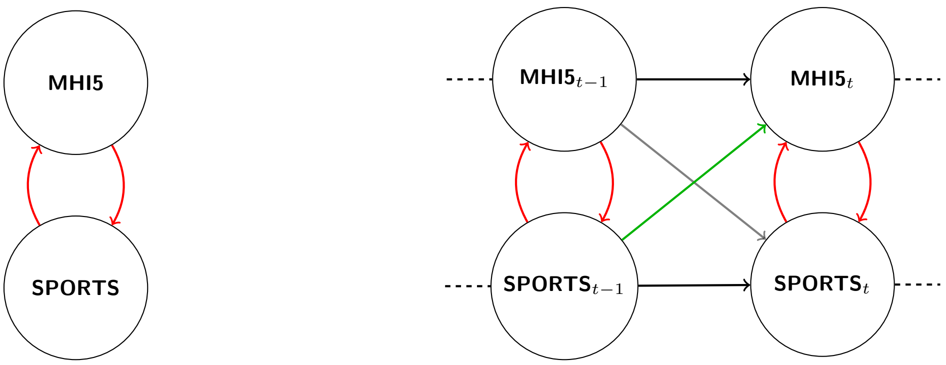
This assumption is called the ignorability assumption or the assumption of no unobserved confounders. The controls are included to lend credibility to the assumption, as they remove biases in comparing treated individuals to individuals in the control group. Selection bias, MNAR data and the assumption's namesake in no unobserved confounders can all equivalently be considered violations of the ignorability assumption. The crucial difficulty that necessitates the assumption is that for any one individual i, only either $Y_i(T)$ or $Y_i(C)$ is observed, and thus we cannot directly observe the difference in potential outcomes. However, under the ignorability assumption, this difference can be estimated by $Y_i(T) - Y_j(C)$ for $j \neq i$, which is a quantity that can be observed directly.

Considering the research question at hand is whether physical exercise is an effective intervention for mental wellbeing, the aim is not to quantify the exact effect, but rather to find whether a significant effect exists. To that end, the ignorability assumption can be relaxed slightly to assuming that in so far as there are unmeasured confounders, they do not change the statistical significance (nor the sign) of the estimated effect.

3.1.2 Reverse Causality

Now consider the aim of the present study, namely estimating the effect of exercise on mental health, $Y_i(T) - Y_i(C)$. In a cross-sectional dataset, this effect is not identified, because if mental health influences the probability to engage in exercise, the ignorability assumption is violated. If for instance better mental health makes one more likely to engage in exercise, and assuming the greater mental health does not disappear as soon as one engages in exercise, then the *potential* outcomes Y_i are increased for individuals with better mental health. That is, in the observed sample, $Y_i(T) - Y_j(C)$ will be inflated with respect to $Y_i(T) - Y_i(C)$. This holds true even if the treatment effect itself is not influenced by a priori mental health. Figure 3.1a gives a graphical representation of how the forward and reverse effect are not simultaneously identified.

On the other hand, with panel data, we can exploit the fact that cause must precede effect. The graphical representation in Figure 3.1b shows the instantaneous effects, along with presumed autoregressive effects and a lagged effect. The latter is now identified. Crucially, the instantaneous effect of sports on MHI5 is not identified, nor is the effect of lagged sports through the autoregressive behaviour of MHI5. Recalling that the established mechanisms through which sports may improve mental health can be split into short-term and long-term mechanisms, it can thus be concluded that observational data provides no way to quantify the short-term effects, at least not for any effects that last much shorter than the time difference between two waves of the panel. The elevated endorphin levels post-exercise for instance would likely last on the order of hours (though there is no research on the exact duration), which is clearly not identifiable on the yearly time-scale of the LISS panel. Considering the various mechanisms for a positive short-term effect, and assuming a positive long-term effect is found, it is reasonable to postulate that the short-term effect would also be positive. Also assuming positive autoregressive coefficients, both the instantaneous effect and the effect through autoregressive behaviour will also be positive. To the end of answering the research question then, we may conclude that the total benefit of exercise is at least as large as the found long-term benefit. Thus, while the unidentified effects mean decreased power in answering the research question, significance in the sense of the type I error rate is preserved. Do note that in a regression context, in order for the effect of SPORTS_{t-1} to be identified with respect to the simultaneous effects, SPORTS_t should be included as a regressor, as the autoregressive patterns otherwise obscure its effect. An important implication of this is that the effect represented by the green arrow is the long-term effect only in so far as it is not controlled for by the direct effect, that is, it only measures the effects of long-term mechanisms that are cumulative with total engagement in exercise across the years. An example would be the improvement to one's body image due to cumulative physiological adaptation. On the other hand, an mechanism that cannot be measured might be the satisfaction with oneself for the fact that one is exercising currently, as for that purpose there is likely no additional benefit to having exercised last year given that one is presently engaging in exercise.



(a) Cross-sectional data

(b) Panel data. Note the effect of MHI5_{t-1} on SPORTS_t is identified, but is considered a nuisance parameter. The green arrow represents the effect of interest

Figure 3.1: Graph representations of the hypothesised interactions between MHI5 score and sports. Controls are left out for simplicity. The green arrow indicates the effect of interest, while red arrows indicate unidentified effects

While many alternative software pacakges exist, for the present research, the package *lavaan* in R is used (Rosseel, 2012). This choice was made because *lavaan* is a mature and feature-rich project, whose reliability is exemplified by its extensive use in the literature.

3.2 Structural Equation Modelling

SEM can be considered a generalisation of the linear model, where rather than one regression equation which explains the variability of the regressand with regards to a set of regressors, multiple regression equations are estimated simultaneously to explain the total covariance structure of all variables involved. The following will be a minimal introduction into SEM for the purpose of this work, in which accuracy is sacrificed to some degree in favour of simplicity. For a full introduction, consider textbooks such as Kline (2023). While SEM also allows for modelling latent variables in its general form, such constructs are not considered in this work. This is because the author possesses no a priori knowledge as to what latent constructs might exist, and Lüdtke and Robitzsch (2022) find in a simulation study that empirically deciding on latent structures "is only of limited usefulness, because the different model[l]ing approaches provide almost equivalent representations of [the data]."

Consider then a vector z_i, which contains for individual i the outcome variable of interest y_i as well as all regressors x. For the purpose of maximum likelihood estimation of the population parameters, note the well-known likelihood (density) of a single observation

$$f(z_i; \mu, \Sigma) = (2\pi)^{-\frac{p}{2}} |\Sigma|^{-\frac{1}{2}} e^{-\frac{1}{2}(z_i-\mu)'\Sigma^{-1}(z_i-\mu)}, \tag{3.3}$$

where p denotes the dimension of z_i and μ and Σ are respectively the mean and covariance of z_i, and lastly $\pi \approx 3.14$. Assuming independent observations and dropping the constant, the sample log likelihood is

$$l(z) = \sum_{i=1}^{N} \log(f(z_i; \mu, \Sigma)) = -\frac{N}{2} \log(|\Sigma|) - \frac{1}{2} \sum_{i=1}^{N} (z_i - \mu)'\Sigma^{-1}(z_i - \mu), \tag{3.4}$$

which for the purposes of optimisation can be rewritten to an equivalent fit function F, defined in terms of the sample mean $\bar{x}$ and covariance matrix S (Preacher, 2016) as

$$F(\mu, \Sigma) = \log|\Sigma| + \mathrm{tr}(S\Sigma^{-1}) - \log|S| - p + (\bar{z} - \mu)'\Sigma^{-1}(\bar{x} - \mu), \tag{3.5}$$

with $\mathrm{tr}(\cdot)$ denoting the trace of a matrix and the minimum of F coincides with the maximum likelihood estimate. Note this fit function does not directly involve any observation z_i. Rather it is defined purely in terms of the sample moments $\bar{z}$ and S, which is to say that while Equation (3.4) and Equation (3.5) are theoretically equivalent, the latter operates on a higher level of abstraction.

At this stage, the elements of μ and Σ may be estimated directly through numerical optimisation. Firstly, note that μ can always be estimated as $\hat{\mu} = \bar{z}$, such that the last term in Equation (3.5) vanishes. It can thus be estimated separately from Σ, and because the research question pertains specifically to the variability of variables, the mean term is ignored in further discussion. To see how this general multivariate likelihood approach relates to the linear model, consider the very simple example regression of

$$y = \alpha + \beta_1 x_1 + \beta_2 x_2 + \epsilon. \tag{3.6}$$

From this equation, the model-implied covariances between y and x_1 and x_2 can be readily defined in terms of the regressor covariances as

$$\begin{aligned} \Sigma_{yx_1} &= \beta_1 \Sigma_{x_1} + \beta_2 \Sigma_{x_1 x_2} \text{ and} \\ \Sigma_{yx_2} &= \beta_1 \Sigma_{x_1 x_2} + \beta_2 \Sigma_{x_2}, \end{aligned} \tag{3.7}$$

where Σ_{x_1} (Σ_{x_2}) denotes the variance of x_1 (x_2) and $\Sigma_{x_1 x_2}$ denotes the covariance between x_1 and x_2. Estimating Σ_{yx_1} and Σ_{yx_2} thus corresponds directly to estimating β_1 and β_2. In general, the upper-right row of elements of the covariance matrix of z is $\Sigma_{xy} = \Sigma_x \beta$ for a vector of regressors x and a vector of parameters β, where Σ_x is the covariance matrix of x. For completeness, the diagonal elements of Σ are estimated directly as well as the covariance elements between the regressors, at which point estimating the above regression equation is just a matter of reparametrisation as compared to estimating the corresponding elements of Σ directly; the two approaches are completely equivalent.

A benefit of the higher-level abstraction in SEM as compared the canonical linear model, is that multiple regressions can be estimated simultaneously. Consider for instance

$$\begin{aligned} y_1 &= \alpha_1 + \gamma y_2 + \epsilon_1; \\ y_2 &= \alpha_2 + \beta x + \epsilon_2. \end{aligned} \tag{3.8}$$

Note the subscripts in y_1 and y_2 denote different variables altogether, not necessarily the same variable at different points in time. Now, the model-implied $\Sigma_{y_1 x} = \gamma\beta\Sigma_x$. However, because in general the second equation in Equation (3.8) does not fully explain the variance in y_2 ($R^2 < 1$), this may not fully explain the covariance between y_1 and x. That is, there may be a residual covariance $\phi_{y_1 x}$, such that $\Sigma_{y_1 x} = \gamma\beta\Sigma_x + \phi_{y_1 x}$. Note also that with three total variables, there are three covariance elements in Σ, but $\{\gamma, \beta\}$ constitutes only two parameters to estimate, which is too few parameters to exactly estimate the full covariance structure. Additionally, $\Sigma_{y_1} = \phi_{y_1} + \gamma\phi_{y_2} + \gamma\beta\Sigma_x$, where ϕ_{y_1} denotes the residual variance of y_1 and likewise ϕ_{y_2}. That is, the variance of y_1 is not just defined in terms of its regressors, but also in terms of its regressors' regressors (and so on).

A general implication of the higher level of abstraction is that while canonically, the linear model has $N - k$ degrees of freedom if there are k parameters to be estimated, in SEM there are $\frac{p(p+1)}{2} - k$ degrees of freedom for a model that involves p variables. Note $\frac{p(p+1)}{2}$ is the number of unique elements in the covariance matrix. For example, the model in Equation (3.6) involves three variables (again, neglecting the mean component), so again three covariance elements in Σ. Two of these are implied as in Equation (3.7), but because both x_1 and x_2 only show up as regressors, the model does not imply any structure to their covariance, and it is simply estimated as $\Sigma_{x_1 x_2} = \phi_{x_1 x_2}$. The residual variance of y is also estimated along with the two variances of the regressors, which leaves $\frac{p(p+1)}{2} - k = 6 - 6 = 0$ degrees of freedom. This is referred to as a model that is just identified. The model in Equation (3.8) differs in that it implies all three covariances, but with only two parameters. If the model is not supplemented with $\phi_{y_1 x}$, there is $6 - 5 = 1$ degree of freedom, which is to say that the model is overidentified. While the example is trivial, in a more complex model we may exploit overidentification to quantify whether the proposed model adequately describes the data. In other words, fit indices can be derived from these degrees of freedom, in some sense analogous to the Sargan-Hansen test for the generalised method of moments.

A model specification in SEM is simply the set of regression pathways and residual variances to be estimated as free parameters. SEM lends itself well to the present research, because it necessitates very few restrictions on the model. This makes it a natural choice for exploring a potentially complex and unknown relationship between variables. A panel regression fits into the SEM framework by having one regression for each wave of the panel, i.e. $y_{i,1} = \ldots; y_{i,2} = \ldots$, and so on. The framework then allows for instance adding autoregressive terms (dynamic panels), having (co)variances vary across waves or even two-way fixed effects (i.e. time dummies and individual-specific effects). Fundamentally, the only restriction imposed by SEM is that the covariance matrix is sufficient to identify the parameters. Notably, while Arellano-Bond (AB) estimation of dynamic panel models relies on first-differencing the model for identification, SEM does not and as such it is possible to include time-invariant controls beyond just the catch-all individual-specific effect. Additionally, AB estimation necessitates a choice of instruments which model validity crucially depends on (Bazzi & Clemens, 2013), and SEM was empirically found by Leszczensky and Wolbring (2022) to be more efficient than AB while also being unbiased in all situations where the model was correctly specified. Altogether, SEM is the preferred choice for the present study.

3.2.1 Fixed and Free Parameters

In *lavaan*, a parameter can either be fixed to a specific value or estimated freely. There are two forms of parameters, namely regression coefficients and additional (residual) covariances (i.e. $\phi_{x_1 x_2}$). If a variable is a regressand or if one of its covariances is set as a free parameter, then all of its covariances must be either estimated through free parameters or fixed to zero to ensure the model-implied covariance matrix is positive definite. In that sense, it is meaningful to talk about a variable as whole to be treated as fixed or not.

Treating variables as fixed makes it impossible to examine the covariances between them, for instance to test whether $\mathrm{Cov}(x_1, x_2) = 0$. However, for the present work, the choice to treat all regressors as fixed comes naturally, because the covariance structure between regressors is not relevant to the research question; doing so improves model parsimony; and considering fit indices are defined in terms of the degrees of freedom, a good model fit in terms of the regressors may obscure a poor model fit for the outcome variable, decreasing the indices' value to the present study.

3.2.2 Panel Model Formulation

The following model formulation is adapted from Allison et al. (2017). In a simplified form, the central regression equation is

$$y_{it} = \alpha_t + \alpha_i + \rho y_{i,t-1} + \beta x_{it} + \omega' w_{it} + \delta' z_i + \epsilon_{it}. \tag{3.9}$$

y_{it} is the MHI5 score of individual i at time t while α_t represents a time dummy, x_{it} the exercise status, w_{it} is a vector of time-varying controls and z_i a vector of time-invariant controls. This equation is simplified in the sense that it only contains a single autoregressive (AR) term and a single lag of x, i.e. no distributed lags (DL). This is not a necessary restriction, but is done here for simplicity of the introduction; the restriction is done away with when developping the model for the present study (Chapter 4). Equation (3.9) has to be complemented with the initial conditions for y. If only one autoregressive lag is included, only $y_{i,1}$ is required, but for a higher lag order more initial conditions are required. If distributed lags are included, then likewise for x. A practical implication of this is that the higher the autoregressive (distributed) lag order, the fewer waves are available for analysis. This is especially relevant in the present study, because the missingness of the MHI5 score in 2014 means twice as many waves are lost as would be the case if the Health study had been conducted that year. The fact that time-invariant controls z_i may be included is beneficial for controls that vary so little in time that treating subsequent values as separate variables causes numerical instability (colinearity). For such a variable, the first observed (non-NA) value of each individual is used as the time-invariant approximation. While this choice is ambiguous, the very fact that the variable must be modelled as a time-invariant implies that the exact choice of approximation matters very little.

The main identifying assumption is (Moral-Benito, Allison & Williams, 2019)

$$E(\epsilon_{it}|y_i^{t-1}, x_i^t, \alpha_t, w_i^t, z_i) = 0 \,\forall\, \{i, t\}, \tag{3.10}$$

where a superscript t denotes all observations of the corresponding variable up to time t. Verbally, the assumption entails that all included regressors are exogenous. Note the exogeneity of x is also implied by the ignorability condition (Equation (3.2)). Furthermore, while all regressors are included in the identifying assumption, if a control is endogenous it simply leads to inconsistent estimation of the corresponding parameter, that has a weaker influence on the estimation of the parameter of interest (β) than endogeneity of x itself, and is thus of lesser concern in practice. Beyond Equation (3.10), in a random effects specification, the time-invariant controls must also be uncorrelated with the individual-specific effects, in order to differentiate between α_i and δ.

The coefficient β in Equation (3.9) cannot be interpreted directly as the effect that x (exercise) has at time t on y (MHI5 score), due to the autoregressive behaviour. However, it can be interpreted as a change in the equilibrium value of y_{it}. In a generalised model with autoregressive coefficients $\{\rho_{l_y}|l_y \in [1, L_y]\}$, and distributed lag coefficients $\{\beta_{l_x}|l_x \in [0, L_x]\}$, The total effect can be interpreted as follows. If for an individual x_{it} changes from 0 to 1, i.e. they did not engage in exercise but have started doing so, they equilibrium value of y_{it} changes by

$$\frac{\sum_{l_x=0}^{L_x} \beta_{l_x}}{1 - \sum_{l_y=1}^{L_y} \rho_{l_y}}. \tag{3.11}$$

Refer to Appendix B for a derivation.

To briefly note, Equation (3.9) assumes a linear influence of all regressors onto y. However, all regressors are included as dummies, i.e. on a binary scale. For such a scale, linearity holds exactly. The only exceptions are the autoregressive terms, but since even a small number of autoregressive terms can already model highly nonlinear temporal behaviour, it is likely a reasonable approximation.

3.2.3 Controls and Mediators

As discussed extensively already, the selection of controls is crucial to avoid unmeasured confounders. However, a second important consideration is the action of mediators. Mediators are variables that explain the effect of x on y, in the sense that x causes some mediator m which causes y. An example of a mediator in the present study might be physical health. If physical health is included as a control in the regression, the interpretation of β becomes "the effect of sports on MHI5 score, *given* the physical health status of an individual." However, improvement of physical health may well be a strong mechanism through which sports affects mental health, which should very much be included in β for the purpose of answering the research question. The subtleties of mediation are not often discussed in the literature (Imbens, 2024), e.g. Chekroud et al. (2018) simply include physical health as a control. Such mediation might be measured directly while still effectively controlling for confoundedness due to the mediator as in the following, simplified example:

$$\begin{aligned} y_{it} &= \alpha_y + \beta x_{it} + \eta m_{it} + \epsilon_y; \\ m_{it} &= \alpha_m + \zeta x_{it} + \epsilon_m. \end{aligned} \tag{3.12}$$

Then, the total effect of x on y is given as $\beta + \zeta\eta$, the sum of the direct and the indirect effects. Conveniently, these two regressions may be estimated simultaneously in SEM.

Thus, when determining the controls used, attention must be paid to which variables may be mediators and those should be modelled as in Equation (3.12). There is a significant price to be paid in terms of model parsimony though, as a mediator cannot be a fixed variable, potentially adding many additional parameters to the model. If a mediator is simply excluded from the regression altogether, this model complexity is avoided, while the indirect effect (e.g. $\zeta\eta$) is absorbed into the main parameter (β). However, in doing so, the mediator, in so far as it is not fully explained by x, also functions as a potential unmeasured confounder. Because it is not clear a priori which approach is preferred, the results for both will be given in the present study. In this way, it can also be directly examined to which degree the mediators are confounders by comparing the estimated coefficients β between the two approaches.

When multiple mediators are simultaneously modelled, there can be either parallel mediation or serial mediation (Hayes, 2017). In parallel mediation (Figure 3.2a), the mediators do not influence each other, whereas in serial mediation (Figure 3.2b) one mediator causes the next mediator. If multiple mediators affect each other and the outcome variable as in Figure 3.2c, there is another form of simultaneity in the model. While this could be modelled with panel data just as the main simultaneity is modelled in the present study, that would entail significant model complexity. Instead, the present study models multiple mediators as parallel mediation, which effectively makes the assumption that, conditional on the set of controls and sports, there is no causal dependence between the mediators. The residual covariance of the mediators can be estimated in the SEM model to quantify to what extent this approximation is violated. Clearly, different dummy levels of the same categorical mediator must be causally dependent, which necessarily poses a limitation of this study.

The simplified example in Equation (3.12) does not include controls or autoregression. In order for the parameters ζ and η to be meaningfully combined, the same set of controls should be present in the mediation regression as in the main regression. Because of this, all the regressors in the main regression are added to the mediation regression, including the lagged $y_{i,t-l}$. However, because of the modelling choice of parallel mediation, mediators are not included in the mediation regressions of other mediators.

An additional concern in mediation is that the mediator may also be a vehicle for the reverse

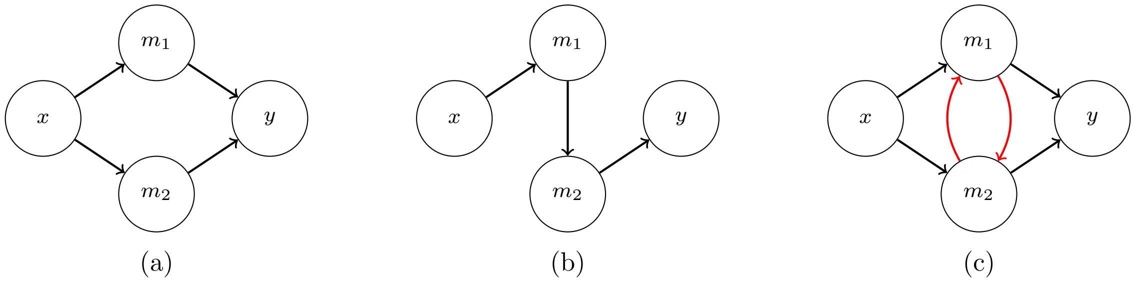


Figure 3.2: Graph representations of respectively parallel mediation (a), serial mediation (b), and simultaneity in mediation (c)

effect. Just as β in Equation (3.12) cannot differentiate between the forward- and reverse effects, neither can η nor ζ. That is, in mediation, there is a concern for both the reverse effect of y_{it} onto m_{it} and the reverse effect of m_{it} onto x_{it}. Just as in Figure 3.1b, we may measure only lagged effects in both equations, at the cost of model parsimony and only being able to judge the effect of $x_{i,t-2}$ on y_{it}. If on mechanistic grounds the reverse causality in either equation is expected to be negligible, it can be justified to measure the instantaneous effect in that regression. For the interpretation of the long-run effect of x, Equation (3.11) shows that each lag β_l has the same influence on the outcome. As such, regardless of the lag structure decided on in mediation, the sum of the direct and indirect effects can be meaningfully interpreted as the total effect.

Because mediators cannot be treated as fixed variables, a consideration is which of their residual covariances to set as free parameters. While there may be autoregressive behaviour for the mediator variables, this is controlled for by setting the covariance between any two consecutive values of mediators as a free parameter, with these parameters being allowed to vary freely across time to eliminate all associated degrees of freedom. An implication of this is that if in reality there is AR behaviour to the mediators, the total effect of sports through them is underestimated (assuming positive AR coefficients). The approximation thus maintains type I significance. The AR nature could also be explicitly modelled, but doing so would make modelling much more complex and error-prone, so the fact that α-significance is maintained justifies accepting the reduced statistical power as a compromise. Additionally, if a mediator is a categorical variable, there must be a negative correlation between its different dummy variables, so correlations between different dummy levels of the same variable are also set as free parameters.

3.2.4 Fit Indices

There is an extensive set of fit indices for SEM models available in the literature. These derive from the degrees of freedom in various ways. No single fit index is definitive for model fit, so it is prudent to consider multiple indices together for a more complete view. A canonical set of fit indices is described hereafter. However, first two general remarks are in order. For one, if a model is just identified, each of these fit indices will always indicate a perfect fit, which is to say there is then no value in interpreting the indices. Secondly, these tests do not necessarily provide a way to compare competing models. Considering they all measure the extent to which the model-implied covariance matrix differs from the sample covariance matrix, if two competing models involve a different set of variables, the indices cannot be directly compared. That is, if model A fits the sample covariance matrix S_A better than model B fits S_B, it does not necessarily follow that model A is better than model B. For example, a model which has no controls would likely yield better fit indices because it is a much simpler model with fewer parameters to be estimated, but that does not make it the preferred model over a model which includes a set of relevant control variables. Section 3.2.5 will discuss the alternative approach used in this work for model selection.

χ^2 test

The χ^2 test is the most general (and the original) fit index used (T. D. Smith & McMillan, 2001). It is a badness-of-fit test, in the sense that the null hypothesis is that the model explains the data perfectly. To be precise, the test statistic is the discrepancy between the model-implied covariance matrix and the real covariance matrix, and a significant test result thus implies a significant discrepancy. In practice with ML estimation, the test statistic is calculated as

$$\chi^2 = (N-1)F(\hat{\Sigma}), \tag{3.13}$$

where $F(\cdot)$ is the objective function as in Equation (3.5). Under the null hypothesis, the statistic is distributed as χ^2_{df} if the model has $df = \frac{p(p+1)}{2} - k$ degrees of freedom (Zheng & Bentler, 2025).

However, a shortcoming of the χ^2 test is that it is sensitive to sample size, in the sense that as the number of observations N increases, the null is less likely to be maintained. This is not a desirable property of a fit index, which has given rise to other fit indices (T. D. Smith & McMillan, 2001). As an alternative, Jöreskog and Sörbom (1993) propose using the ratio χ^2/df as an indicator of goodness-of-fit, where a ratio below 2 represents "good" fit and below 3 "acceptable". However, this does not fundamentally eliminate the sensitivity to sample size; rather, it just proposes more lenient critical values.

Comparative Fit Index

The Comparative Fit Index (CFI) derives from the χ^2 test. It compares the χ^2 test statistic of the model to that of a baseline model. While what constitutes the baseline model is subjective (f.i. Van Laar and Braeken (2021)), typically the baseline model is a model in which the variances of all variables are estimated, whereas the covariances are not (i.e. fixed to 0). The statistic is then

$$\text{CFI} = 1 - \frac{\max(\chi^2 - df, 0)}{\max(\chi^2 - df, \chi^2_b - df_b, 0)}. \tag{3.14}$$

Here, χ^2 and df denote the test statistic and degrees of freedom of the model and the same variables with a subscript b are those of the baseline model (Schermelleh-Engel, Moosbrugger, Müller et al., 2003). While no analytical distribution is available for this statistic, its value is in the range $[0, 1]$, with a higher value indicating better fit. It reaches a value of 1 if the ratio of χ^2 to df is less than 1, and a value of 0 if the baseline model fits the data better than the proposed model. Typically a cutoff value of 0.95 is taken to indicate good model fit (Hu & Bentler, 1999).

Tucker-Lewis Index

Similar to the CFI, Schermelleh-Engel et al. (2003) define the Tucker-Lewis Index (TLI) as

$$\text{TLI} = \frac{\chi_b^2/df_b - \chi^2/df}{\chi_b^2/df_b - 1}. \tag{3.15}$$

While not strictly confined to the range of $[0, 1]$, the TLI is typically in that range, only exceeding it if the baseline model outperforms the proposed model, or if model fit is so good as to make $\chi^2 < df$. Again, a higher TLI is better, and the cutoff for good fit is taken from Hu and Bentler (1999) as 0.95.

Root Mean Square Error of Approximation

The Root Mean Square Error of Approximation (RMSEA) measures the discrepancy between the model-implied- and sample covariance matrices per degree of freedom, roughly defined as the root mean square difference between the two (Schermelleh-Engel et al., 2003). It improves on the χ^2 statistic by compensating for the degrees of freedom and the sample size.

$$\text{RMSEA}^2 = \frac{\max(\chi^2 - df, 0)}{df(N-1)}. \tag{3.16}$$

The RMSEA has a lower bound of 0 and no upper bound, with a lower RMSEA representing better fit. We use a cutoff of 0.06 to indicate good fit (Hu & Bentler, 1999).

Standardised Root Mean Square Residual

Lastly, the Standardised Root Mean Square Residual (SRMR) is defined most explicitly in terms of $S - \hat{\Sigma}$ without considering degrees of freedom, namely as (Schermelleh-Engel et al., 2003)

$$\text{SRMR}^2 = \frac{\sum_{i=1}^{p}\sum_{j=1}^{i}(\frac{S_{ij}-\hat{\Sigma}_{ij}}{S_iS_j})^2}{p(p+1)/2}. \tag{3.17}$$

The term being summed is the (square) discrepancy between S and $\hat{\Sigma}$, standardised with respect to the sample standard deviations S_i and S_j to eliminate dependence on the scale of variables. Again, it has no upper bound but is bounded below by 0, and lower values indicate better fit. The cutoff used is 0.08 (Hu & Bentler, 1999).

3.2.5 Cross Validation

For the sake of model selection, a model-agnostic measure of model fit is required. To this end, we may borrow from the machine learning literature and use out-of-sample forecasting accuracy through cross validation. This approach can be used to compare any two models, including non-nested ones, and is a fit measure more akin to those used in canonical linear modelling. However, as mentioned before, when comparing different autoregressive lag orders, the lower lag order will have more waves available. It is likely that a model fit to a larger number of waves has a worse fit due to slight unmodelled heterogeneity across the waves, making the comparison between models unfair. Because of this, only the last available wave (2023) is used for cross validation, both for fitting the models as well as for determining the forecasting accuracy. It does not necessarily hold that the model that best fits the final wave is the one that best fits the data as whole, but it is nevertheless taken as a necessary and reasonable approximation.

In model selection, accuracy must be balanced with parsimony. To this end, the decision rule used is the 1-σ rule, where the model chosen is the simplest model whose out-of-sample forecasting accuracy is within one standard deviation of the best-performing model. Specifically, across the v folds, the root mean square prediction error (RMSPE) μ_{RMSPE} is calculated, along with the standard deviation of this prediction error across the folds, σ_{RMSPE}. The simplest model whose μ_{RMSPE} is below the optimal model's $\mu_{\text{RMSPE},opt} + \sigma_{\text{RMSPE},opt}$ is selected. In this, the number of folds v plays a critical role, as when more folds are used, the training sets are larger and the testing sets are smaller, which generally leads to lower μ_{RMSPE}. Typical values are $v = 5$ or $v = 10$. The dataset at hand is large, but considering the high percentage of missing data, a smaller number for v is preferred to avoid unrepresentative test sets, so $v = 5$ is used. To improve the accuracy of the estimated μ_{RMSPE} and σ_{RMSPE}, this cross validation is repeated R times with different random folds in each repetition and the average estimates is taken. Here, the larger R the better, but $R = 50$ is chosen to balance precision and computational tractability. Because uncertainty in the estimates has a significant impact on the 1-σ decision rule, the uncertainties in the estimates of μ_{RMSPE} and σ_{RMSPE} are calculated as the standard deviation of the respective estimates across the repetitions divided by the square root of R. The uncertainty of the decision rule threshold is then found by quadratically adding these two uncertainties. There is the possibility that the model used is not identified or numerically unstable for a given split due to the high degree of missingness. When this occurs, the results for the current repetition are discarded and another repetition is done.

3.2.6 Full Information Maximum Likelihood

SEM, at least when combined with maximum likelihood estimation, provides a natural way to handle (MAR) missing data in the form of Full Information Maximum Likelihood (FIML) (Arbuckle, 2013). The basic premise of FIML is that if a variable is missing for some observation, that observation provides no information as to how the missing variable relates to other variables, but it still provides information for the remaining variables. Formally, consider estimation of the covariance matrix Σ of the vector $x' = (x_1, x_2, x_3)$. Because the total sample likelihood (Equation (3.4)) is the product of the likelihood of each observation, we need not necessarily use the same likelihood specification for each observation. If for some observations x_3 is missing, their contribution to the likelihood is simply calculated with the two-dimensional covariance matrix of the sub-vector $(x_1, x_2)'$. In this way, FIML uses all information available in the dataset, hence its name. It can be applied to regressors as well as to regressands, making it highly valuable for the present study. It is not, however, a solution to a variable completely missing from the data, as is for instance the case with the missing Health study in 2014. In that case there is no information in the sample altogether, i.e. the sample covariance is not known and thus cannot be fit to.

Lavaan provides the option to apply FIML only to the endogenous variables or to all variables. If FIML is only applied to the endogenous variables, listwise deletion is applied for those cases where the exogenous variables are missing. As doing so would eliminate a large portion of the data, FIML is used for all variables in the dataset.

3.2.7 Normality and Robust Maximum Likelihood

The derivation of the objective function in Equation (3.5) heavily relies on the assumption of normality. However, while this assumption might hold approximately for the MHI5 score, it clearly does not hold for all binary regressors. This is of no concern for exogenous variables, as their covariances are simply fixed to the sample covariance, but it does implicate the parameter of interest, namely the effect of exercise on MHI5. Even so, Knief and Forstmeier (2021) find that the normal estimator still behaves well in terms of bias and efficiency. They even argue that it may be preferable to violate the assumption of normality over using specific techniques to adjust for non-normality, as those are error prone. Nevertheless, it would seem worthwhile to use a robust approach to maximum likelihood estimation that are readily available in *lavaan*. While multiple choices exist, ML with Huber-White standard errors is used in this study (often referred to as "MLR"), as it was found to perform well in the face of nonnormality (Zhong & Yuan, 2011), while still allowing for the use of FIML which some robust alternatives prohibit. With MLR in *lavaan*, a robust alternative to the χ^2 statistic is also calculated as in Satorra and Bentler (2001), which means the χ^2 statistic but also all the fit indices that derive from it are robust. In practice it was found that bootstrap standard errors align well with the standard errors implied by MLR estimation, whereas standard errors with regular maximum likelihood were appreciably smaller, which corroborates the decision to prefer robust estimation.

Chapter 4

Model Development

4.1 Regressors

As covariates, we include a basic set of sociodemographic variables available in the Background Variables of the LISS panel, namely age, ethnicity, gender, marital status, education level, employment status and net household income. While the first three are (largely) determined at birth, the last four might be hypothesised as mediators based on the literature (Spiker (2014); Hjorth et al. (2016); Frijters, Johnston and Shields (2014); Thomson et al. (2022) respectively). However, all of these variables were found to vary so little in time in the dataset that including them as time-variant covariates caused numerical instability, so they could only be included as time-invariants. This precludes modelling them as mediators of the time-variant variable sports, but the fact that they vary so little indicates that their effect as mediators could only be weak (ζ must be small), so the error in estimating the total effect due to not modelling them as mediators could only be marginal. Beyond this set, based on the literature and availability in the data, we include (self-reported) physical health and presence of diagnosed diseases as additional mediators (Westcott, 2012), as well as BMI as a proxy for body-image (Westcott, 2012). While the Health study also queries more nuanced variables like hospital admittance and medication use, these are quite correlated with general health and disease status (e.g. $\rho \approx 0.55$ for medication use and disease status), and are thus excluded for the sake of parsimony, noting the significant increase in complexity that mediators bring. Both of these mediators are binary variables (after dummy encoding), so a logit regression would be preferred. However, while *lavaan* does support binary variables, it is not possible to use the MLR estimator nor FIML, and crucially, numerical stability was poor when treating the mediators as binary variables. Thus, the approximation is made that they are linear variables (i.e. variables on a ratio scale). By virtue of the Taylor approximation, this approximation holds adequately if the estimated effect sizes of the regressors are moderate.

Body composition, aerobic fitness and disease have been found to affect exercise adherence (Abernethy et al., 2012). Additionally, Ingledew and Sullivan (2002) find BMI is a predictor of some exercise motives. For all mediators thus, the reverse effect of the mediator on sports engagement is of concern. Additionally, the reduced self-efficacy associated with poor mental health is a known cause for eating disorders and general bad diet habits (Oellingrath, Svendsen & Hestetun, 2014), influencing physical health. The same mechanism also pertains to mediation through disease status, as diet is known to be a significant determinant of immune function (Childs, Calder & Miles, 2019), and naturally eating habits influence BMI. The conclusion is therefore that for each of the three mediators, reverse causality is of concern for both steps of the mediation action, necessitating that only the lagged influence of regressors on regressands is ever considered.

Because only the long-term effect of sports on mental health is considered (recall Section 3.1.2), it would be natural to use the cumulative years that someone has exercised as the variable of interest, rather than the yearly exercise status. However, because it is not known how many years one has exercised at the time of joining this panel, this variable can only be roughly approximated through a running sum. Additionally, information missing in one year would complicate using the variable in all future years. As such, sports is used directly, while examining different orders of the distributed lags to model effects beyond one year ahead.

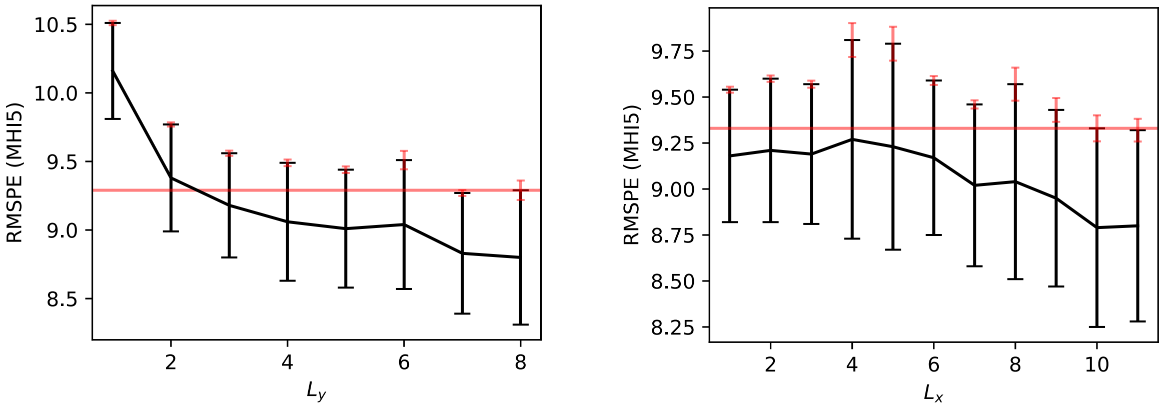
This study chooses to not include individual-specific effects α_i in the model. While they help justify the ignorability assumption through eliminating unmeasured confounders, they also potentially obscure the effects of time-invariant mediators, which equally invalidate the findings. The approach is thus instead to model individual-specific variability through the time-invariant controls z_i. Additionally, inclusion of fixed effects entails estimating N additional parameters (the incidental parameter problem). Since it is likely that $N > \frac{p(p+1)}{2}$, the model would not be identified. Nothing prevents modelling random effects however, and in fact this is commonly done in SEM (for instance Heck (2001)). The author leaves it as an avenue for further research.

As a minor final comment, some dummy levels of controls were excluded, because they occurred so infrequently in the data that including them as regressors led to numerical instability. These were a non-binary gender ("other" in the data), and perhaps surprisingly, an annual household income between € 15 000 and € 50 000.

4.2 Lag Selection

For determining the autoregressive lag order L_y and the distributed lag order L_x, cross validation was run as described in Section 3.2.5. However, for computational tractability, mediators were not modelled explicitly as such but simply included as controls. This should have only a minor impact on forecasting MHI5, but makes a higher number of repeats $R = 50$ feasible. It is assumed that the optimal model structure found in this way also applies when mediation regressions are also included. Additionally, it was found that only applying FIML to the endogenous variables yielded very similar parameter estimates and thus similar forecasts. To then further improve computational tractability in cross validation, listwise deletion was used for the exogenous variables (i.e. the controls).

Both L_y and L_x were varied from 1 to the highest number available based on the data. Due to the missing Health study in 2014, this is $L_y = 8$, and because the sports has only been included since 2012, $L_x = 11$. The optimal L_y is first estimated, as it has a more profound role in the model than the distributed lag. When doing so, $L_x = 1$ is used as the most minimal model. When optimising L_x, the optimal set of AR lags is used. It could technically be possible that a better model fit is found when not including all lags between the lowest and the highest lag, for instance having the set of lags $\{1, 2, 4\}$. This was however not tested as it seems improbable given the mechanisms at play, and thus would likely be overfitting. Figure 4.1 visualises the found RMSPEs.



(a) Varying maximum autoregressive lag (L_y)

(b) Varying maximum distributed lag (L_x)

Figure 4.1: Cross validated out-of-sample forecasting accuracy for varying lag orders, measured by root mean square error μ_{RMSPE}. Error bars are standard deviations of accuracy across folds. The horizontal line represents the 1-σ decision rule. The smaller red error bars represent uncertainty in the 1-σ decision rule, i.e. uncertainty in $\mu_{\text{RMSPE}} + \sigma_{\text{RMSPE}}$

For the autoregressive lags, the most complex model with AR lag order $L_y = 8$ performs best. The decision rule then indicates $L_y = 3$ is best, though the estimation uncertainty makes $L_y = 4$ also worth considering. Recalling that the cross validation findings may not generalise as it is only done on the data for 2023, and noting that simpler models generalise better, $L_y = 3$ is chosen. For the distributed lags, while the prediction error trends downwards with increasing model complexity, the model with $L_x = 1$ is clearly favoured.

It should be noted that both figures show that especially with more complex models, σ_{RMSPE} and the estimation uncertainties are significantly larger. This is likely evidence for some of the testing folds having erratic values. While this can potentially be fixed by either stratifying testing folds on missingness, experimenting with fold counts other than 5 or through increasing the number of repetitions R, the impact of these outliers on the decision rule is minor and does not influence the outcome, so this was not done in the end.

4.3 Fixing Parameters across Time

In the SEM model formulation, a fixing a parameter across time is effected by imposing an equality constraint on the parameters to be estimated. It is possible to quantify the validity of these parameter constraints in terms of the χ^2 statistic. Namely, when relaxing such a constraint, a single degree of freedom is won. The improvement (decrease) in the χ^2 statistic can then be compared to a $\chi^2(1)$ distribution for statistical significance, where the null is that the parameter constraint is appropriate. When performing this test on the 180 constraints imposed in the model without mediators, the highest found test statistic was for the first autoregressive parameter in wave 2023. It was 11.6, which is greater than the critical value of 3.84. However, multiple testing ought to be considered. When simply applying a Bonferroni correction for doing 180 tests, the critical value becomes 13.2, thus none of the imposed constraints are put into question. While an alternative correction would maintain more power and might reject the null, especially because the Bonferroni correction assumes the tests are independent but because the parameters are fixed across multiple regressions this is clearly not true, it should also be noted that the χ^2 test's sensitivity to sample size means the null is rarely maintained. As such, the conclusion is drawn that fixing the regression parameters across time is appropriate. It is assumed that this finding generalises to the model with mediators.

However, the same cannot be said for the residual variances of y. Because of the way that SEM estimates the parameters when regressands are also used as regressors (as in Equation (3.8)), the residual variance of MHI5 in 2023 is smaller than it is in the earlier waves. The model could be adjusted to prevent this by setting the residual variances between MHI5-values that do not occur in the same regression as free parameters (eliminating associated degrees of freedom). However, the residual variances are not of interest for the present research question, so for simplicity's sake the residual variances of MHI5 are simply not constrained across time.

However, the same cannot be said for the residual variances of y. These vary somewhat across the waves, and fixing them made model fit appreciably worse. This can be attributed to the fact that a covariance matrix must be positive definite, so fixing diagonal elements also imposes a restriction on associated off-diagonal elements in the same row (or equivalently in the same column). Because the residual variances are not of interest for the present research question, the variability of the residual variance across time will not be examined further.

For the definitive models in *lavaan* syntax, refer to the programming code (Appendix C).

Chapter 5

Results and Discussion

5.1 Excluding Mediation

The regression estimates for the model without mediation are first discussed. In this approach, mediation regressions are not included and neither are the mediators included as regressors, gaining model parsimony at risk of violating the ignorability assumption. The regression parameters are listed in Table 5.1. Since besides the autoregressive terms each variable included is a binary variable, the parameters can be interpreted as the percentage point change in mental wellbeing (MHI5) as a result of that variable. In general, very few estimated parameters are significant, and even those that are significant represent only a marginal impact, no greater than 1.4 points MHI5 for an income above € 50 000 as compared to no income. Contrast this with the interquartile range in MHI5 of about 20 (Figure 2.1).

The results may especially be put into question for the very small instantaneous association between sports and MHI5. While statistically significant, an average improvement of 0.48 on a scale of 0 to 100 for individuals who exercise is in stark contrast with cross-sectional analyses in the literature. Recall for instance the 43% decrease in days of poor mental health found in Chekroud et al. (2018), or the review by Noetel et al. (2024) who find effect sizes of between 0.2 and 0.8 times the sample standard deviation on various measures. The estimated long-term effect of exercise is highly insignificant ($p = 0.888$), and hence the null hypothesis that no such long-term benefit exists is maintained.

The CFI and TLI are just above 0.95, indicating good fit, while the RMSEA and SRMR are far below their respective cutoff values, which reflects excellent fit. Altogether, the model fit then appears quite good. In time series analysis, it is also customary to examine the stability of the data, as stability is typically a necessary assumption for estimation. While SEM does not rely explicitly on this assumption, absence of stability would at least make the assumption that parameters are constant in time contentious, and the derivation of the long-term effect as a change in equilibrium value (Equation (3.11)) does rely on stability. Based on the reported autoregressive coefficients, the roots of the characteristic polynomial are $z_1 = 1.10$, $z_2 = -1.16 + 1.78i$ and $z_3 = -1.16 - 1.78i$, which all fall decidedly outside of the unit circle, indeed indicating a stable time series.

Table 5.1: Parameter estimates and fit indices for the base regression. Estimates are changes in mean MHI5 scores (except for the AR estimates), with respect to the dummy level in parentheses where applicable. Fit indices are robust variants where applicable

Regressor	**Estimate**	**Std. Error**	**z-value**	**p-value**
MHI5_{t-1}	0.397	0.007	54.254	0.000***
MHI5_{t-2}	0.248	0.008	30.737	0.000***
MHI5_{t-3}	0.202	0.007	26.939	0.000***
sports_t	0.432	0.177	2.746	0.013*
sports_{t-1}	−0.025	0.177	−0.140	0.888
Age (below 18 years)				
18-24 years	−0.343	0.372	−0.923	0.356
25-39 years	−0.107	0.438	−0.244	0.807
40-66 years	0.700	0.443	1.579	0.114
over 67 years	0.331	0.490	0.676	0.499
Income (none)				
below € 15 000	1.042	0.536	1.944	0.052^{+}
over € 50 000	1.331	1.178	1.129	0.259
Immigration status (Dutch)				
first generation western	−0.688	0.257	−2.683	0.007**
first generation non-western	−0.959	0.268	−3.576	0.000***
second generation western	−0.403	0.223	−1.809	0.070^{+}
second generation non-western	−0.245	0.277	−0.885	0.376
Gender (female)				
male	0.562	0.103	5.474	0.000***
Marital status (divorced)				
married	0.155	0.178	0.873	0.383
never been married	−0.651	0.207	−3.139	0.002**
separated	−0.813	0.859	−0.947	0.344
widow or widower	0.337	0.289	1.167	0.243
Education level (havo-vwo)				
hbo	−0.176	0.193	−0.914	0.361
mbo	0.021	0.196	0.110	0.913
primary school	−0.382	0.273	−1.401	0.161
vmbo	−0.056	0.205	−0.273	0.785
university (wo)	−0.436	0.218	−0.273	0.046*
Employment status (employed)				
homemaker	−0.510	0.195	−2.618	0.009**
retired	0.063	0.191	0.327	0.744
student	−0.594	0.337	−1.764	0.078^{+}
unable to work	−1.409	0.313	−4.505	0.000***
unemployed	−0.415	0.365	−1.137	0.256
Observations	12920			
Parameters	225 (180 equality constraints)			
χ^2	1530.6 ($df = 270$, $p = 0.000$)			
CFI	0.956 (cutoff = 0.95)			
TLI	0.951 (cutoff = 0.95)			
RMSEA	0.019 (cutoff = 0.06)			
SRMR	0.026 (cutoff = 0.08)			

Significance levels: $^{+}$ 0.10, * 0.05, ** 0.01, *** 0.001

5.2 Including Mediation

To examine the relevance of mediators and build a more robust view of the effect of interest, the regression estimates for the analysis that explicitly models mediation will now be discussed. The main findings of interest in this analysis are to what extent the found effect is explained by the mediators, and the degree to which the mediators confounded the result as indicated by the change in the estimated total effect. The model contains an overwhelming number of parameters, which would be difficult to interpret. Hence, Table 5.2 lists the main parameters of interest, namely those of sports in the mediation regressions and those of sports and the mediators in the main regression. For the complete parameter estimates, refer to Appendix D. Table 5.3 reports the total effects derived from the results.

The instantaneous effect of sports as well as the (direct) lagged effect are now notably more negative than when no mediators are included, changing by -0.390 ± 0.244 and -0.142 ± 0.247 respectively. This points towards there indeed being a positive effect through the mediators, with the large estimated effects of physical health showing it especially is an important factor. The change in the instantaneous association also provides some evidence for mediation of the reverse action, i.e. that being sick or being in poor physical health decreases chance to exercise, although the difference is not significant ($p = 0.110$ based on the above numbers). The effect of lagged sports is insignificant at -0.167 ± 0.172 with a p-value of 0.332.

Being ill decreases mental wellbeing ($p < 0.001$), but only moderately with a -1.384 percentage point change in MHI5 on average. Interesting is that having been ill last year has a similarly large but positive effect of 1.474 percentage points, indicating that having recovered from a disease improves mental wellbeing and/or that having just fallen ill is associated with a larger mental burden than having been ill for a longer time. We do not find a significant long-term effect of exercise on disease status ($p = 0.155$). This indicates that exercise does not seem to strengthen the immune system in the long run, and because the LISS panel also queries bone fractures, exercise may also not have a beneficial effect towards strengthening the skeleton, regardless of for instance Hong and Kim (2018)'s findings that exercise increases bone mass. However, because this includes various forms of disease simultaneously, the finding does not preclude a positive effect of exercise on some forms of disease as in Westcott (2012), if those effects are offset with a negative effect on other forms of disease. In total, the causal long-term effect of physical exercise on mental wellbeing as moderated by disease is -0.009 percentage points, which is statistically insignificant at $p = 0.168$.

Physical health is found to have by far the greatest impact on MHI5 of any regressor, with effect sizes as high as -19.840 percentage points. There is a clear trend that worse physical health is associated with worse mental health. Strikingly however, the lagged effects all have an opposite sign, that is, a positive association with mental wellbeing. This is evidence of a similar rebound mechanism as with disease, where having recently had physical health improve is cause for happiness, and vice versa. Exercise generally relates to better physical health, but effect sizes are modest, with the greatest change found being that exercise is associated with a 4.0% increased probability of being in good physical health. Lagged exercise significantly decreases probability of moderate physical health (-2.4%, $p < 0.001$) while increasing the probability of very good mental health (2.3%, $p < 0.001$). Interesting is the finding that the probabilities of reporting poor or excellent health are only weakly influenced by instantaneous and lagged sports, indicating that at the extremes of physical health, the effects of sports are overwhelmed by the effects of other (unmeasured) factors. Combined with the large detrimental effect of last year's physical health on MHI5, we find a causal effect of (-0.117 ± 0.022) percentage points MHI5 ($p < 0.001$). The negative sign of this effect is contrary to expectations based on the literature, which find a positive effect if any. This oddity is due to the aforementioned rebound effect.

MHI5 is found to be positively predicted instantaneously by being overweight (1.241, $p = 0.025$) and being obese (1.232, $p = 0.041$), both as compared to being underweight. These associations are actually more positive than the effect of being normal weight, though not statistically significantly so. Because we are controlling for physical health and disease status, these findings suggest that the effects of a negative body image are more significant in underweight individuals than in overweight or obese individuals. There is a significant instantaneous association between sports and being normal weight (1.7%, $p = 0.009$) as well as being obese (−1.8%, $p < 0.001$), with no association found for being underweight or overweight. Lagged exercise only has a significant effect on the probability of being normal weight, increasing it by 0.9% ($p = 0.038$), with all other effects trending towards decreased probabilities. This small change leads to a total effect of sports on MHI5 as mediated by BMI of 0.002 with an associated p-value of 0.095.

Combining the direct effect and the effects through the three mediators, we conclude that engaging in exercise decreases MHI5 on average by -0.290 ± 0.174 percentage points ($p = 0.095$), equivalent to a long-run effect of −1.45 percentage points. The total effect is but weakly significant because the effect through physical health is overshadowed by the uncertainty in the direct effect. −0.290 is a small impact as compared to the IQR of 20 percentage points, and considering the weak significance the negative sign should not be given much interpretation beyond the aforementioned rebound effect in physical health. The total effect is not very different from the direct effect of −0.025 found in in the analysis without mediation (Table 5.1), from which we may conclude that the mediators did not appear to have a significant effect as unmeasured confounders.

In terms of the model quality, the fit indices are appreciably worse than in the simpler model, as is to be expected considering the significantly increased complexity. Note there are 3100 model parameters compared to the 225 before. While the RMSEA of 0.027 still indicates good and in fact excellent fit, the SRMR of 0.089 is just below the threshold of a good fit and the CFI and TLI are around 0.85 which is decidedly smaller than the cutoff value for good fit of 0.95. Considering the majority of the non-fixed variables are the mediators, the relatively poor fit is already an indicator that the assumption of parallel mediation is not accurate, i.e. that there are a lot of relationships between the mediators that are not accurately modelled. This is confirmed in the estimated residual covariances between different dummy levels of the same mediator, which are all statistically significant with $p \ll 0.01$ and z-scores as high as 70. While this does pose a threat to the model validity, the relationships between mediators are only of interest in so far as they alter estimations of the parameters of interest (Table 5.2), which is likely not an overwhelming influence. Combined with the acceptable to excellent SRMR and RMSEA, the results are taken to be sufficiently accurate for the purpose of answering the research question. Considering the large number of insignificant effects in table 5.2, the model might be simplified by removing insignificant mediators. This is however not done in the present study because of the strong mechanistic grounds for each of the chosen mediators. Additionally, such a general-to-specific model selection process is more likely to cause overfitting when parameter estimates are generally insignificant, because type I and type II errors are more likely the closer the significance is to the threshold of say $p = 0.05$. Nevertheless, it is something worth considering in future research.

Out of the parameters of interest, the largest effect size found in mediation regressions is 0.044. Some other parameters are larger, like 0.283 for the effect of being over 67 years old on disease status, but none of the parameters of interest are as large and the vast majority of parameters is below 0.050, so the approximation of using linear models over a logit analysis is largely justified. The AR parameters are very similar to those in the model without mediation, so time series stability is expected. Indeed, the roots of the characteristic polynomial are at $z_{1,2} = -1.19 \pm 1.85i$ and $z_3 = 1.13$, which all fall outside the unit circle.

5.3 Discussion and Future Research

There are two main conclusions that can be drawn from the results. First, we do not find strong evidence for a long-term benefit of exercise on mental health. Second, the complex model design obscures many of the effects of exercise that are very much of real-world interest. Both conclusions inform important design choices in future research and will thus be discussed in the following.

It is always a possibility that the absence of a strong long-term effect is due to various imperfections in the present study. For instance, it can naturally not be guaranteed that there are no unmeasured confounders (i.e. that the ignorability condition holds). Additionally, while perhaps not very likely, it may well be that the average effect is negligible but that there are significant and opposite effects in subgroups. That is there may be cause for moderation analysis. A different form of mediation than parallel mediation may also be considered, though it is not likely this would majorly change the findings. Lastly, it may simply be that a dataset where the a priori correlation between sports and mental health is much larger than the present $\rho < 0.095$ provides more statistical power towards finding an effect. A larger dataset naturally also yield greater statistical significance, but it would not change the estimated effect size and thus not change the real-world relevance of the effect. Assuming none of these considerations majorly compromise the present results, the conclusion follows that the mechanisms through which exercise may have a lasting cumulative effect on mental wellbeing are weak. These include structural changes to the brain, physiological adaptations to for instance improve body image and improve sleep, and better habits through improved self-efficacy. Improvements in these factors due to exercise are either small, they do not persist when one stops exercising, or they are not cumulative with total exercise. However, there is an extensive literature on the persistency of exercise's benefits on cognition, referred to as cognitive reserve (Cheng, 2016; Stern, 2009). This makes the prior interpretation favoured. While a lack of effect finding is consistent with some literature which find no strong benefit (e.g. Chalder et al. (2012)), it stands in stark

Table 5.2: Parameters of interest in the mediation analysis; controls are not reported. Regressands are in bold. Estimates are increases in mean MHI5 scores (except for the AR estimates), with respect to the dummy level in parentheses where applicable. Fit indices are robust where applicable

Regressor	Estimate	Std. Error	z-value	p-value
MHI5$_t$				
MHI5$_{t-1}$	0.391	0.007	54.301	0.000***
MHI5$_{t-2}$	0.227	0.008	29.093	0.000***
MHI5$_{t-3}$	0.182	0.007	25.401	0.000***
sports$_t$	0.042	0.168	0.249	0.803
sports$_{t-1}$	−0.167	0.172	−0.969	0.332
disease status$_t$	−1.384	0.216	−6.398	0.000***
disease status$_{t-1}$	1.474	0.221	6.677	0.000***
physical health$_t$ (excellent)				
good	−6.366	0.310	−20.566	0.000***
moderate	−12.818	0.402	−31.907	0.000***
poor	−19.840	0.861	−23.050	0.000***
very good	−2.785	0.283	−9.859	0.000***
physical health$_{t-1}$ (excellent)				
good	2.952	0.342	8.631	0.000***
moderate	6.176	0.422	14.642	0.000***
poor	10.746	0.820	13.102	0.000***
very good	1.694	0.320	5.288	0.000***
BMI_t (underweight)				
normal weight	0.306	0.518	0.591	0.554
overweight	1.241	0.552	2.247	0.025*
obese	1.232	0.603	2.042	0.041*
BMI_{t-1} (underweight)				
normal weight	0.347	0.567	0.612	0.541
overweight	−0.020	0.602	−0.033	0.973
obese	0.207	0.656	0.315	0.752
Disease status$_t$				
sports$_t$	−0.007	0.004	−1.608	0.108
sports$_{t-1}$	−0.006	0.004	−1.423	0.155
Physical health$_t$ (excellent)				
good				
sports$_t$	−0.009	0.007	−1.400	0.162
sports$_{t-1}$	−0.009	0.007	−1.400	0.162
moderate				
sports$_t$	−0.020	0.007	−3.007	0.003**
sports$_{t-1}$	−0.024	0.005	−4.906	0.000***
poor				
sports$_t$	−0.007	0.002	−4.610	0.000***
sports$_{t-1}$	0.001	0.002	0.957	0.339
very good				
sports$_t$	0.040	0.005	7.810	0.000***
sports$_{t-1}$	0.023	0.005	4.422	0.000***
BMI$_t$ (underweight)				
normal weight				
sports$_t$	0.017	0.004	4.011	0.009**
sports$_{t-1}$	0.009	0.005	2.075	0.038*
overweight				
sports$_t$	0.003	0.005	0.632	0.527
sports$_{t-1}$	−0.002	0.005	−0.329	0.742
obese				
sports$_t$	−0.018	0.003	−5.894	0.000***
sports$_{t-1}$	−0.004	0.003	−1.372	0.170
Observations	12920			
Parameters	3100 (1891 equality constraints)			
χ^2	52855.2 (df = 5061, p = 0.000)			
CFI	0.864 (cutoff = 0.95)			
TLI	0.835 (cutoff = 0.95)			
RMSEA	0.027 (cutoff = 0.06)			
SRMR	0.089 (cutoff = 0.08)			

Significance levels: $^+$ 0.10, * 0.05, ** 0.01, *** 0.001

Table 5.3: Effect through each mediator and direct effect, as derived from Table 5.2. Standard errors in total effect are determined by the delta method

Regressor	Estimate	Std. Error	z-value	p-value
Direct effect	−0.167	0.172	−0.969	0.332
Effect disease status	−0.009	0.007	−1.380	0.168
Effect physical health	−0.117	0.022	−5.399	0.000***
Effect BMI	0.002	0.003	0.762	0.761
Total effect	−0.290	0.174	−1.671	0.095

Significance levels: $^{+}$ 0.10, * 0.05, ** 0.01, *** 0.001

contrast with other research (e.g. Philippot et al. (2022)) and even with this extensive literature on cognitive reserve. The present finding of an insignificant effect, in fact one that is negative if anything, may be partially attributable to the biases resulting from self-reporting and MNAR data. Varying impacts of this bias have been found in the literature, from a negligible impact in Leroux, Rizzo and Sickles (2012) to effects frequently switching from significantly positive to significantly negative and vice versa in Brown et al. (2018). This makes it hard to say how relevant it is. Beyond these biases, a more appropriate set of mediators than the small presently used set of three may help in finding an effect. For instance, body image may be measured directly as opposed to BMI for better precision, and especially the very broad concept of "physical health" might be refined. There is thus a need for further research in a similar vein to the present study but with more precise ways of measuring relevant mediators and outcomes, as well as with close attention paid to avoiding missingness.

In pursuit of a causal effect, this study only examines the effect of exercise a year ago on present mental health, or even of exercise two years ago for the mediated effects. This precludes estimating the impact of many of the hypothesised mechanisms, like the endorphin release which likely only lasts on the order of hours, or the improved self-efficacy which may well only persist on the order of weeks to months after one stops exercising. Additionally, if the benefit in for instance self-efficacy is instantaneous but not greater for an individual who has been exercising for multiple years as compared to someone who just started, the effect cannot be measured. In general, any mechanism whose effect is not both cumulative with the total amount of exercise and (approximately) permanent cannot be quantified in this approach, yet these mechanisms are manifold. Considering the literature either reports an insignificant effect or a benefit for exercise, yet the present finding is a negative effect through physical health and a weakly negative total effect, it is likely that these mechanisms are important to consider. In fact, because the instantaneous associations in Table 5.2 are consistently larger than the lagged effects and point consistently towards a positive association, the present data leaves much room for these effects. This informs an emphasis in future research on the short-term or direct effect of exercise over the long-term effect.

In summary then, further research into the benefit of exercise for mental wellbeing should emphasise data quality while finding an alternative approach to control for reverse causality. For the purpose of data quality, it is important to conduct a prospective study, where the variables being measured are determined a priori for the specific purpose of the study, as opposed to a retrospective study on a general dataset. That is, variables should be selected to more accurately dissect the suspected mediators based on expert knowledge of the mechanisms at play. In this way, more powerful mediators may be modelled and fewer mediators may be necessary, improving model fit. Additionally, it may be hypothesised that is not just important whether someone exercises, but also how often they do so and what form of exercise they engage in. Such moderation was not considered in this work. Furthermore, as opposed to aggregating everything to a singular MHI5 score, the impact of sports on various components of mental wellbeing may be examined separately, as for instance Atlantis, Chow, Kirby and Singh (2004) find appreciably different outcomes on such different components. There are additional benefits to be had in using an objective measure of mental health over self-reporting and in tight quality control so as to avoid MNAR missingness, although perhaps solving those problems is wishful thinking. The randomisation in RCTs would control effectively for reverse causality. It is however surprising that the findings even among RCTs in the literature are so varied, and the present study yields no insight as to why that may be. A further consideration is that tightly controlling the environment when measuring long-term effects is infeasible, necessarily making measuring this effect more complicated, although a difference-in-differences design may partially offset this downside. In an observational setting it is much more feasible to measure long-term effects, but the present study shows that causal analysis in such a context is infeasible. An alternative approach may be to use instrumental variables, but considering the complexity of all the psychological, physiological and social mechanisms at play in the subject of mental health, it is not likely that an instrument can be found for which the assumption that it is exogenous with mental health is justifiable. It appears more worthwhile for retrospective observational studies to be focused on Granger causality, which should be combined with mechanistic research and randomised controlled trials for a better means to discover causality.

Chapter 6

Conclusion

For the purpose of answering the research question of whether physical exercise is an effective intervention to improve mental wellbeing, the present study emphasises causal analysis in an observational setting, noting the compelling mechanisms for reverse causality in this context. The studied data is of the LISS panel, a representative Dutch panel with 7500 participants. To be precise, the effect of previous exercise on present wellbeing is studied through two regression analyses, one without modelling mediators and the other an explicit mediation analysis. The prior finds a highly insignificant effect of -0.025 percentage points on the MHI5 scale ($p = 0.888$). The latter finds an average effect of -0.290 percentage points, which is also not significant at $p = 0.095$. The negative sign can be attributed partly to the statistical insignificance and partly to a significant rebound effect that was found around physical health, where a poor physical condition in the previous year was associated with better mental wellbeing, due to either happiness from recovery or lesser sadness due to for instance developed coping mechanisms.

These findings mainly highlight the difficulty of causal analysis through observational data for a topic as complex and nuanced as human mental wellbeing. Nevertheless, some directions for future research can be drawn from the present study. Beyond the obvious but perhaps infeasible objective of gathering high-quality data, there is a clear benefit in a prospective study design where the gathered data is tailored to the study objective, as opposed to studying data generally available in public datasets. The findings also underline once more the importance of randomisation in trials as a mechanism to control for potential reverse causality, as opposed to post-factum analytical approaches. For the purpose of studying causality in mental wellbeing, randomised controlled trials and mechanistic research are likely more feasible than observational research, which appears a futile effort based on the present study.

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Appendix A

LISS Questions for Studied Variables

The following describes how each variable was derived from the questions in the LISS panel, as well as providing descriptive statistics.

MHI5

Each of the five parts of the Mental Health Inventory-5 asks how often one felt a specific feeling over the past month. It queries how often the participant felt anxious; so down that nothing could cheer them up; calm and peaceful; depressed and gloomy; and happy. The questions take the form of "this past month, i felt [...]", and the possible responses are never; seldom; sometimes; often; mostly; and continuously. Figure 2.1a may be referred to for descriptive statistics of the MHI5 variable.

Sports

The question is "Do you practice sports?". Figure 2.1b shows the frequency of the response "yes".

Physical Health

The question is "How would you describe your health, generally speaking?". We have the responses and their corresponding frequencies

- poor (1.4%)
- moderate (15.9%)
- good (42.3%)
- very good (19.9%)
- excellent (5.1%)

Disease Status

There is a series of questions of the form "Has a physical told you this last year that you suffer from one of the following diseases / problems?". The final one of these asks for "no diseases /

problems". Disease status is taken as the inverse of the responses to this question, so for disease status the findings are

- yes (47.8%)
- no (52.2%)

BMI

BMI is derived from the questions "How much do you weigh, without clothes and shoes?" and "How tall are you?". It is then stratified by the WHO guidelines (World Health Organization, 2010) into the following four groups.

- underweight (2.3%)
- normal weight (47.9%)
- overweight (35.2%)
- obese (14.8%)

Age

The question is "Age of the household member".

- under 18 (2.3%)
- 18 to 24 (7.6%)
- 25 to 39 (19.0%)
- 40 to 66 (48.5%)
- over 67 (22.6%)

Income

The question is "Net household income in Euros".

- none (€ 0) (0.9%)
- under € 15 000 (99.0%)
- € 15 000 to € 50 000 (0.0%)
- over € 50 000 (0.1%)

Ethnicity

The question is "Origin".

- Dutch (83.8%)
- First generation foreign, Western background (3.7%)
- First generation foreign, non-Western background (4.4%)
- Second generation foreign, Western background (5.1%)
- Second generation foreign, non-Western background (2.9%)

Gender

The question is "Gender self-identification". While the possible responses include various options like intersex, non-binary and transgender, in the data they are summarised to only male, female and other.

- male (53.7%)
- female (46.3%)
- other (0.1%)

Marital status

The question is "Civil status".

- married (54.0%)
- separated (0.4%)
- divorced (9.7%)
- widow or widower (5.7%)
- never been married (30.1%)

Education level

The question is "Level of education in CBS (Statistics Netherlands) categories".

- primary school (8.3%)
- vmbo (22.1%)
- havo/vwo (10.9%)
- mbo (23.6%)
- hbo (24.2%)
- wo (10.9%)

Employment

Employment status is derived from the question "Primary occupation" as explained in Section 2.2, yielding the following distribution.

- employed (46.3%)
- homemaker (8.2%)
- retired (23.0%)
- student (8.7%)
- unable to work (4.0%)
- unemployed (2.4%)

Appendix B

Long-run Effect in ARDL Model

Consider the following model with both autoregressive and distributed lags.

$$y_{it} = \sum_{l=1}^{L_y} \rho_l y_{i,t-l} + \sum_{l=0}^{L_x} \beta_l x_{i,t-l} + \epsilon_{it} \tag{B.1}$$

Controls are left out for simplicity. With controls, the following expressions would hold conditional on the controls. The coefficients β_l can be interpreted as causing a shift in the equilibrium value of y_{it}. In equilibrium we have

$$E(y_{it}) = E(y_{i,t-1}) = y^*, \tag{B.2}$$

and $x_{it} = x^*$. Substituting in Equation (B.1), we get

$$y^*(1 - \sum_{l=1}^{L_y} \rho_l) = x^* \sum_{l=0}^{L_x} \beta_l \tag{B.3}$$

Thus, if a binary variable x_{it} changes from a stable value of 0 to 1, the equilibrium value of y_{it} changes by

$$\frac{\sum_{l=0}^{L_x} \beta_l}{1 - \sum_{l=1}^{L_y} \rho_l} \tag{B.4}$$

Appendix C

Programming code

All code used for the research as well as for the figures in this report is available at https://github.com/Encephala/econometrics-master-thesis under an MIT license.

Appendix D

Results of Mediation Regression

In each wave of the mediation analysis, nine regressions are done. The following reports the full parameter estimates of these regressions. Table D.1 lists the estimates for the regressand MHI5, where coefficients indicate percentage points changes in MHI5 score. Next, Table D.2 reports the coefficients for disease status, where a coefficient indicates a change in probability to have any disease. Then, in Tables D.3 to D.6, the estimates for the four different dummy levels of physical health are reported, where a coefficient indicates an increase probability of the dummy level of the regressand. Lastly, in Tables D.7 to D.9 the coefficients for the various dummy levels of BMI are reported, where a coefficient is again an increased probability of observing the dummy level fo the regressand. In each of these tables, the coefficients for lagged MHI5 have a different and nuanced interpretation, but their coefficients are only interpreted for the regression of MHI5.

Table D.1: Regression parameters for MHI5

Regressor	Estimate	Std. Error	z-value	p-value
MHI5_{t-1}	0.391	0.007	54.302	0.000***
MHI5_{t-2}	0.227	0.008	29.093	0.000***
MHI5_{t-3}	0.182	0.007	25.401	0.000***
sports_t	0.042	0.168	0.249	0.803
sports_{t-1}	−0.167	0.172	−0.969	0.332
disease status	−1.384	0.216	−6.398	0.000***
physical health$_t$ (excellent)				
good	−6.366	0.310	−20.566	0.000***
moderate	−12.818	0.402	−31.907	0.000***
poor	−19.840	0.861	−23.050	0.000***
very good	−2.785	0.283	−9.859	0.000***
physical health$_{t-1}$ (excellent)				
good	2.952	0.342	8.631	0.000***
moderate	6.176	0.422	14.642	0.000***
poor	10.746	0.820	13.102	0.000***
very good	1.694	0.320	5.288	0.000***
BMI_t (underweight)				
normal weight	0.306	0.518	0.591	0.554
overweight	1.241	0.552	2.247	0.025*
obese	1.232	0.603	2.042	0.041*
BMI_{t-1} (underweight)				
normal weight	0.347	0.567	0.612	0.541
overweight	−0.020	0.602	−0.033	0.973
obese	0.207	0.656	0.315	0.752
age (below 18 years)				
18-24 years	0.031	0.358	0.087	0.931
25-39 years	0.576	0.421	1.368	0.171
40-66 years	1.969	0.432	4.563	0.000***
over 67 years	1.843	0.479	3.845	0.000***
income (none)				
below € 15 000	1.129	0.447	2.527	0.012*
over € 50 000	2.259	0.336	6.714	0.000***
immigration status (Dutch)				
first generation western	−0.844	0.252	−3.348	0.001**
first generation non-western	−0.911	0.260	−3.508	0.000***
second generation western	−0.360	0.220	−1.634	0.102
second generation non-western	−0.388	0.272	−1.426	0.154
gender (female)				
male	0.502	0.102	4.940	0.000***
marital status (divorced)				
married	0.101	0.171	0.591	0.554
never been married	−0.739	0.200	−3.692	0.000***
separated	−0.245	0.834	−0.293	0.769
widow or widower	0.177	0.279	0.635	0.525
education level (havo-vwo)				
hbo	−0.293	0.189	−1.552	0.121
mbo	−0.059	0.192	−0.308	0.758
primary school	−0.208	0.268	−0.778	0.437
vmbo	0.030	0.202	0.146	0.884
university (wo)	−0.820	0.215	−3.821	0.000***
employment status (employed)				
homemaker	−0.377	0.192	−1.965	0.049*
retired	0.372	0.190	1.957	0.050^+
student	−0.686	0.321	−2.136	0.033*
unable to work	0.136	0.333	0.407	0.684
unemployed	−0.206	0.348	−0.591	0.555

Significance levels: $^+$ 0.10, * 0.05, ** 0.01, *** 0.001

Table D.2: Regression parameters for disease status

Regressor	Estimate	Std. Error	z-value	p-value
MHI5_{t-1}	−0.001	0.000	−8.432	0.000***
MHI5_{t-2}	−0.001	0.000	−5.496	0.000***
MHI5_{t-3}	−0.001	0.000	−4.574	0.000***
sports_{t}	−0.007	0.004	−1.608	0.108
sports_{t-1}	−0.006	0.004	−1.432	0.155
age (below 18 years)				
18-24 years	0.046	0.018	2.477	0.013
25-39 years	0.084	0.022	3.727	0.000***
40-66 years	0.222	0.024	9.361	0.000***
over 67 years	0.283	0.027	10.503	0.000***
income (none)				
below € 15 000	0.025	0.034	0.722	0.470
over € 50 000	0.027	0.056	0.482	0.629
immigration status (Dutch)				
first generation western	−0.037	0.017	−2.198	0.028*
first generation non-western	−0.004	0.015	−0.274	0.784
second generation western	0.002	0.014	0.109	0.913
second generation non-western	−0.055	0.018	−3.087	0.002**
gender (female)				
male	−0.016	0.006	−2.529	0.011*
marital status (divorced)				
married	−0.010	0.011	−0.886	0.376
never been married	−0.028	0.013	−2.082	0.037*
separated	−0.034	0.060	−0.568	0.570
widow or widower	0.017	0.018	0.955	0.339
education level (havo-vwo)				
hbo	−0.007	0.012	−0.539	0.590
mbo	−0.005	0.012	−0.422	0.673
primary school	0.035	0.014	−1.685	0.092^{+}
vmbo	0.024	0.012	1.986	0.047*
university (wo)	−0.024	0.014	−1.685	0.092^{+}
employment status (employed)				
homemaker	0.015	0.012	1.284	0.199
retired	0.060	0.012	5.104	0.000***
student	0.011	0.017	0.612	0.541
unable to work	0.162	0.015	11.029	0.000***
unemployed	0.012	0.026	0.478	0.633

Significance levels: $^{+}$ 0.10, * 0.05, ** 0.01, *** 0.001

Table D.3: Regression parameters for physical health - good

Regressor	**Estimate**	**Std. Error**	**z-value**	**p-value**
$\mathrm{MHI5}_{t-1}$	0.000	0.000	−0.905	0.366
$\mathrm{MHI5}_{t-2}$	0.001	0.000	2.542	0.011*
$\mathrm{MHI5}_{t-3}$	0.000	0.000	1.343	0.179
sports_{t}	−0.020	0.007	−3.007	0.003**
sports_{t-1}	−0.009	0.007	−1.400	0.162
age (below 18 years)				
18-24 years	−0.018	0.023	−0.770	0.441
25-39 years	0.004	0.028	0.149	0.881
40-66 years	0.037	0.029	1.263	0.207
over 67 years	0.009	0.033	0.277	0.782
income (none)				
below € 15 000	0.072	0.034	2.086	0.037*
over € 50 000	0.121	0.105	1.152	0.249
immigration status (Dutch)				
first generation western	0.025	0.018	1.375	0.169
first generation non-western	0.000	0.017	0.020	0.984
second generation western	−0.011	0.016	−0.685	0.494
second generation non-western	−0.001	0.020	−0.044	0.965
gender (female)				
male	−0.023	0.008	−3.104	0.002**
marital status (divorced)				
married	0.023	0.013	1.727	0.084^{+}
never been married	−0.001	0.015	−0.049	0.961
separated	−0.043	0.058	−0.736	0.462
widow or widower	0.020	0.022	0.931	0.352
education level (havo-vwo)				
hbo	−0.003	0.014	−0.195	0.846
mbo	0.014	0.014	0.956	0.339
primary school	−0.043	0.018	−2.440	0.015*
vmbo	−0.006	0.015	−0.380	0.704
university (wo)	−0.060	0.016	−3.650	0.000***
employment status (employed)				
homemaker	−0.015	0.014	−1.101	0.271
retired	0.005	0.015	0.349	0.727
student	−0.040	0.022	−1.786	0.074^{+}
unable to work	−0.203	0.021	−9.546	0.000***
unemployed	−0.054	0.025	−2.121	0.034*

Significance levels: $^{+}$ 0.10, * 0.05, ** 0.01, *** 0.001

Table D.4: Regression parameters for physical health - moderate

Regressor	Estimate	Std. Error	z-value	p-value
$\mathrm{MHI5}_{t-1}$	-0.001	0.000	-6.399	0.000***
$\mathrm{MHI5}_{t-2}$	-0.001	0.000	-7.905	0.000***
$\mathrm{MHI5}_{t-3}$	-0.001	0.000	-6.669	0.000***
sports_t	-0.019	0.005	-4.906	0.000***
sports_{t-1}	-0.024	0.005	-4.906	0.000***
age (below 18 years)				
18-24 years	0.075	0.015	4.862	0.000***
25-39 years	0.106	0.020	5.401	0.000***
40-66 years	0.175	0.020	8.644	0.000***
over 67 years	0.217	0.024	9.021	0.000***
income (none)				
below € 15 000	0.002	0.024	0.067	0.947
over € 50 000	-0.026	0.093	-0.279	0.780
immigration status (Dutch)				
first generation western	-0.020	0.013	-1.521	0.128
first generation non-western	0.015	0.014	1.124	0.261
second generation western	0.023	0.012	1.953	0.051^{+}
second generation non-western	-0.007	0.013	-0.545	0.586
gender (female)				
male	-0.002	0.005	-0.545	0.586
marital status (divorced)				
married	-0.018	0.010	-1.709	0.087^{+}
never been married	-0.003	0.012	-0.280	0.780
separated	-0.030	0.046	-0.653	0.514
widow or widower	-0.004	0.018	-0.225	0.822
education level (havo-vwo)				
hbo	-0.007	0.010	-0.684	0.494
mbo	0.004	0.010	0.356	0.722
primary school	0.052	0.014	3.711	0.000***
vmbo	0.025	0.011	2.307	0.021*
university (wo)	-0.031	0.011	-2.842	0.004***
employment status (employed)				
homemaker	0.019	0.011	1.758	0.079^{+}
retired	0.025	0.012	2.101	0.036*
student	0.000	0.015	0.018	0.986
unable to work	0.215	0.020	10.735	0.000***
unemployed	0.044	0.020	2.214	0.027*

Significance levels: $^{+}$ 0.10, * 0.05, ** 0.01, *** 0.001

Table D.5: Regression parameters for physical health - poor

Regressor	**Estimate**	**Std. Error**	**z-value**	**p-value**
MHI5_{t-1}	0.000	0.000	−2.483	0.013*
MHI5_{t-2}	0.000	0.000	−2.708	0.007**
MHI5_{t-3}	0.000	0.000	−4.258	0.000***
sports_{t}	−0.007	0.002	−4.610	0.000***
sports_{t-1}	0.001	0.002	0.957	0.339
age (below 18 years)				
18-24 years	0.000	0.006	−0.077	0.939
25-39 years	0.000	0.007	−0.061	0.951
40-66 years	0.000	0.007	−0.036	0.971
over 67 years	0.003	0.008	0.362	0.717
income (none)				
below € 15 000	0.010	0.003	2.820	0.005**
over € 50 000	0.008	0.025	0.332	0.740
immigration status (Dutch)				
first generation western	−0.007	0.004	−1.686	0.092^{+}
first generation non-western	0.014	0.006	2.175	0.030*
second generation western	−0.001	0.003	−0.374	0.709
second generation non-western	0.001	0.005	0.112	0.911
gender (female)				
male	0.003	0.002	1.714	0.087^{+}
marital status (divorced)				
married	−0.007	0.004	−1.665	0.096^{+}
never been married	−0.011	0.005	−2.338	0.019*
separated	0.067	0.034	1.998	0.046*
widow or widower	−0.015	0.006	−2.747	0.006^{+}
education level (havo-vwo)				
hbo	−0.010	0.004	−2.892	0.004*
mbo	−0.009	0.004	−2.458	0.014*
primary school	0.000	0.006	0.008	0.994
vmbo	−0.002	0.004	−0.473	0.636
university (wo)	−0.009	0.004	−2.457	0.014*
employment status (employed)				
homemaker	0.006	0.004	1.567	0.117
retired	0.008	0.003	2.550	0.011*
student	−0.008	0.005	−1.631	0.103
unable to work	0.077	0.011	6.935	0.000***
unemployed	0.011	0.007	1.597	0.110

Significance levels: $^{+}$ 0.10, * 0.05, ** 0.01, *** 0.001

Table D.6: Regression parameters for physical health - very good

Regressor	Estimate	Std. Error	z-value	p-value
$MHI5_{t-1}$	0.001	0.000	5.952	0.000***
$MHI5_{t-2}$	0.001	0.000	3.742	0.000***
$MHI5_{t-3}$	0.001	0.000	5.213	0.000***
$sports_{t}$	0.040	0.005	7.810	0.000***
$sports_{t-1}$	0.023	0.005	4.422	0.000***
age (below 18 years)				
18-24 years	0.052	0.019	−2.673	0.008**
25-39 years	−0.091	0.023	−3.915	0.000***
40-66 years	−0.163	0.024	−6.911	0.000***
over 67 years	−0.186	0.026	−7.217	0.000***
income (none)				
below € 15 000	−0.085	0.031	−2.720	0.007**
over € 50 000	−0.100	0.040	−2.467	0.014*
immigration status (Dutch)				
first generation western	−0.007	0.014	−0.503	0.615
first generation non-western	−0.029	0.012	−2.458	0.014*
second generation western	−0.018	0.012	−1.518	0.129
second generation non-western	−0.005	0.016	−0.286	0.775
gender (female)				
male	0.011	0.006	1.947	0.052^{+}
marital status (divorced)				
married	0.006	0.009	0.713	0.476
never been married	0.009	0.010	0.898	0.369
separated	0.020	0.042	0.484	0.628
widow or widower	0.006	0.014	0.414	0.679
education level (havo-vwo)				
hbo	0.018	0.011	1.693	0.090^{+}
mbo	−0.002	0.011	−0.189	0.850
primary school	−0.012	0.012	−0.970	0.332
vmbo	−0.014	0.011	−1.299	0.194
university (wo)	0.078	0.013	5.875	0.000***
employment status (employed)				
homemaker	−0.006	0.010	−0.559	0.576
retired	−0.027	0.010	−2.637	0.008**
student	0.028	0.019	1.474	0.141
unable to work	−0.086	0.008	−10.340	0.000***
unemployed	−0.021	0.016	−1.275	0.202

Significance levels: $^{+}$ 0.10, * 0.05, ** 0.01, *** 0.001

Table D.7: Regression parameters for BMI - normal weight

Regressor	**Estimate**	**Std. Error**	**z-value**	**p-value**
MHI5_{t-1}	0.000	0.000	1.946	0.052^{+}
MHI5_{t-2}	0.000	0.000	−0.213	0.832
MHI5_{t-3}	0.000	0.000	2.404	0.016*
sports_{t}	0.017	0.004	4.011	0.000***
sports_{t-1}	0.009	0.005	2.075	0.038*
age (below 18 years)				
18-24 years	−0.053	0.020	−2.695	0.007**
25-39 years	−0.067	0.024	−2.748	0.006**
40-66 years	−0.098	0.025	−3.959	0.000***
over 67 years	−0.069	0.028	−2.479	0.013*
income (none)				
below € 15 000	−0.074	0.032	−2.311	0.021*
over € 50 000	−0.057	0.057	−0.999	0.318
immigration status (Dutch)				
first generation western	−0.011	0.015	−0.701	0.483
first generation non-western	−0.016	0.017	−0.978	0.328
second generation western	−0.001	0.013	−0.113	0.910
second generation non-western	−0.027	0.019	−1.422	0.155
gender (female)				
male	−0.024	0.006	−3.678	0.000***
marital status (divorced)				
married	0.021	0.011	1.887	0.059^{+}
never been married	0.041	0.013	3.200	0.001**
separated	0.066	0.061	1.081	0.280
widow or widower	−0.003	0.018	−0.139	0.889
education level (havo-vwo)				
hbo	0.002	0.012	0.127	0.899
mbo	−0.035	0.012	−2.887	0.004**
primary school	−0.028	0.015	−1.944	0.052^{+}
vmbo	−0.023	0.012	−1.937	0.053^{+}
university (wo)	0.063	0.014	4.584	0.000***
employment status (employed)				
homemaker	−0.004	0.011	−0.342	0.733
retired	−0.004	0.012	−0.386	0.700
student	0.029	0.019	1.524	0.128
unable to work	0.014	0.015	0.934	0.344
unemployed	−0.026	0.023	−1.148	0.251

Significance levels: $^{+}$ 0.10, * 0.05, ** 0.01, *** 0.001

Table D.8: Regression parameters for BMI - overweight

Regressor	Estimate	Std. Error	z-value	p-value
MHI5_{t-1}	0.000	0.000	−1.306	0.192
MHI5_{t-2}	0.000	0.000	0.935	0.350
MHI5_{t-3}	0.000	0.000	−0.946	0.344
sports_{t}	0.003	0.005	0.632	0.527
sports_{t-1}	−0.002	0.005	−0.329	0.742
age (below 18 years)				
18-24 years	0.051	0.019	2.728	0.006**
25-39 years	0.048	0.023	2.043	0.041*
40-66 years	0.083	0.024	3.485	0.000***
over 67 years	0.077	0.028	2.799	0.005**
income (none)				
below € 15 000	0.033	0.030	1.128	0.259
over € 50 000	−0.043	0.054	−0.791	0.429
immigration status (Dutch)				
first generation western	−0.010	0.017	−0.571	0.569
first generation non-western	0.031	0.016	1.899	0.058^{+}
second generation western	−0.009	0.013	−0.709	0.479
second generation non-western	0.015	0.017	0.864	0.388
gender (female)				
male	0.054	0.007	7.950	0.000***
marital status (divorced)				
married	0.008	0.012	0.632	0.528
never been married	−0.026	0.014	−1.922	0.055^{+}
separated	−0.053	0.059	−0.897	0.370
widow or widower	0.025	0.020	1.262	0.207
education level (havo-vwo)				
hbo	0.022	0.013	1.716	0.086^{+}
mbo	0.044	0.013	3.412	0.001**
primary school	0.008	0.015	0.510	0.610
vmbo	0.024	0.013	1.854	0.064^{+}
university (wo)	−0.016	0.014	−1.164	0.244
employment status (employed)				
homemaker	−0.014	0.013	−1.063	0.288
retired	−0.013	0.013	−0.995	0.320
student	−0.026	0.019	−1.429	0.153
unable to work	−0.044	0.016	−2.721	0.007**
unemployed	−0.003	0.025	−0.105	0.916

Significance levels: $^{+}$ 0.10, * 0.05, ** 0.01, *** 0.001

Table D.9: Regression parameters for BMI - obese

Regressor	**Estimate**	**Std. Error**	**z-value**	**p-value**
MHI5_{t-1}	0.000	0.000	−0.596	0.551
MHI5_{t-2}	0.000	0.000	−0.688	0.491
MHI5_{t-3}	0.000	0.000	−0.773	0.440
sports_{t}	−0.018	0.003	−5.894	0.000***
sports_{t-1}	−0.004	0.003	−1.372	0.170
age (below 18 years)				
18-24 years	0.033	0.014	2.438	0.015*
25-39 years	0.053	0.017	3.153	0.002**
40-66 years	0.054	0.017	3.133	0.002**
over 67 years	0.031	0.020	1.562	0.118**
income (none)				
below € 15 000	0.044	0.023	1.931	0.053^{+}
over € 50 000	0.067	0.042	1.596	0.111
immigration status (Dutch)				
first generation western	0.020	0.012	1.622	0.105
first generation non-western	−0.010	0.013	−0.765	0.444
second generation western	0.011	0.010	1.046	0.296
second generation non-western	0.007	0.013	0.541	0.588
gender (female)				
male	−0.026	0.005	−5.664	0.000***
marital status (divorced)				
married	−0.021	0.009	−2.445	0.014*
never been married	−0.013	0.010	−1.293	0.196
separated	0.001	0.044	0.031	0.975
widow or widower	−0.014	0.016	−0.899	0.369
education level (havo-vwo)				
hbo	−0.017	0.009	−1.900	0.057^{+}
mbo	0.000	0.009	−0.038	0.970
primary school	0.019	0.011	1.736	0.083^{+}
vmbo	0.005	0.009	0.492	0.623
university (wo)	−0.044	0.009	−4.637	0.000***
employment status (employed)				
homemaker	0.011	0.010	1.134	0.257
retired	0.015	0.009	1.666	0.093^{+}
student	−0.004	0.013	−0.306	0.759
unable to work	0.021	0.013	1.653	0.098^{+}
unemployed	0.029	0.020	1.468	0.142

Significance levels: $^{+}$ 0.10, * 0.05, ** 0.01, *** 0.001