Does working less pay off?

A study on the effect of part-time work on mental and physical health of Dutch women

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Abstract

Dutch women are known for working part-time. As the legislative setting in the Netherlands makes working part-time particularly attractive, the effect of working on part-time on physical and mental health can be examined. This is done within this study, using longitudinal data from a Dutch sample. As the causation between part-time work and health is likely to be two-sided, a fixed effects model with an instrumental variable is used. I find that switching from full- to part-time working is beneficial for the mental health of employed Dutch women. Moreover, I provide evidence for reverse causality between part-time work and mental health. The effect of part-time work on physical health remains unclear.

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1 Introduction

In the last decades there has been a noticeable upward trend of part-time work in the European Union. This can partly be explained by recent profound changes in working conditions, especially for women. The Netherlands show the highest presence of part-time work in Europe and has been labelled the '*first part-time economy*' (Visser 2002). In 2016, 73.3% of all part-time workers in the Netherlands were women. Table 1 presents the female part-time employment as a share of total female employment comparing the Netherlands with Austria, Germany, Greece, Norway, France and the EU-Total in 2016.

Figure 1: Employment rate and part-time share of women 2016

The figure above indicates that in 2016 in the Netherlands, 59.8% of the employed women were working part-time, a percentage significantly higher than other European countries (OECD Labour Force Statistics 2018a).

Part-time work has a number of benefits for both employers and employees compared to full-time work. Besides decreasing unemployment, part-time work can reduce employers' costs, such as costs related to absenteeism, turnover costs and health care costs, which are often underestimated (Halpern, 2005). Productivity gains might arise, as employees' preferences are more considered, which can lead to more commitment and motivation.

Moreover, part-time work enables those with family care obligations to enter the labour market, which is not always manageable while working full-time.

In fact, a 2016 Labour Force Survey reports that women tend to provide family care more often than men do, even when both genders are employed (OECD Labour Force Statistics 2018b). A full-time job will often not leave enough time for family responsibilities. Therefore, part-time work might be the solution for these women to balance the simultaneous obligations at work and at home. In their research, Booth & Van Ours (2009) indicate that women are most content when working part-time, supporting this idea.

Working while simultaneously taking care of family comes at a cost, however. Sapolsky et al. (1994) show that workers with demanding family responsibilities often suffer from chronic stress. The stress hormone cortisol damages the hippocampus, which is the area of the brain that establishes and navigates memory. Moreover, studies have shown that stress has a lasting negative effect on health. It impairs the function of the immune system, it is associated with depression and even a higher risk of cancer (Reiche et al. 2004). In other words, stress damages both mental and physical health.

Working part-time rather than full-time therefore logically reduces stress, especially for women with demanding family responsibilities, as it gives them more time to take care of their family. This hypothesis combined with the fact that stress impairs both mental and physical health brings me to my research question:

How does a shift from full-time to part-time work affect the mental and physical health of Dutch women?

In order to answer my research question, I have formulated two hypotheses. The first hypothesis states that part-time work, relative to full-time work, has a positive effect on the mental and physical health of Dutch women. The second one is that the positive effect of part-time work, relative to full-time work, on the health of Dutch women is stronger for married women than unmarried women as well as for women with young children rather than without.

I answer these hypotheses by exploiting panel data of Dutch employed women. The results indicate that the first hypothesis only partially holds. I find that switching from full- to part-time work has a positive effect on women’s mental health. However, the results indicate that part-time work has a negative effect on the physical health of Dutch women.

The setup of this paper is as follows: chapter 2 provides a brief overview of existing related studies and their theoretical implications. Chapter 3 describes the data used in this analysis and the econometric model. The results are stated in chapter 4. A critical discussion as well as the concluding remarks are given in chapter 5.

2 Theoretical Framework

This section is organised as follows. First, existing empirical studies on the relationship between working hours and health will be introduced and a brief overview of the results will be given. Then, theoretical models that are linked to those results will be discussed.

2.1 Empirical evidence of working hours, stress and health

The effect of working hours on physical health has been a prominent subject of former research. In a meta-analysis, Sparks & Cooper (1997) provide a broad overview of existing research on the relationship between health and hours of work. They find a small but significant positive relationship between hours of work and health symptoms, such as increased stress and fatigue. Furthermore, the authors find the relationship between working hours and health to be non-linear and suggest that there should be a distinction between part- and full-time contracts in future research.

Switching this argument around, Bamford's (1993) results suggest that more free time leads to less unhealthy behaviour and reduced stress of workers. When they have more free time, workers tend to spend it on health improving behaviours such as physical activities and a balanced diet.

Mattingly and Sayer (2006) take this further by analysing men and women separately. Their findings suggest that the two genders experience significantly different time pressure. Time pressure is a cause of stress because one perceives to not have enough time to complete all their tasks. The authors find the highest perceived time pressure for married women with children. One important factor underlying these findings is that the leisure time of women is often accompanied with household activities, whereas that of men is not. The transition of women working more did not eliminate their perceived responsibilities for domestic work, which is why their subjective time demands increased. Another finding is that there is a family penalty for women due to more responsibilities that are child-related. Those tasks, e.g. taking care of a sick child, cannot be predicted and women are more likely to take care of that (Mattingly & Sayer 2006, Nelson 2010).

Moreover, Roxburgh (2004) evaluates the effect of time pressure on men and women and concludes that it is significantly associated with distress for both genders. Furthermore, she claims that subjective time pressure partly explains the higher depression rates of employed women. One explanation for that is the nature of the household tasks women perform besides their work.

This is in line with the findings of Sayer et al. (2009), who find that mothers have a higher household workload in families in which both parents work. Even as the participation of women in the labour force increased, there is no proportional increase in the share of men helping in the house. Moen & Yu (2000) estimate that family responsibilities create the same workload as one additional full-time job per household.

2.2 Theoretical models on the relationship between work and health

Demand, control, support

Van der Doef & Maes (1999) examine studies that deal with the Job-Demand-Control model implemented by Karasek (1979), which attempts to explain occupational distress. The components of the model that formulate the 'strain hypothesis' are job demands and job control. Job demands consider how demanding a job is and job control refers to the freedom of decisions one has at their job. According to this model, workers that experience high demand and low control are more likely to experience psychological distress, burnout or in general a lower emotional well-being. Adding social support to the model, making it the Job-Demand-Control-Support model, (Johnson & Hall 1988, Sanne et al. 2005), indicates that a highly demanding job that has a low decision latitude and low social support lead to the most negative health outcomes.

Role Strain and work-life-conflict

Another hypothesis that explains negative health outcomes resulting from high demands (both at home and at work) is the role strain hypothesis. It explains that demands from work and family compete on employees' attention, time and energy (Grönlund and Öun 2010).

The same is suggested by Roeters (2014) by the conflict approach. It states that working consumes those resources that are also needed to sustain personal relationships to children and spouses.

Offer & Schneider (2011) find that the effect of a work-life-imbalance differs for women and men. Normative expectations for mothers and a resulting work-life-imbalance leads to a worse mental well-being due to this conflict and increased stress. A work-family conflict is defined as the feeling that responsibilities of work and family are not compatible with each other. A general increase in the work-family conflict is found due to a simultaneous increase in women's labour force participation and the increase in men's commitment for household chores, which leads to a decrease in free time for both (Offer & Schneider 2011).

In contrast to these findings, Nomaguchi (2009) examined the cause of the increase in work-life-conflict and found that gender does not play a significant role and a lack of evidence for other studies. This is mostly due to the inability of quantifying domestic work. Potentially, women might perceive a higher workload as they perceive a higher sense of responsibility for their children. Discrepancies in results might arise from using different concepts of health and conflicts. Comparing those studies therefore requires to carefully review the outcomes used (perceived distress, observed physical health outcomes or self-assessed health). There are studies suggesting that the effects of working hours on health are homogenous for both genders. Interpreting those studies therefore requires the identification of the focus, the time loss due to multiple tasks or the increase of negative feelings about it (Offer & Schneider 2011).

<u>Traditional sex role theory</u>

The traditional sex role theory is applied by Hill (2005). It implies that working hours are stronger negatively associated with overall life satisfaction for women than for men. Women experience a higher work-family conflict, especially if there is more job pressure. In general, mothers invest less in work but more in family compared to fathers. Several studies show a gendered effect between psychological distress and performing multiple roles. Voydanoff and Donelly (1999) predict a higher importance for more demanding family roles for women, which are also stronger related to stress for women than for men. Booth & Van Ours (2009) also find evidence that contradicts a symmetrical division of household and market work division. Women that have a higher market work share than men are not proportionally more supported by their husbands when it comes to house work.

Taking reverse causality into account

The Job-Demand-Control-Support model and the sex role theory have in common that the causation is seen as one-directional (De Lange et al. 2004); namely, that household and market work cause distress. It is important to keep in mind that it could be one's distress making one work part-time rather than full-time, then the causation flows the other way. Additionally, the decision of part-time or full-time work could be based on attitudes towards work. There have been few empirical studies taking that into account. Feldman (1990) proposed that demographic factors, along with work-context factors and job attitudes impact the types of part-time work contracts. De Lange et al. (2004) try to establish evidence for reciprocal relationships between work and health factors. In their analysis, De Lange et al. (2004) examine three effects: First, they investigate the effect of job demands, control and social support on mental health. Then they explore the reversed relationship between those factors and lastly, they test the hypothesis stating that there is a reciprocal causal relationship between mental health and those working conditions. This is done by combining time lags of 1, 2 and 3 years of length. It is found that indeed, all of the three hypotheses apply and that a one-year lag is most appropriate to establish the relationship of job characteristics and mental health.

3 Data and methodology

To my knowledge, there have not been any studies that examine the effect of part-time work on health while also controlling for individual heterogeneity and reverse causality. Previous literature suggests that hours worked might be positively correlated to stress and other health symptoms for women, especially those with children. Stress can be linked to both, mental and physical health outcomes. Based on this, the following two hypotheses are tested:

H1: Part-time work, relative to full-time work, has a positive effect on mental and physical health of Dutch women.

H2: The positive effect of part-time work, relative to full-time work, on the health of Dutch women is stronger for married women than unmarried women as well as for women with young children rather than without.

3.1 Data

The empirical estimation is based on the LISS (Longitudinal Internet Studies for the Social sciences) panel data, which is a representative survey of the Dutch population, provided by CentERdata in Tilburg. It is conducted online and repeated every year since 2007. To ensure reliable results, those individuals without online access (mostly elderly groups) are loaned a so called "simPC", which facilitates access to the online questionnaire for those with less technological experience (Scherpenzeel 2011). I combined the two core panels of *Health* and *Work & Schooling* with the available background variables for the respective time periods. The panels have been collected for the years 2007 to 2017. However, only 2008, 2009, 2010, 2011, 2012, 2015, 2016 and 2017 are used to create the panel, as not both data sets are available for every year. The study is conducted in Dutch, so individuals with a foreign background (and insufficient language skills) are not included into the analysis. However, I do not expect this to bias the outcome of my research.

To construct the dataset, the following core panel waves have been used:

- Work & Schooling (LISS Core Study: wave 1, 2, 3, 4, 5, 8, 9, 10)
- Health (LISS Core Study: wave 2, 3, 4, 5, 6, 8, 9, 10)
- Background variables (Nov. 2008, 2009, 2010, 2011, 2012, 2015, 2016, 2017)

After downloading the files in stata format, the variables that are not relevant were dropped out of the sample. Those that could be of importance were renamed in the same way for every wave. The background variables are provided for every month. I chose to include those that were collected from the same month as the *Health* survey. Next, the waves of each core panel and the background variables are merged, sorted by the ID number and the time indicator *year*. Finally, those three panels are merged to one. The variables included were investigated, outliers were dropped and the sample was restricted to employed women between 16 and 65 years of age. After the data cleaning, the database consists of 3011 individuals and 9,142 observations. Due to missing values for the instrumental variable, the 2SLS fixed effects estimation only uses 7,895 observations from 2,751 individuals, corresponding to 86.36% of the total observations. In order to make the results of the models comparable, the number of observations for the other models is restricted to those observations as well. The panel is unbalanced, meaning that not every individual is present in each point of observation. In the final dataset, 6.14%, corresponding to 185 respondents, are present in every wave of the research period. As this attrition would be a threat for causality if it follows a pattern, attrition tests are performed[1]. The results of the attrition tests indicate random attrition. Therefore, the representativeness of the sample of analysis is not reduced, the only consequence is a smaller sample size over time.

As some variables in the survey are dropped, added or changes in subsequent waves, I ensured that the variables are present in all waves and that the scales are consistent. This is of great importance, as variations in scales might have a biasing effect on the result (see Burson et al. 2009).

3.2 Variables

Based on the findings of existing studies introduced in chapter 1, the following variables are included.

3.2.1 Dependent variables

The main outcome variables of interest relate to the self-assessed physical and mental health.

<u>Self-assessed health (SAH):</u>
The first dependent variable is the self-assessed health of the respondents. It ranges from 1 to 5, indicating a poor, moderate, good, very good or excellent health state. As it is commonly used in previous employment-related research (e.g. Böckerman & Ilmakunnas 2009, Crossley 2002), I consider it a reliable measure of the perceived health of women, especially as I am not comparing women but rather look at the within effect. In the survey, the respondents are shown their answer of the previous wave, which creates an awareness that contributes positively to the reliability of this measure.

[1] This is done by creating a dummy that takes the value 1 if an individual is present in every wave. This dummy is included into the models, to see whether being present in all waves has a significant effect on mental or physical health. The same is done for being present in the next wave. Both tests show that the attrition is random.

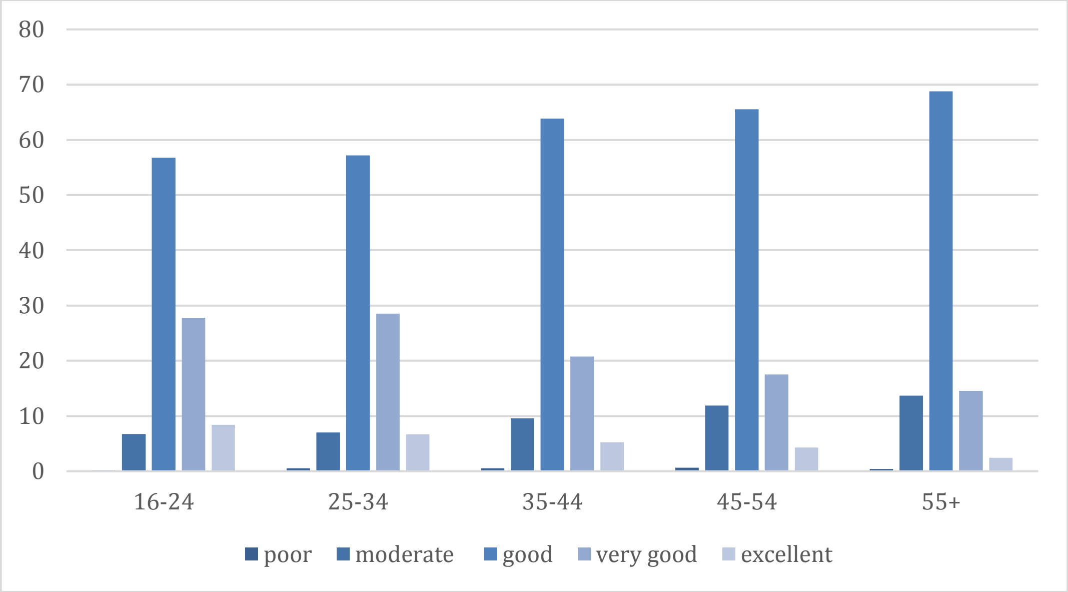

Figure 3.1: Self-assessed health of employed women among age groups

Figure 3.1 shows that ‘very good’ and ‘excellent’ health is reported more often among the two lowest age groups, whereas more women in the higher age groups indicate their health as ‘moderate’. Being in ‘good’ health is most common among all health groups. The mean SAH is 3.2, i.e. between ‘good’ and ‘very good’ health.

<u>Mental health (MHI-5):</u>

The variable Mental Health Inventory (MHI-5), which reflects the mental health of the individuals, serves as the second dependent variable. This variable has been found to be a reliable predictor for mental disorders (e.g. Thorsen et al. 2013). The MHI-5 is a part of the Short Form Health Survey (SF-36). It represents the shortened form of the MHI-18, covering the main mental health issues such as anxiety and depression (Berwick et al. 1991).
It includes questions on how the respondents felt last month: *‘I felt very anxious’, ’I felt so down that nothing could cheer me up’, ‘I felt calm and peaceful’, ‘I felt depressed and gloomy’* and *‘I felt happy’*. The answers range from 1 to 6 (corresponding to *‘never’, ‘seldom’, ‘sometimes’, ‘often’, ‘mostly’, ‘continuously’*). The standard way of calculating the score is as follows: first, the scores for the negative outcomes (‘*feel very anxious*’, ‘*feel so down that nothing could cheer me up*’, ‘*feel depressed and gloomy*’) are reversed. Then both positive and negative outcomes are transformed to a 0-5 scale. A higher score indicates a more desirable mental state (e.g. ‘*I continuously felt happy*’ or ‘*I never felt anxious*’ both corresponds to a value of 5). The maximum score is 25. In order to make the outcome more sensitive to small changes and to

facilitate the understanding, the obtained scores are then multiplied by 4. Accordingly, the range is between 0 and 100, with 100 representing a mental state with a complete absence of depressed, anxious or down feelings and a continuous state of happiness (Yamazaki et al. 2005).

There is no universal cut-off point, separating "good" from "bad" mental health, as demographic differences lead to very heterogeneous outcomes. I used the cross-sectional mean to construct a cut-off point. Outcomes below one standard deviation of the mean indicate a mental health disorder. This corresponds to a value of approximately 58 on a scale from 0 to 100. Individuals with a MHI-5 value below 58 show depressive symptoms (Van den Beukel et al. 2012). This is in line with previous cut-off points used in empirical research, which range from 52 to 76 (Thorsen et al. 2013). Applying this to the analysed sample shows that 26.82% of the women show depressive symptoms at least once during the survey period. Figure 3.2 indicates that the distribution of the MHI-5 is left-skewed, supporting the finding that the majority of employed women has a MHI-5 above the cut-off point of 58.

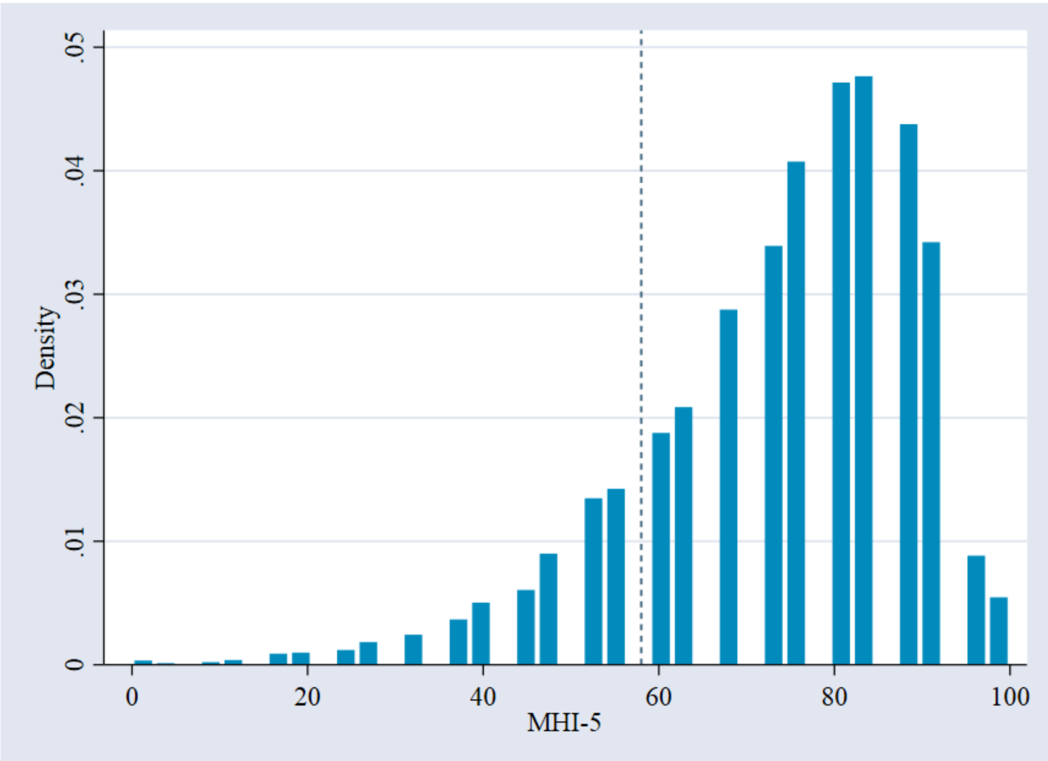

Figure 3.2: Distribution of the MHI-5 among employed women

The mean MHI-5 score for women in 2017 is slightly higher than in 2008 (75.11 compared to 73.83). As figure 3.3 shows, the highest score can be observed for 2015 (76.23). There is a noticeable lower participation rate in that year (803 observations compared to 1,055 in 2008). That suggests that individuals with worse mental health might have dropped out of the sample. Attrition tests, however, indicate random attrition, meaning that not being present in all waves does not significantly influence the results regarding mental health.

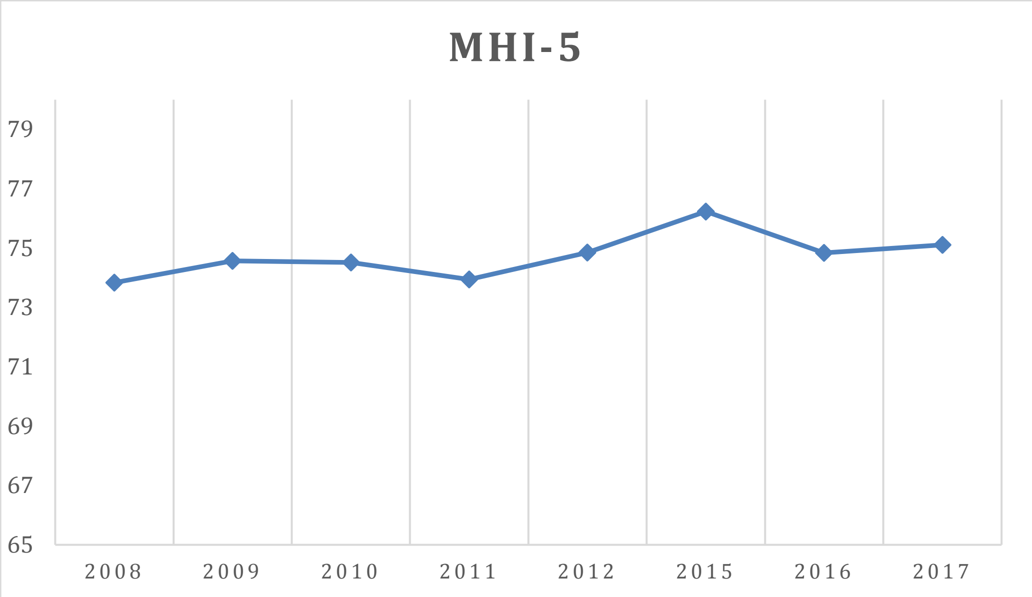

Figure 3.3: Mean MHI-5 value of employed women 2008-2017

Older age groups show a higher prevalence of very good mental health. Figure A1 in Appendix A provides an overview of mental health among age groups.

3.2.2 Explanatory variables

<u>Part-time work:</u>

The measure of part-time work is based on the individual's contractual working hours per week. The part-time status is fulfilled if weekly working hours range from 1 to 32, which corresponds to a 4-day working week and seems appropriate for the Dutch labour market (Wielers & Raven 2011). In 2008, approximately 69% of the women in this sample were working part-time. At the end of the survey period 62% work part-time. This difference in part-time work prevalence can be attributed to the non-random attrition in this sample.

Working part-time is distributed differently among age groups. Women in the age of 35-44, 45-54 and older than 55 years show a higher prevalence of working part-time (71.5%, 70.7%

and 69.5%, respectively) compared to those women in age 16-24 and 25-34 (54.3% and 49.6%, respectively).

Moreover, women that work part-time show a slightly lower average value for their self-assessed health compared to full-time (3.18 compared to 3.23). The average mental health is higher for women that work part-time compared to those working full-time (74.21 vs. 73.55).

Covariates:

Along the main independent variable of interest, part-time work, I included a set of covariates. They are split into socioeconomic variables and health related variables, including age, number of children, living in a rural or urban area, providing informal care, net household income, marital status, educational status, having a longstanding disease or handicap, suffering from sleeping problems and engaging in unhealthy habits, like smoking or immoderate alcohol consumption. Additionally, for the examination regarding mental health, a dummy variable describing job uncertainty is included.

Age:

The average age of women in this sample is 42.5 years. To see how the women's age interacts with working part-time and to show potential non-linearities in the effect of age, I created age categories. In this sample, the highest prevalence of part-time working is shown for women aged 35-44.

Education:

For this variable, I collapsed the 6 available education categories to 3, namely low, medium and high education. Low education corresponds to only having primary education, medium includes secondary school and high education corresponds to academic education (HBO, WO). 3.4% of the employed women have a low education, 58.6% medium and 38% have a high diploma. Mattingly & Sayer (2006) find that more education leads to more demands and the perception of feeling rushed more easily, which suggests a mediating effect of education on stress. Education is included to account for different effects that academic women might perceive balancing work life and family demands. The within variation over the whole time period is rather small, as most of the women have finished their education at the age of 25.

Job uncertainty:

Existing research has shown an increased level of stress for individuals that are uncertain about whether their job is going to continue (Pollard 2001). This is especially important for mental health. Both part- and full-time working women in this sample are rather certain about the continuity of their jobs.

Situation at home:

To account for the situation at home and multiple demands, dummies for having a child below the age of 8 years, marital status and the household income were included. 35% of the women in this sample report to have children younger than 8 years, 55.8% of the women are married and the mean household income is €3251. The net household income is included using 4 categories, ranging from €0-€1500, €1501-€3000, €3001-€5000 and >€5000. Household income might play an important role for perceived stress, as a higher income allows outsourcing of certain household tasks (Mattingly & Sayer 2006).

Unhealthy behaviour:

This variable is included as we expect unhealthy habits to influence physical health. Recent studies show that there are also links to worse mental health outcomes (Vermeulen-Smit et al. 2015). This is taken into account by a constructed variable, combining unhealthy lifestyle habits like smoking, drinking alcohol 3 or more times a week and having a Body Mass Index (BMI) that exceeds 30. The BMI serves as a proxy for the consequence of an unhealthy diet combined with a lack of physical exercise, leading to an unproportioned weight/height ratio. Berk et al. (2013) found that the risky behaviours mentioned above all lead to a higher risk for depression.

In this sample, 15% of the women fall into that category. 34.4% of the women are currently smoking, 25% are consuming a lot of alcohol. 15% of the women have a BMI exceeding 30, which is considered being obese (Garrouste-Orgeas et al. 2004).

Appendix A1 shows the variables, the corresponding survey questions and answer possibilities (table A1) and a descriptive table of all variables (table A2).

3.2.3 Instrumental variable

Preferred working hours per week:

There is reason to assume that there is reverse causality between part-time work and health. In other words, it is possible that the individual's health state influences whether individuals work part-time. The instrument used in the analysis is the variable preferred hours of work. The respondents were asked "*How many hours per week in total would you like to work?*" the answer range is between 0 and 100 hours. On average, the women in this sample prefer to work 26.5 hours per week, which falls under the definition of part-time work. The highest number of preferred working hours is found for employed women of 25-34 years. Figure A2 in Appendix A shows the distribution of preferred working hours among employed women.

3.3 – Econometric model

Two investigations are carried out to explore the research question empirically. The first one focuses on the self-assessed physical health of individuals, the second one on mental health. First, a pooled OLS model is used to investigate the cross-sectional differences between the individuals. Then, individual heterogeneity is taken into account by implementing the fixed effects model. Finally, the two-stage least squares (2SLS) approach is used as the direction of causality might be two-sided.

3.3.1 - Pooled OLS

Starting the analysis, a pooled OLS model is estimated. The model exploits the within and between variation. The mental and physical health of women, denoted as $y_{i,t}$ is defined as follows:

$$y_{i,t} = \beta_0 + \beta_p p_{i,t} + \beta_x x_{i,t} + \alpha_i + \varepsilon_{i,t} , \qquad (1)$$

where *t* indexes time and *i* indexes the individual. $p_{i,t}$ represents the binary variable part-time work. $x_{i,t}$ is a set of observable exogenous regressors, the individual's characteristics, such as age, income and socio-economic characteristics. β represents the effect of those sets of parameters on the dependent variable, where the main effect of interest is β_p. Last, α_i describes the unobserved time-invariant individual heterogeneity that potentially affects the individual's health (such as genes), and $\varepsilon_{i,t}$ describes the idiosyncratic (time-variant) error term. α_i and $\varepsilon_{i,t}$ form the composite error $v_{i,t}$.

This model is estimated under the assumption of no correlation between any part of the unobserved effects and the regressors. In other words, I assume that individual characteristics that are not taken into account in the model are not correlated to the regressors. This is important, as otherwise the measured effects would be biased.

In order to prevent serial correlation between the error terms, the standard errors are clustered on the individual level. This is necessary, because the composite errors show a positive serial correlation over time (Wooldridge 2002, 2010). For the standard errors to be valid, the composite errors of time *t* and *s* should not be correlated, i.e. $Corr(v_{i,t}, v_{i,s})=0$ for all $t \neq s$.

3.3.2 – Fixed effects

As individual characteristics not captured by the control variables might influence the decision to work part-time, it cannot be assumed that the regressors and the error term are uncorrelated, i.e. $E(v_{i,t}|p_{i,t}) \neq 0$. In this case, the zero conditional mean assumption does not hold. It is very likely that individuals with less career aspirations self-select themselves to work part-time. The effect of part-time work on health could not be claimed as causal, due to inconsistent estimates (Wooldridge 2002, 2014). To overcome this confounding impact of unobserved individual heterogeneity, a fixed effects model is used. The fixed effects approach estimates the within variation of the individuals over time. Since α_i is fixed over time, the unobserved time-invariant characteristics are eliminated. The within transformation of equation (1) leads us to:

$$(y_{i,t} - \bar{y}_i) = \beta_x(x_{i,t}-\bar{x}_i) + \beta_p(p_{i,t}-\bar{p}_i) + (\varepsilon_{i,t}-\bar{\varepsilon}_i) + (\alpha_i-\alpha_i) \quad (2)$$

Equation (2) shows that exploiting the panel dimension allows α_i to be correlated with the explanatory variables, as it is differenced out (Wooldridge 2002).

3.3.3 - Two-Stage Least Squares (2SLS) Fixed Effects

There might be reverse causality between working part-time and the individual's health, i.e. women with a bad physical or mental health rather decide to work part-time. In that case, the effect of part-time work on health would be overestimated (Berniell & Bietenbeck 2017).
In that case, equation (1) is extended to:

$$y_{i,t} = \beta_p p_{i,t} + \beta_x x_{i,t} + \alpha_i + \varepsilon_{i,t} \quad (1)$$

$$p_{i,t} = \pi_y y_{i,t} + \pi_x * x_{i,t} + \pi_z z_{i,t} + \gamma_i + \delta_{i,t}, \quad (4)$$

where $x_{i,t}$ describes the individual's characteristics at time *t* and $z_{i,t}$ describes the instrument, in this case preferred working hours of individual *i* at time *t*.

Reverse causality is found if mental or physical health has an effect on part-time work, i.e. when $\pi_y \neq 0$. Not accounting for this endogeneity of $p_{i,t}$ would lead to inconsistent and biased estimates, which do not provide a causal effect of part-time work on physical or mental health. An instrumental variable approach is used, to ensure unbiased and consistent estimates.

There are two vital conditions for the instrument to be valid: The first one is that the instrument is relevant, i.e. that there is a (preferably strong) correlation between the instrument and the potential endogenous variable, so that $E(p_{i,t}\ z_{i,t}|x_{i,t}) \neq 0$. Second, the instrument must not be directly correlated with the dependent variable or any other regressor. The instrument should influence physical or mental health solely through part-time work. Then, the pure effect of our endogenous variable is isolated by the instrument, leading to an unbiased result.

In the first stage of the 2SLS model, part-time work is regressed on the instrument and $x_{i,t}$, to isolate the part of part-time work that is uncorrelated with $v_{i,t.}$ This is the stage that reveals whether the instrument is relevant or not. As long as the coefficient of the instrument on part-time is non-zero and statistically significant, the instrument is relevant (Stock & Watson 2015).

The second stage uses the predicted value of part-time work ($\hat{p}$) estimated in the first stage, which is now uncorrelated with any unobserved effects. The health outcome variable of interest is regressed on $\hat{p}$ and the covariates, leading to consistent and unbiased estimates.

3.3.4 Sensitivity analysis

The findings are tested for robustness in a sensitivity analysis. It reveals whether certain restrictions in the model lead to different outcomes, and whether the replacement of our variables of interest lead to similar effects.

To provide evidence that part-time work is endogenous to the dependent variable health, the reversed model is tested. I estimate a pooled OLS and a FE regression using part-time work as a dependent variable and include SAH and MHI-5 dummies along with demographic covariates. To further estimate whether there is a lagged effect of those health outcomes, the same models are tested with one- and two-year lagged SAH and MHI-5 dummies.

Then, using the 2SLS FE model, the variable part-time work is replaced by the continuous variable working hours per week.

To see the effect for restricted subsamples, restrictions for age categories, marital status and having young children are tested.

4 Results

For the purpose of the following analyses the effect of part-time work compared to full-time work along employed Dutch women is examined. The effects presented in this section are under the assumption that all else is kept constant.

4.1 Pooled OLS

The following presents the results obtained for the SAH and MHI-5 model, respectively. A pooled OLS estimation with clustered standard errors is estimated, assuming exogeneity in all explanatory variables.

On average, working part-time shows a statistically insignificant effect on both self-assessed physical and mental health. Thus, according to this cross-sectional approach, working part-time compared to full-time does not affect the women’s health.

For the SAH, shown in table 4.1, column (1), the explanatory variables providing informal care, age, the two lowest income categories compared to the highest, high education compared to low education and having a disease, sleeping problems and behaving in an unhealthy manner show significant effects in the expected direction. The coefficients for having children under 8 years of age, living in a rural area compared to urban, being in the third income category compared to the fourth, low education compared to basic, being married compared to not being married are not significant at a 10% level.

Table 4.1 column (2) shows the results of the analysis of part-time work on mental health. Significant effects are found for having young children, providing informal care, experiencing job uncertainty, age, being in the two lowest income categories compared to the highest, having a longstanding disease or sleeping problems.

Living in a rural area compared to an urban, being in the 3rd income category compared to the 4th, having obtained medium or high education compared to low education, being married and engaging in unhealthy behaviours do not show any significant effect on the MHI-5 in this cross-sectional analysis.

Table 4.1: Pooled OLS estimation

	SAH	MHI-5
Part-time	-0.005 (0.024)	0.012 (0.537)
Children <8y	-0.040 (0.028)	-1.187+ (0.636)
Informal care	-0.064* (0.025)	-1.602** (0.596)
Uncertainty		-3.228** (0.455)
Age	-0.006** (0.001)	0.177** (0.026)
Rural	-0.017 (0.030)	0.731 (0.676)
Household income 1	-0.158** (0.041)	-3.498** (1.026)
Household income 2	-0.119** (0.029)	-1.699** (0.641)
Household income 3	-0.002 (0.027)	0.649 (0.561)
Education (med)	0.052 (0.065)	1.291 (1.216)
Education (high)	0.145* (0.067)	1.736 (1.238)
Married	0.001 (0.026)	0.913 (0.599)
Disease	-0.398** (0.022)	-3.853** (0.510)
Sleeping problems	-0.413** (0.067)	-14.255** (1.976)
Unhealthy habits	-0.193** (0.028)	0.737 (0.781)
Constant	3.607** (0.076)	67.761** (1.544)
Observations	7,895	7,895
Individuals	2,751	2,751
R-Squared	0.1457	0.0831

Note: ** p<0.01 * p<0.05 + p<0.1, SE in parentheses

4.2 Fixed effects

After accounting for unobserved individual heterogeneity, the effect of part-time work on SAH stays negative but becomes significant. Now, working part-time shows a much stronger effect. This is somewhat surprising, as this implies that switching from full- to part-time work has a negative effect on the physical health of women, namely it decreases the SAH by 0.07 on a scale from 1 to 5. It cannot be excluded, however, that this is due to reversed causality.

Table 4.2, column (1) shows that becoming one year older, switching to a higher educational status (from primary education), becoming sick or beginning to suffer from sleeping problems has a significant effect on the SAH. Becoming sick or developing sleeping problems now shows a weaker effect on SAH compared to the pooled OLS estimation.

Table 4.2, column (2) presents the results for the MHI-5. Changing from full-time to part-time work still shows an insignificant, but negative effect. Most of the covariates show the same effect direction and significance as in the pooled OLS model. The effect of an additional year of age shows a higher effect on the MHI-5 than in the pooled OLS estimation.

The coefficients of becoming sick or getting a sleeping problem are weaker compared to the pooled OLS estimation. The latter can be expected, as a within change might not have an immediate strong effect on psychological distress. It might take longer for this effect to show.

Table 4.2: Fixed Effects estimation

	SAH	MHI-5
Part-time	-0.071**	-0.677
	(0.027)	(0.641)
Children <8y	-0.045	-0.685
	(0.038)	(0.896)
Informal care	0.002	-1.432*
	(0.024)	(0.570)
Uncertainty		-0.355
		(0.395)
Age	-0.005*	0.329**
	(0.002)	(0.056)
Rural	0.105	0.159
	(0.068)	(1.617)
Household income 1	-0.017	-0.775
	(0.046)	(1.103)
Household income 2	-0.014	0.187
	(0.030)	(0.712)
Household income 3	0.015	0.432
	(0.026)	(0.618)
Education (med)	0.190*	-0.004
	(0.090)	(2.141)
Education (high)	0.189*	-0.282
	(0.094)	(2.226)
Married	-0.002	1.222
	(0.041)	(0.965)
Disease	-0.201**	-1.857**
	(0.021)	(0.493)
Sleeping problems	-0.201**	-8.353**
	(0.060)	(1.438)
Unhealthy habits	-0.021	-0.553
	(0.036)	(0.848)
Constant	3.312**	61.228**
	(0.134)	(3.197)
Observations	7,895	7,895
Individuals	2,751	2,751
R-Squared	0.0251	0.0457

Note: ** p<0.01 * p<0.05 + p<0.1, SE in parentheses
The R-Squared describes the within R-Squared

Although the fixed effects model accounts for individual differences that might influence the outcome of interest, it does not solve the potential confounding effect of reverse causality. It is plausible that the associations found have an underlying effect in both directions, which cannot be fully observed. A fixed effects model might not be sufficient to provide consistent estimates.

4.3 Two-Stage Least Squares Fixed Effects

The 2SLS FE approach accounts for this persistent endogeneity. Although the fixed effects estimator accounts for time invariant individual heterogeneity, it might not be sufficient, as the potential reverse causality is not addressed. I account for this by using an instrumental variable approach combined with the fixed effects estimator.

For the instrument to be consistent, two conditions need to be satisfied: the instrument used must be relevant and valid. The first stage results presented in table 4.3 prove that $corr(p_{i,t},z_{i,t})\neq 0$, namely we can see that the coefficient of preferred working hours is highly statistically significant and different from zero. This means that preferred working hours affect the probability of working part-time. The coefficients in the first stage for the SAH and the MHI-5 model differ slightly, as job uncertainty is only included into the analysis of mental health.

Table 4.3: First stage results for the 2SLS FE model (Part-time work as dependent variable)

	SAH	MHI-5
Preferred working hours	-0.009** (0.001)	-0.008** (0.001)
Observations	7,895	7,895
Individuals	2,751	2,751
R-Squared	0.1939	0.1941

Note: ** p<0.01 * p<0.05 + p<0.1, SE in parentheses
The R-Squared stated describes the overall R-Squared

To test the relevance of an instrument, in practice, the rule of thumb is for the F-statistic in the first stage of the 2SLS to be greater than 10 (Staiger & Stock 1997, Stock et al. 2002). This assumption is fulfilled in both models, with corresponding Cragg-Donald Wald F statistic values of 174.752 and 173.963 for SAH and MHI-5, respectively. Based on these results, we can apply the decision rule implemented by Stock et al. (2002). Thus, we can reject the null hypothesis that the instrument used is weak.

The second requirement addresses the instrument's validity, i.e. the instrument must not be correlated with any unobserved determinant of physical or mental health. That means that preferred working hours must affect mental or physical health only indirectly, through the instrumented variable part-time work. This assumption cannot be tested. However, I expect one's preferred working hours to be correlated to their health only through their type of contract (part-time or full-time). In other words, it is implausible that one's health is directly influenced by preferred working hours, other than through the number of hours one actually works.

The endogeneity test has the null hypothesis, that the potentially endogenous variable is exogenous. For the SAH model, the null hypothesis cannot be rejected, suggesting that part-time is not endogenous, i.e. there is no evidence of reverse causality between part-time work and SAH (p-value=0.7633). This suggests that results obtained by the fixed effects model without any instrumental variable are more efficient for the SAH model. The instrumental variable approach does not include the whole variation, as it is limited to the variation that is not linked to any part of the unobservable error term. This is further examined in the sensitivity analysis in section 4.4.

For the endogeneity test of the MHI-5 model, the null hypothesis can be rejected at a significance level of 5%, providing evidence that there is reverse causality between women's mental health and working part-time (p-value=0.0146). Therefore, the approach to treat part-time as endogenous is appropriate.

As shown in table 4.4, column (1), the effect of part-time work on SAH turns insignificant. Overall, this finding combined with the endogeneity test suggest that the fixed effects instrumental variable approach is not appropriate to examine the effect of part-time work on SAH.

The findings for the MHI-5 reveal a different picture. As column (2) in table 4.4 shows, switching from full-time to part-time work significantly increases the MHI-5 by 7.81 points on a scale from 0 to 100. With this coefficient becoming significant and changing its sign, it can be concluded that part-time work indeed needs to be treated as endogenous. As those covariates that stay significant show a similar and reasonable effect, there is no evidence of a model misspecification. Starting to provide informal care leads to a lower MHI-5 of 1.33 points. An additional year of age still shows a positive effect on the MHI-5, it increases by 0.32 points. Compared to the fixed effects estimation, the coefficient of getting married now becomes significant, indicating that getting married results in a MHI-5 increase of 1.14 points.

Table 4.4: 2SLS Fixed effects estimation

	SAH	MHI-5
Part-time	-0.028	7.811*
	(0.148)	(3.599)
Children <8y	-0.036	1.166
	(0.049)	(1.194)
Informal care	0.002	-1.332*
	(0.024)	(0.581)
Uncertainty		-0.605
		(0.415)
Age	-0.005*	0.323**
	(0.002)	(0.057)
Rural	0.104	0.011
	(0.068)	(1.646)
Household income (1)	-0.021	-1.652
	(0.049)	(1.179)
Household income (2)	-0.016	-0.175
	(0.031)	(0.740)
Household income (3)	0.014	0.244
	(0.026)	(0.633)
Education (med)	0.192*	0.429
	(0.090)	(2.184)
Education (high)	0.196*	1.097
	(0.097)	(2.336)
Married	-0.003	1.137**
	(0.041)	(0.982)
Disease	-0.201**	-1.833**
	(0.021)	(0.502)
Sleeping problems	-0.200**	-8.183
	(0.061)	(1.464)
Unhealthy habits	-0.019	-0.240**
	(0.036)	(0.872)
Constant	3.289**	56.710**
	(0.155)	(3.758)
Observations	7,895	7,895
Individuals	2,751	2,751
R-Squared	0.1114	0.0274

Note: ** p<0.01 * p<0.05 + p<0.1, SE in parentheses
The R-Squared describes the overall R-Squared

4.4 Sensitivity analysis

Reverse causality:

In order to confirm that the causality actually is bi-directional, the model is turned around, i.e. working part-time is regressed on physical or mental health.

First, using part-time work as the dependent variable, a pooled OLS regression with SAH dummies and the covariates age, household income, education, marital status and the binary variable of having young children is estimated. Poor self-assessed health (SAH=1) serves as reference category. In this model, having excellent health compared to poor health decreases the probability of working part-time by 13.9 percentage points.

The SAH dummies are then included as one- and two-year lags. This is done to see whether the physical health of previous years has an effect on working part-time. While none of the dummies for the health of the previous year show a significant effect on working part-time, the two-year lagged SAH dummies are all highly significant, indicating that reporting a moderate, good, very good or excellent health compared to poor health two years ago decreases the probability of working part-time rather than full-time (see table 4.5).

As this study is examining within effects, fixed effects models including SAH dummies of the current year, the year before and two years before are estimated. Table 4.5, columns (3), (4) and (5) show that changing from poor health to better health at time *t*, *t-1* and *t-2* does not have a significant effect on the probability of working part-time. This is in line with the endogeneity test conducted in section 4.3, where the within effect of part-time work has not been found to be endogenous.

Unsurprisingly, the findings of the 2 lag pooled OLS estimation suggest that women that have a good physical health are less likely to work part-time compared to women with poor health. However, the insignificance of the coefficients of the SAH dummies in the FE models, shown in table 4.5, column (4) to (6), suggest that there is no reverse causality for health changes within women. It is possible, that the changes of the women’s health status affects the probability of working part-time over a longer or even shorter period of time, which is not captured in this model.

Table 4.5: Test for reversed causality, part-time work as dependent variable

	Pooled OLS	Pooled OLS (lag 1)	Pooled OLS (lag 2)	FE	FE (lag 1)	FE (lag 2)
SAH=2	-0.112 (0.078)	-0.108 (0.130)	-0.307** (0.062)	-0.025 (0.057)	0.102 (0.096)	0.003 (0.141)
SAH=3	-0.112 (0.077)	-0.119 (0.129)	-0.292** (0.049)	-0.032 (0.057)	0.107 (0.096)	0.027 (0.141)
SAH=4	-0.106 (0.078)	-0.117 (0.130)	-0.274** (0.053)	-0.060 (0.058)	0.091 (0.097)	0.004 (0.142)
SAH=5	-0.139+ (0.083)	-0.144 (0.135)	-0.290** (0.066)	-0.064 (0.061)	0.098 (0.100)	-0.019 (0.014)
Observations	7,895	4,242	2,575	7,895	4,242	2,575
Individuals	2,751	1,644	1,231	2,751	1,644	1,231
R-Squared	0.1238	0.1290	0.1352	0.0336	0.0282	0.0133

Note: ** p<0.01 * p<0.05 + p<0.1, SE in parentheses
The R-Squared stated for the FE estimation describes the within R-Squared

To test for reverse causality in mental health changes and the probability of working part-time, MHI-5 dummies are created. The range of 0-100 (with 100 equals being in the optimal mental state) is collapsed into quintiles. Here, the lowest MHI-5 quintile (0-20 points on a scale from 0-100) serves as reference category.

Table 4.6, column (1) to (3) show that in the pooled OLS model, only the MHI-5 dummies of the current year have a significant effect on working part-time. Women, that have a MHI-5 that is higher than 20 points are less likely to work part-time compared to women with a mental health state of lower than 20 points. The MHI-5 of the previous year or two years before do not show a significant effect on working part-time.

Again, for this study the within changes of mental health are relevant. Table 4.6, column (4) shows that changes in current mental health have a significant effect on working part-time. Changing from very poor mental health (MHI-5 between 0 and 20 points) to a better mental health decreases the probability of working part-time. For example, changing from a MHI-5 value between 0-20 to 21-40 decreases the probability of working part-time by 8.5 percentage points.

Mental health changes from the previous year or from two years before do not show any significant effect on the probability of working part-time. All of the lagged MHI-5 dummies turn insignificant and change their sign, which indicates that they do not affect women's probability to work part-time. This indicates that the probability of working part-time is sensible to current mental health changes.

Table 4.6: Test for reversed causality: Part-time work as dependent variable

	Pooled OLS	Pooled OLS (lag 1)	Pooled OLS (lag 2)	FE	FE (lag 1)	FE (lag 2)
Mh2	-0.126+	0.035	-0.041	-0.085+	0.118	0.209
	(0.071)	(0.116)	(0.131)	(0.049)	(0.083)	(0.132)
Mh3	-0.119+	-0.001	-0.103	-0.105*	0.117	0.188
	(0.066)	(0.108)	(0.120)	(0.048)	(0.080)	(0.132)
Mh4	-0.125+	-0.008	-0.115	-0.103*	0.115	0.199
	(0.065)	(0.107)	(0.118)	(0.047)	(0.080)	(0.131)
Mh5	-0.119+	-0.008	-0.088	-0.108*	0.117	0.221
	(0.066)	(0.108)	(0.119)	(0.048)	(0.080)	(0.135)
Observations	7,895	4,242	2,575	7,895	4,242	2,575
Individuals	2,751	1,644	1,231	2,751	1,644	1,231
R-Squared	0.1238	0.1289	0.1350	0.0332	0.0280	0.0153

Note: ** p<0.01 * p<0.05 + p<0.1, SE in parentheses
The R-Squared stated for the FE estimation describes the within R-Squared

The findings of this analysis prove the two-directional causation between part-time work and mental health. Therefore, it can be concluded that the instrumental variable approach used is appropriate and necessary to find the causal effect of part-time work on mental health.

Another interesting finding of this investigation about reverse causality is the noticeable significant positive association of household income with part-time. Intuitively, one could assume that having a lower household income increases the probability of women to work full-time. As the coefficients of the household income dummies show a positive effect on working part-time, it is plausible that causality is reversed as well. Those women that work part-time, which results in less paid hours, are more likely to have a lower income. Table B1 and B2 in Appendix B provide the corresponding results.

<u>Replacing part-time work with working hours per week:</u>

As table B3, column (1) in Appendix B shows, changing the binary variable part-time work to the continuous variable working hours per week, does not show a significant effect on SAH for the pooled OLS model. Taking individual heterogeneity into account, presented in column (2) of table B3, the fixed effects model shows a significant effect, an additional working hour per week increases SAH by 0.003 points. Instrumenting the working hours per week with preferred working hours does not show any significant effect on SAH for an additional hour worked per week.

For women's mental health, exchanging part-time work to working hours per week does not show any significant effect in any of the three models (see table B4 in Appendix B).

Those findings indicate that including women's working hours as a continuous variable does not lead to significant results. This might be the case because a change from 1 to 2 working hours per week are compared with changes from 40 to 41 hours.

<u>Restricted models:</u>

The results shown in table 4.7 and 4.8 show that restricting the sample to either of the 5 age categories, to married and non-married and to having children or not does not show any significant results for part-time work on the SAH, using the 2SLS model.

Table 4.7: 2SLS FE with SAH as dependent variables, restricted by age categories

	16-24 years	25-34 years	35-44 years	45-54 years	55+ years
Part-time	0.680 (0.593)	-0.229 (0.418)	0.618 (0.580)	0.052 (0.668)	-0.919 (0.630)
Observations:	602	1,506	2,024	2,473	1,290
Individuals	397	773	907	977	495
R-squared:	0.0007	0.0522	0.0026	0.1014	0.0208

Note: ** p<0.01 * p<0.05 + p<0.1, SE in parentheses
The R-Squared describes the within R-Squared

Table 4.8: 2SLS FE with SAH as dependent variables and restrictions

	Married	Non-married	Child<8y	No child<8y
Part-time	0.213 (0.237)	-0.049 (0.239)	0.116 (0.244)	0.093 (0.265)
Observations	4,404	3,491	2,763	5,132
Individuals	1,452	1,437	1,201	1,718
R-Squared	0.0444	0.0922	0.0525	0.0792

Note: ** p<0.01 * p<0.05 + p<0.1, SE in parentheses
The R-Squared describes the overall R-Squared

Part-time work shows a significant and high effect on the MHI-5 of employed women of age 25-34 and 35-44, indicated in table 4.9, column (2) and (3). We expect women in that age range to be more likely to have children. The findings of significant results for women in this age is consistent with the findings of Mattingly & Sayer (2006), who find the highest level of stress for married women with children.

Table 4.9: 2SLS FE with MHI-5 as dependent variable, restricted by age categories

	16-24 years	25-34 years	35-44 years	45-54 years	55+ years
Part-time	4.375	22.418*	29.648*	6.689	3.425
	(12.385)	(10.373)	(15.003)	(16.491)	(15.77)
Observations	602	1,506	2,024	2,473	1,290
Individuals	397	773	907	977	495
R-Squared	0.0005	0.0020	0.0017	0.0015	0.0265

Note: ** p<0.01 * p<0.05 + p<0.1, SE in parentheses
The R-Squared describes the overall R-Squared

The results for restricting the model to married and non-married women are shown in column (1) and (2) of table 5. Switching from full- to part-time work shows significant positive effects on the MHI-5 for married and non-married employed women. This effect is stronger for married women (13.82 compared to 12.36).

Restricting the sample to employed women with children under 8 years does not show a significant result of switching from full- to part-time work. In contrast to the expected outcome, women that report to have young children however show a 17.1 point higher MHI-5 when switching from full- to part-time work.

Table 5: 2SLS FE with MHI-5 as dependent variable and restrictions

	Married	Non-married	Child<8y	No child<8y
Part-time	13.817*	12.355*	6.409	17.104*
	(5.778)	(6.039)	(5.801)	(6.652)
Observations	4,404	3,491	2,763	5,132
Individuals	1,452	1,437	1,201	1,718
R-Squared	0.0104	0.0062	0.0271	0.0036

Note: ** p<0.01 * p<0.05 + p<0.1, SE in parentheses
The R-Squared describes the overall R-Squared

5 Discussion and conclusion

In the Netherlands, it is common for women to work part-time. The quality of part-time work compared to full-time work can be assumed to be similar in the Netherlands, as it is supposed to be the same by law (Roeters 2014). For this reason, the effect found in this analysis is unlikely to be underestimated due to potential negative working conditions.

This study examines the effect of working part-time rather than full-time on physical and mental health of employed Dutch women. As working part-time and having a good or bad heath status is likely to influence each other, a fixed effects model combined with an instrumental variable approach is estimated. Part-time work, in this case, is instrumented by the women's preferred working hours per week. This instrument is found to be valid and relevant, however, endogeneity tests only find evidence for part-time work to be endogenous in the MHI-5 model. Therefore, it is more appropriate to use the fixed effects model to examine the impact of working part-time on SAH.

As hypothesis 1 states, I expected part-time work to have a positive effect on both the physical and mental health of employed Dutch women. However, the analysis only provides evidence for mental health. The results obtained in the final model show that switching from full- to part-time work increases the MHI-5 of Dutch women by 7.8 points on a scale from 0 to 100. Surprisingly, the examination of physical health (using the fixed effects estimator, as this is more efficient in this case) reveals that switching from full- to part-time work decreases the SAH of Dutch women by 0.07 on a scale from 1 to 5. Those findings suggest that part-time work is beneficial for women's mental health but harmful for their physical health. However, the effect found for physical health might still be spurious, as reverse causality between SAH and working part-time cannot fully be excluded. Physical health changes might influence the probability of working part-time on a shorter or longer lagged effect, which cannot be observed within this study.

The sensitivity analysis provides evidence on reverse causality between part-time work and mental health. As previous research suggests, the reverse effect of mental health of the current year, the last and two years before is tested (De Lange et al. 2004). Mental health changes are found to have an immediate effect on the probability of working part-time. This proves that it is indeed necessary to account for reverse causality using an instrumental variable approach.

Regarding the mental health of Dutch women, particularly strong effects are shown for women between 25 and 44 years of age, and no effect for women that are younger or older than that. This suggests that part-time work has an effect on the mental health of employed Dutch women who face multiple responsibilities, but no effect on those that do not. Further investigation into this, however, leads to a surprising finding. Restricting the model to women with a child does not show an effect of part-time work on mental health. Women without a child, however, show a 17.1 point increase in the MHI-5 when switching from full- to part-time work. This is against the expectation that part-time work is beneficial for the emotional well-being of women with a more demanding family life, suggested by previous research. Offer & Schneider (2011) find that women rather feel responsible for their children, increasing the psychological distress of work-life-imbalances.

It is essential to mention that my findings are not generalizable to other countries, as they are highly dependent of the labour law and thus the legal status of part-time compared to full-time contracts. In countries where part-time work is associated with more exploitation or uncertainty, other effects might be visible. Legal protection plays a big role in the relationship between part-time work and health. Another factor that influences analyses about part-time work and work-family conflict is the childcare system in the respective country (Roeters 2014).

Further, my study does not take involuntary part-time work into account, which can also cause emotional distress. The effect measured on the MHI-5 might therefore be underestimated. In this sample, however, I do not see this as a problem, since the reported preferred working hours are found to be in the range of part-time work.

The complexity of the concept of health makes it difficult to assess all potential influences. Reverse causality is likely to be existent for many factors, which might have a mediating effect on the effect of part-time work and health (e.g. income). Further research is recommended to take that into account and to examine over which time period the factors influence each other.

In conclusion, part-time work shows a great potential for women to maintain their work-life-balance. Emotional well-being, which is easy to prevent if it is the result of time pressure, is a factor that affects a nation as a whole, as it comes with high (societal) costs.

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Appendices

Appendix A

Table A1: Variables, survey questions, answer possibilities

Variable	Survey question	Answers
SAH	How would you describe your health, generally speaking?	1 poor 2 moderate 3 good 4 very good 5 excellent
MHI-5	This past month… - I felt very anxious - I felt so down that nothing could cheer me up - I felt calm and peaceful - I felt depressed and gloomy - I felt happy	1 never 2 seldom 3 sometimes 4 often 5 mostly 6 continuously
Part-time work	How many hours per week are (were) you employed in your (last) job, according to your employment contract?	[0, 100]
Age	What is your age?	Integer
Education	Level of education in CBS (Statistics Netherlands) categories	1 primary school 2 vmbo (intermediate secondary education, US: junior high school) 3 havo/vwo (higher secondary education/preparatory university education, US: senior high school) 4 mbo (intermediate vocational education, US: junior college) 5 hbo (higher vocational education, US: college) 6 wo (university)
Employment uncertainty	It is uncertain whether my job will continue to exist.	1 disagree entirely 2 disagree 3 agree 4 agree entirely
Children <8years	Do you have children younger than 8 years?	1 yes 2 no

Married	Civil status	1 Married 2 Separated 3 Divorced 4 Widow or widower 5 Never been married
Informal care	Do you provide informal care?	1 yes 2 no
Rural	Urban character of place of residence	1 Extremely urban 2 Very urban 3 Moderately urban 4 Slightly urban 5 Not urban
Household income	Net household income in Euros	Imputed monthly income of all household members combined.
Disease	Do you suffer from any kind of long-standing disease, affliction or handicap, or do you suffer from the consequences of an accident?	1 yes 2 no
Sleeping problems	Do you regularly suffer from sleeping problems?	0 no 1 yes
Current smoker	Do you smoke now?	1 yes 2 no, I stopped
Alcohol consumption	Now think of all the sorts of drink that exist. How often did you have a drink containing alcohol over the last 12 months?	1 almost every day 2 five or six days per week 3 three or four days per week 4 once or twice a week 5 once or twice a month 6 once every two months 7 once or twice a year 8 not at all over the last 12 months
Weight	How much do you weigh, without clothes and shoes?	Integer
Height	How tall are you?	Integer
Preferred working hours	How many hours per week in total would you like to work? This concerns the amount of hours worked in all of your jobs combined.	Integer

Table A2: Descriptive Statistics

	Observations	Mean	SD	Min	Max
SAH	7,895	3.214	0.706	1	5
MHI-5	7,895	74.713	15.324	0	100
Part-time	7,895	0.655	0.475	0	1
Age	7,895	42.479	11.376	16	65
Education (low)	7,895	0.034	0.182	0	1
Education (medium)	7,895	0.586	0.493	0	1
Education (high)	7,895	0.380	0.485	0	1
Uncertainty	7,895	0.290	0.454	0	1
Children<8y	7,895	0.350	0.477	0	1
Married	7,895	0.558	0.497	0	1
Household income (1)	7,895	0.087	0.281	0	1
Household income (2)	7,895	0.337	0.473	0	1
Household income (3)	7,895	0.416	0.493	0	1
Household income (4)	7,895	0.185	0.388	0	1
Disease	7,895	0.349	0.477	0	1
Unhealthy behaviour	7,895	0.150	0.357	0	1
Preferred working hours per week	7,895	26.548	9.060	0	72
Working hours per week	7,203	26.110	9.855	0	66

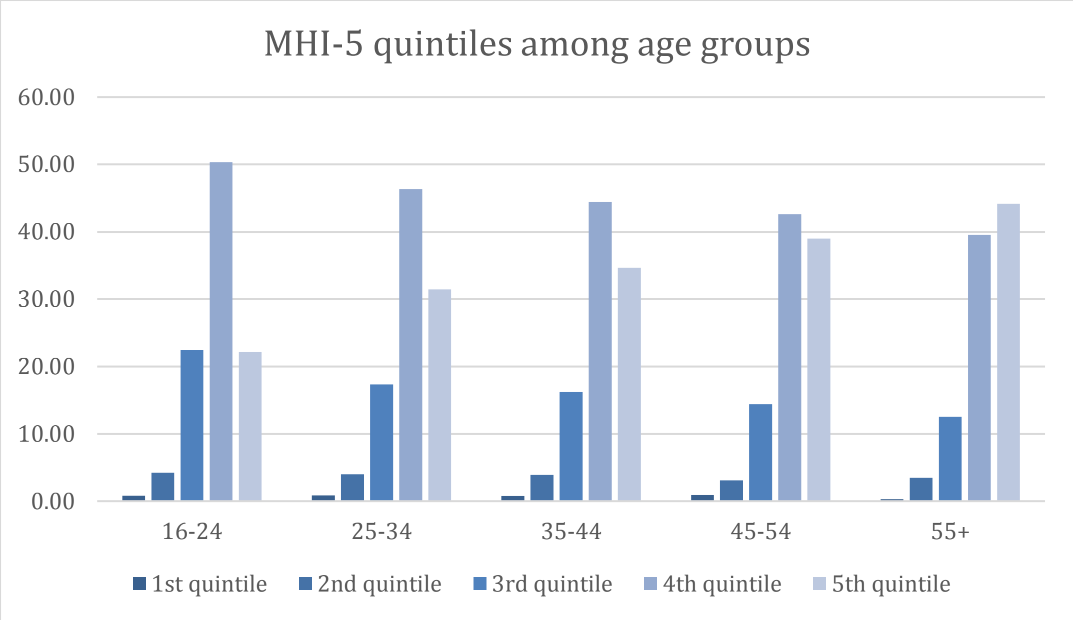

Figure A1: MHI-5 quintiles among age groups

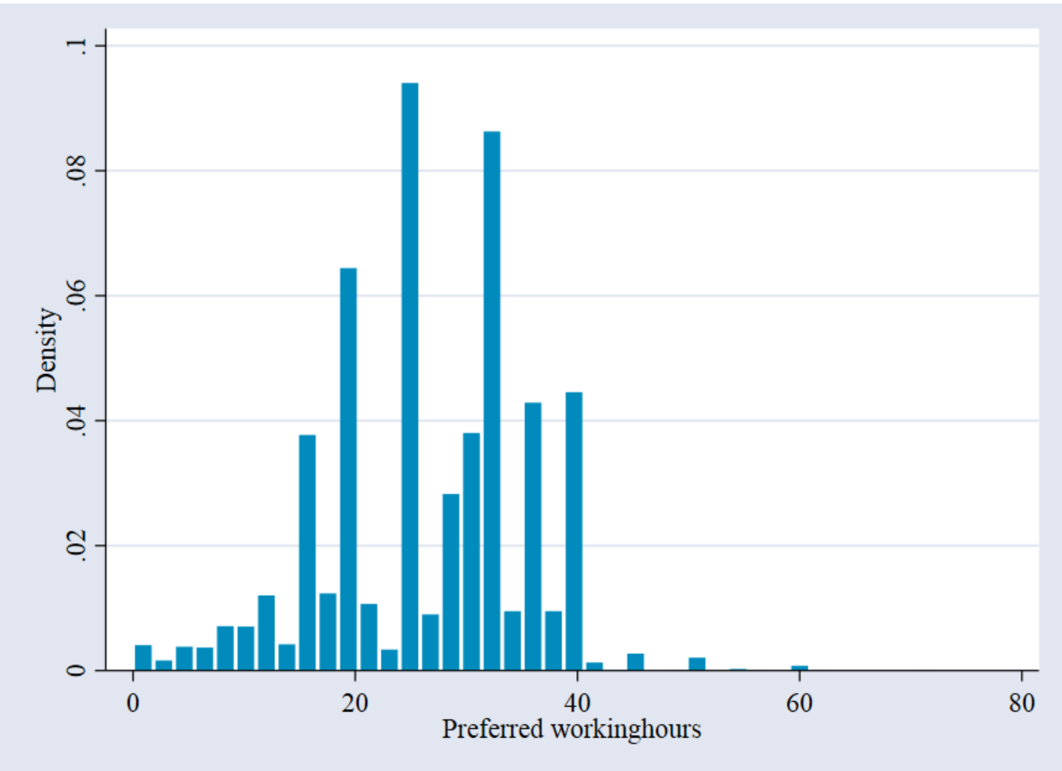

Figure A2: Distribution of preferred working hours among employed women

Appendix B

Table B1: Test for reversed causality, part-time work as dependent variable

	Pooled OLS	Pooled OLS (lag 1)	Pooled OLS (lag 2)	FE	FE (lag 1)	FE (lag 2)
SAH=2	-0.112	-0.108	-0.307**	-0.025	0.102	0.003
	(0.078)	(0.130)	(0.062)	(0.057)	(0.096)	(0.141)
SAH=3	-0.112	-0.119	-0.292**	-0.032	0.107	0.027
	(0.077)	(0.129)	(0.049)	(0.057)	(0.096)	(0.141)
SAH=4	-0.106	-0.117	-0.274**	-0.060	0.091	0.004
	(0.078)	(0.130)	(0.053)	(0.058)	(0.097)	(0.142)
SAH=5	-0.139+	-0.144	-0.290**	-0.064	0.098	-0.019
	(0.083)	(0.135)	(0.066)	(0.061)	(0.100)	(0.014)
Age	-0.001	0.001	0.002	0.001	0.004*	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Household income 1	0.146**	0.131**	0.101+	0.103**	0.109**	0.062
	(0.037)	(0.050)	(0.059)	(0.024)	(0.034)	(0.044)
Household income 2	0.079**	0.099**	0.116**	0.042**	0.055**	0.038
	(0.022)	(0.028)	(0.032)	(0.015)	(0.021)	(0.029)
Household income 3	0.076**	0.088**	0.093**	0.021	0.025	0.028
	(0.021)	(0.027)	(0.031)	(0.013)	(0.018)	(0.024)
Educ (med)	0.020	0.031	0.112	-0.045	-0.090	0.118
	(0.051)	(0.073)	(0.081)	(0.047)	(0.094)	(0.176)
Educ (high)	-0.109*	-0.100	-0.032	-0.157**	-0.089	0.006
	(0.052)	(0.074)	(0.082)	(0.048)	(0.097)	(0.150)
Married	0.095**	0.089**	0.087**	0.011	0.023	-0.004
	(0.022)	(0.028)	(0.032)	(0.021)	(0.030)	(0.044)
Children<8y	0.255**	0.250**	0.239**	0.219**	0.183**	0.127**
	(0.023)	(0.029)	(0.033)	(0.019)	(0.026)	(0.038)
Constant	0.539**	0.470**	0.523**	0.571**	0.317*	0.405+
	(0.095)	(0.151)	(0.107)	(0.090)	(0.152)	(0.238)
Observations	7,895	4,242	2,575	7,895	4,242	2,575
Individuals	2,751	1,644	1,231	2,751	1,644	1,231
R-Squared	0.1238	0.1290	0.1352	0.0336	0.0282	0.0133

Note: ** p<0.01 * p<0.05 + p<0.1, SE in parentheses
The R-Squared stated for the FE estimation describes the within R-Squared

Table B2: Test for reversed causality: Part-time work as dependent variable

	Pooled OLS	Pooled OLS (lag 1)	Pooled OLS (lag 2)	FE	FE (lag 1)	FE (lag 2)
Mh2	-0.126+	0.035	-0.041	-0.085+	0.118	0.209
	(0.071)	(0.116)	(0.131)	(0.049)	(0.083)	(0.132)
Mh3	-0.119+	-0.001	-0.103	-0.105*	0.117	0.188
	(0.066)	(0.108)	(0.120)	(0.048)	(0.080)	(0.132)
Mh4	-0.125+	-0.008	-0.115	-0.103*	0.115	0.199
	(0.065)	(0.107)	(0.118)	(0.047)	(0.080)	(0.131)
Mh5	-0.119+	-0.008	-0.088	-0.108*	0.117	0.221
	(0.066)	(0.108)	(0.119)	(0.048)	(0.080)	(0.135)
Age	-0.001	0.001	0.002	0.001	0.004*	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Household income 1	0.145** (0.037)	0.130* (0.050)	0.098 (0.059)	0.103** (0.024)	0.109** (0.034)	0.065 (0.044)
Household income 2	0.079** (0.022)	0.099** (0.028)	0.114** (0.032)	0.042** (0.015)	0.055** (0.021)	0.036 (0.029)
Household income 3	0.077** (0.021)	0.088** (0.027)	0.094** (0.031)	0.021 (0.013)	0.025 (0.018)	0.028 (0.024)
Educ (med)	0.018	0.030	0.107	-0.047	-0.091	0.137
	(0.051)	(0.073)	(0.081)	(0.047)	(0.094)	(0.176)
Educ (high)	-0.110*	-0.102	-0.034	-0.161**	-0.089	0.032
	(0.052)	(0.074)	(0.082)	(0.048)	(0.097)	(0.150)
Married	0.095**	0.090**	0.087**	0.009	0.023	-0.007
	(0.022)	(0.028)	(0.032)	(0.021)	(0.030)	(0.044)
Children<8y	0.254**	0.250**	0.241**	0.220**	0.183**	0.121**
	(0.024)	(0.029)	(0.033)	(0.019)	(0.026)	(0.038)
Constant	0.548**	0.355*	0.344*	0.633**	0.306*	0.213
	(0.088)	(0.137)	(0.151)	(0.084)	(0.142)	(0.230)
Observations	7,895	4,242	2,575	7,895	4,242	2,575
Individuals	2,751	1,644	1,231	2,751	1,644	1,231
R-Squared	0.1238	0.1289	0.1350	0.0332	0.0280	0.0153

Note: ** p<0.01 * p<0.05 + p<0.1, SE in parentheses
The R-Squared stated for the FE estimation describes the within R-Squared

Table B3: Part-time work exchanged with working hours, SAH as dependent variable			
	Pooled OLS	FE	2SLS FE
Working hours/week	0.002	0.003+	0.003
	(0.001)	(0.002)	(0.004)
Children<8y	0.057*	0.041	0.041
	(0.029)	(0.039)	(0.041)
Informal care	-0.052+	0.008	0.008
	(0.026)	(0.025)	(0.025)
Age	-0.007**	-0.007**	-0.007*
	(0.001)	(0.002)	(0.003)
Rural	-0.010	0.076	0.076
	(0.032)	(0.071)	(0.071)
Household income 1	-0.125*	-0.055	-0.055
	(0.044)	(0.049)	(0.050)
Household income 2	-0.110**	-0.012	-0.012
	(0.030)	(0.032)	(0.032)
Household income 3	0.010	0.016	0.016
	(0.028)	(0.028)	(0.028)
Educ (med)	0.061	0.292**	0.292**
	(0.070)	(0.101)	(0.101)
Educ (high)	0.153*	0.268*	0.269*
	(0.073)	(0.105)	(0.108)
Married	0.007	-0.003	-0.003
	(0.027)	(0.042)	(0.043)
Disease	-0.388**	-0.194**	-0.194**
	(0.023)	(0.022)	(0.022)
Sleeping problems	-0.415**	-0.213**	-0.213**
	(0.071)	(0.064)	(0.064)
Unhealthy behaviour	-0.193**	-0.009	-0.009
	(0.029)	(0.037)	(0.037)
Constant	3.548**	3.190**	3.191**
	(0.083)	(0.150)	(0.176)
Observations	7,203	7,203	7,203
Individuals	2,522	2,522	2,522
R-Squared	0.1448	0.0249	0.1058

Note: ** p<0.01 * p<0.05 + p<0.1, SE in parentheses
The R-Squared stated for the FE estimation describes the within R-Squared

Table B4: Part-time work exchanged with working hours, MHI-5 as dependent variable			
	Pooled OLS	FE	2SLS FE
Working hours/week	0.018	0.030	-0.071
	(0.027)	(0.038)	(0.105)
Children<8y	1.559*	0.486	0.138
	(0.656)	(0.915)	(0.977)
Informal care	-1.407*	-1.221*	-1.221*
	(0.627)	(0.601)	(0.602)
Uncertainty	-3.156**	-0.233	-0.252
	(0.480)	(0.415)	(0.416)
Age	0.166**	0.301**	0.314**
	(0.027)	(0.059)	(0.061)
Rural	0.682	-0.399	-0.357
	(0.725)	(1.675)	(1.677)
Household income 1	-3.128**	-0.513	-0.699
	(1.074)	(1.161)	(1.176)
Household income 2	-1.805**	0.032	-0.030
	(0.686)	(0.760)	(0.764)
Household income 3	0.818	0.208	0.191
	(0.594)	(0.653)	(0.653)
Educ (med)	1.136	-0.478	-0.581
	(1.306)	(2.381)	(2.385)
Educ (high)	1.420	-1.523	-0.914
	(1.336)	(2.489)	(2.560)
Married	1.107+	1.372	1.238
	(0.623)	(0.998)	(1.007)
Disease	-3.915**	-1.870**	-1.892**
	(0.536)	(0.516)	(0.517)
Sleeping problems	-14.291**	-7.281**	-7.363**
	(2.066)	(1.514)	(1.517)
Unhealthy behaviour	0.912	-0.894	-0.877
	(0.821)	(0.869)	(0.870)
Constant	67.461**	62.143**	64.379**
	(1.764)	(3.555)	(4.171)
Observations	7,203	7,203	7,203
Individuals	2,522	2,522	2,522
R-squared	0.0849	0.0145	0.0538

Note: ** p<0.01 * p<0.05 + p<0.1, SE in parentheses
The R-Squared stated for the FE estimation describes the within R-Squared

Table B5: 2SLS FE with SAH as dependent variables, restricted by age categories

	16-24 years	25-34 years	35-44 years	45-54 years	55+ years
Part-time	0.680	-0.229	0.618	0.052	-0.919
	(0.593)	(0.418)	(0.580)	(0.668)	(0.630)
Children<8y	-0.004	0.044	0.045	-0.075	0.028
	(0.431)	(0.129)	(0.155)	(0.124)	(0.085)
Informal care	0.051	0.015	0.056	0.002	-0.029
	(0.407)	(0.125)	(0.062)	(0.038)	(0.070)
Rural	0.333	0.065	0.305	0.057	0.542
	(0.324)	(0.143)	(0.258)	(0.226)	(0.318)
Household	0.365+	-0.079	0.029	-0.047	-0.167
income 1	(0.191)	(0.159)	(0.156)	(0.110)	(0.155)
Household	0.236	-0.158	0.036	-0.027	-0.161+
income 2	(0.162)	(0.098)	(0.078)	(0.061)	(0.095)
Household	0.079	-0.048	0.045	0.004	-0.176*
income 3	(0.156)	(0.081)	(0.073)	(0.047)	(0.082)
Educ (med)	0.455*	0.299	0.702	0.007	0.080
	(0.216)	(0.315)	(0.391)	(0.258)	(0.291)
Educ (high)	0.467+	0.158	-0.113	0.072	0.494
	(0.255)	(0.035)	(0.473)	(0.322)	(0.304)
Married	0.062	-0.056	-0.058	0.048	0.180
	(0.375)	(0.079)	(0.115)	(0.122)	(0.173)
Disease	-0.162	-0.288**	-0.149**	-0.231**	-0.130*
	(0.176)	(0.069)	(0.048)	(0.039)	(0.067)
Sleeping	0.680	-0.103	-0.343+	-0.100	-0.282
problems	(1.015)	(0.239)	(0.176)	(0.115)	(0.178)
Unhealthy	0.317	-0.086	-0.114	0.006	0.021
Behaviour	(0.450)	(0.121)	(0.086)	(0.067)	(0.082)
Constant	2.392**	3.423**	2.394**	3.198**	3.468**
	(0.483)	(0.306)	(0.487)	(0.575)	(0.533)
Observations:	602	1,506	2,024	2,473	1,290
Individuals	397	773	907	977	
R-squared:	0.0007	0.0522	0.0026	0.1014	0.0208

Note: ** p<0.01 * p<0.05 + p<0.1, SE in parentheses
The R-Squared describes the within R-Squared

Table B6: 2SLS FE with MHI-5 as dependent variable, restricted by age categories					
	16-24 years	25-34 years	35-44 years	45-54 years	55+ years
Part-time	4.375	22.418*	29.648*	6.689	3.425
	(12.385)	(10.373)	(15.003)	(16.491)	(15.77)
Children <8y	0.309	-5.567+	-2.723	-0.472	1.367
	(9.001)	(3.216)	(4.006)	(3.069)	(1.734)
Informal care	-7.166	-0.547	-1.383	-0.302	1.388
	(8.541)	(3.054)	(1.616)	(0.940)	(1.086)
Uncertain	0.721	-1.865	-0.320	0.442	-0.476
	(1.895)	(1.348)	(1.010)	(0.753)	(7.854)
Rural	1.901	0.349	-0.056	-0.076	7.183
	(6.801)	(3.471)	(6.682)	(5.598)	(3.837)
Household income 1	0.254	-5.603	-4.546	0.439	-0.316
	(4.011)	(3.889)	(4.045)	(2.716)	(2.380)
Household income 2	0.814	-4.168+	0.432	-0.891	4.142+
	(3.410)	(2.399)	(2.018)	(1.522)	(2.024)
Household income 3	-2.242	-3.143	-0.591	-0.370	2.095
	(3.257)	(1.989)	(1.882)	(1.164)	(7.239)
Educ (med)	3.780	-12.988+	1.517	-6.481	5.194
	(4.519)	(7.729)	(10.111)	(6.399)	(7.545)
Educ (high)	3.237	-18.317*	-27.987*	5.677	7.737
	(5.337)	(8.211)	(12.268)	(7.968)	(4.290)
Married	2.428	1.609	-3.226	1.403	6.157
	(7.837)	(1.942)	(2.989)	(3.022)	(1.670)
Disease	-0.636	0.750	-1.046	-2.620**	-1.286
	(3.679)	(1.695)	(1.244)	(0.962)	(4.400)
Sleeping problems	-8.346	-18.599**	-14.821**	-0.093	-6.502
	(21.286)	(5.835)	(4.560)	(2.839)	(2.042)
Unhealthy behaviour	6.159	-1.418	0.310	0.606	-0.869
	(9.422)	(2.941)	(2.220)	(1.649)	(13.246)
Constant	64.295**	83.297**	68.210**	73.857**	61.033**
	(10.122)	(7.420)	(12.600)	(14.172)	(15.775)
Observations	602	1,506	2,024	2,473	1,290
Individuals	397	773	907	977	495
R-Squared	0.0005	0.0020	0.0017	0.0015	0.0265

Note: ** p<0.01 * p<0.05 + p<0.1, SE in parentheses
The R-Squared describes the within R-Squared

Table B7: 2SLS FE with SAH as dependent variables and restrictions

	Married	Non-married	Child<8y	No child<8y
Part-time	0.213	-0.049	0.116	0.093
	(0.237)	(0.239)	(0.244)	(0.265)
Children<8y	0.042	-0.097	-	-
	(0.065)	(0.083)		
Informal care	-0.015	0.056	0.025	-0.003
	(0.028)	(0.047)	(0.053)	(0.028)
Age	-0.008**	-0.003	0.000	-0.007
	(0.003)	(0.004)	(0.005)	(0.003)
Rural	0.127	0.047	0.118	0.025**
	(0.126)	(0.103)	(0.113)	(0.094)
Household	-0.112	0.048	0.037	-0.080
income 1	(0.107)	(0.065)	(0.077)	(0.069)
Household	-0.112**	0.055	0.067	-0.076
income 2	(0.043)	(0.049)	(0.057)	(0.038)
Household	-0.050	0.048	0.097	-0.037*
income 3	(0.034)	(0.065)	(0.053)	(0.031)
Educ (med)	0.093	0.250*	0.264+	0.117
	(0.173)	(0.120)	(0.125)	(0.153)
Educ (high)	-0.062	0.284+	0.303*	0.010
	(0.175)	(0.147)	(0.149)	(0.164)
Married	-	-	0.044*	-0.044
			(0.071)	(0.061)
Disease	-0.206**	-0.185**	-0.231**	-0.194**
	(0.027)	(0.034)	(0.039)	(0.026)
Sleeping	-0.120	-0.245*	-0.204+	-0.189**
problems	(0.079)	(0.105)	(0.114)	(0.072)
Unhealthy	-0.009	-0.036	-0.035	-0.003
habits	(0.046)	(0.060)	(0.073)	(0.043)
Constant	3.522**	3.179**	2.902**	3.546**
	(0.257)	(0.265)	(0.236)	(0.304)
Observations	4,404	3,491	2,763	5,132
Individuals	1,452	1,437	1,201	1,718
R-Squared	0.0444	0.0922	0.0525	0.0792

Note: ** p<0.01 * p<0.05 + p<0.1, SE in parentheses
The R-Squared stated describes the overall R-Squared

Table B8: 2SLS FE with MHI-5 as dependent variable and restrictions

	Married	Non-married	Child<8y	No child<8y
Part-time	13.817*	12.355*	6.409	17.104*
	(5.778)	(6.039)	(5.801)	(6.652)
Children<8y	2.788+	1.487	-	-
	(1.596)	(2.095)		
Informal care	-0.789	-1.592	-0.723	-1.278+
	(0.692)	(1.169)	(1.242)	(0.699)
Uncertain	-0.662	-0.702	-0.500	-0.874
	(0.542)	(0.721)	(0.749)	(0.553)
Age	0.269**	0.405**	0.348**	0.306**
	(0.074)	(0.104)	(0.118)	(0.073)
Rural	-0.350	-1.834	-1.100	1.570
	(3.068)	(2.590)	(2.679)	(2.372)
Household income 1	-2.845	-1.283	-3.292+	0.380
	(2.618)	(1.624)	(1.809)	(1.744)
Household income 2	-1.344	0.657	-0.275	-0.523
	(1.038)	(1.226)	(1.350)	(0.957)
Household income 3	-0.397	0.552	-0.510	0.290
	(0.825)	(1.144)	(1.257)	(0.789)
Educ (med)	-0.427	2.822	1.607	-1.415
	(4.209)	(3.015)	(2.948)	(3.856)
Educ (high)	-4.539	6.583+	3.791	-5.243
	(4.260)	(3.687)	(3.525)	(4.125)
Married	-	-	0.225	1.059
			(1.676)	(1.526)
Disease	-2.334**	-0.840	-2.899**	-1.438*
	(0.660)	(0.852)	(0.930)	(0.651)
Sleeping problems	-11.182**	-2.220	-11.333**	-6.364**
	(1.928)	(2.624)	(2.696)	(1.819)
Unhealthy	0.219	-0.963	-0.003	-0.096
Behaviour	(1.111)	(1.501)	(1.734)	(1.072)
Constant	59.877**	47.832**	56.813**	51.698**
	(6.302)	(5.679)	(5.581)	(7.718)
Observations	4,404	3,491	2,763	5,132
Individuals	1,452	1,437	1,201	1,718
R-Squared	0.0104	0.0062	0.0271	0.0036

Note: ** p<0.01 * p<0.05 + p<0.1, SE in parentheses
The R-Squared stated describes the overall R-Squared