Mental Health over the Lifecycle

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Mental Health over the Lifecycle
An Economic Perspective

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An Economic Perspective

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"This man is a genius"
R.L. Duffin's recommendation letter for John Nash at Princeton, 1948
(Kuhn et al., 1997)

Acknowledgements

I am taking the liberty of starting this acknowledgements section not with words of thanks but with a note, that I feel is important for this thesis. This thesis starts with a quote from R.L. Duffin about John Nash. John Nash was a mathematician famous in economics for his development of the Nash equilibrium and other contributions to game theory. In 1994 he was awarded the Nobel prize for his work. In 2015 he also received the Abel Prize for his contributions to the theory of nonlinear partial differential equations, making him the only person to be awarded both prizes. For much of his adult life, John Nash also suffered from schizophrenia (Nash, 1994).

Large sections of this thesis focus on the potential negative consequences of poor mental health. However, while these negative consequences may hold true at a population level, the story of John Nash exemplifies an important point of nuance: at the individual level one can suffer from mental health problems and be many other things at the same time. An individual can have poor mental health and be a Nobel Prize winner; suffer from schizophrenia and be a genius.

That said, there are a number of people without whom this thesis would not be in its current form. Firstly, this thesis would not exist without funding from Accare. I am immensely grateful for the opportunity it provided, not just by providing the necessary resources, but also by recognizing that mental health economics is an area that lacks research.

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Hermien Dijk,
Assen, 14 September 2021

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Chapter 1

Introduction

Approximately 20% of the working-age population suffers from a mental disorder at any point in time and lifetime prevalence is estimated to be up to 50% (OECD, 2012). This high prevalence of mental health problems results in a large burden of disease: mental health and behavioral disorders account for approximately 7.4% of all disability adjusted life years (DALYs) worldwide[1] (Murray et al., 2012; Whiteford et al., 2013). Among mental disorders, depressive disorders and anxiety disorders account for most of this burden of disease, with 40.5% and 14.6% of all DALYs attributed to mental and behavioral disorders, respectively (Murray et al., 2012; Whiteford et al., 2013).

Aside from their burden of disease, mental health problems are associated with negative socioeconomic outcomes. Even after controlling for family and neighbourhood characteristics, children and adolescents with mental health problems have lower educational attainment (Fletcher, 2010; Currie & Stabile, 2006; Currie, 2009; Currie et al., 2010) and lower employment and income in adulthood (Mousteri et al., 2019; Fletcher, 2014). Adults with mental health problems are less likely to be employed (OECD, 2012) and more likely to receive social benefits (Einderhand & Ravesteijn, 2017) and to have problematic debts (Fitch et al., 2011; Richardson et al., 2013; Turunen & Hiilamo, 2014; Downing, 2016; French & Vigne, 2019).

Ever since Arrow (1963) and Grossman (1972), health and healthcare markets have been considered subjects deserving economic scrutiny; the first as an anomaly

[1] A disability adjusted life year is defined as the sum of life years lost plus the sum of years lived with disability, where disability is weighted using population preferences for different health states (Murray et al., 2012).

due to its many deviations from the model of perfect competition and the second as an important aspect of human capital. However, until recently, mental health has often either been ignored, or lumped in as merely a component of overall health by many economists. As such, mental health as a stand-alone subject has been understudied by economists (Currie, 2020).

This is problematic because mental health and mental health problems might differ from physical health, and most physical health problems, on some key aspects. Most importantly, mental health problems generally start early in life: half of all lifetime mental disorders start by age 14 and three quarters by age 24 (Kessler et al., 2005). Physical health, on the other hand, is generally considered to be declining with age.[2] As such, functional forms adequately modelling physical health over the lifecycle might be inappropriate for mental health. Moreover, since mental health problems play a larger role at a different point in the lifecycle, the major consequences of mental health problems might be distinctly different from physical health problems. Additionally, mental health problems might affect decision-making in ways distinct from physical health problems. For example, individuals suffering from major depression appear to discount future financial rewards at significantly higher rates, making them more present-focused (Pulcu et al., 2014).

In recent decades, mental health has been garnering more interest by economists. For example, Cunha and Heckman (2007) provide a model that investigates how investments in cognitive and non-cognitive skills, many of which relate to mental health, build human capital in childhood. Other examples include a growing literature that investigates the effect of child mental health on education and employment outcomes (e.g., Currie & Stabile, 2006; Currie et al., 2010; Fletcher, 2010, 2014; Johnston et al., 2014; Mousteri et al., 2019) and the relation between job-loss, or unemployment, and mental health (e.g., Browning & Heinesen, 2012; Marcus, 2013; Breuer, 2015). However, currently, much remains unknown. Consequently, this thesis investigates mental health and its consequences at different points in the lifecycle.

[2] The Grossman model (Grossman, 1972), for example, considers health to generally be declining with age. Recent microeconometric lifecycle models that include health generally also estimate age-dependent Markov processes that, on average, result in declining (population) health with age (e.g., Capatina, 2015; De Nardi et al., 2017; Capatina et al., 2018).

1.1 Defining mental health

The World Health Organization (WHO, 2014) defines mental health as 'a state of well-being in which every individual realizes his or her own potential, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to her or his community.' Hence, according to the WHO definition, individuals need not meet a diagnostic threshold to be considered to have mental health problems.

In this thesis, depending on data availability, we use a slightly narrower definition of mental health and mental health problems. For example, Chapters 3 and 5 focus on psychological distress, which – in the context of this thesis – consists of a state of mind over a period of a few weeks characterized by feelings of nervousness, hopelessness, restlessness, depression, worthlessness, lack of happiness and/or a feeling that everything is an effort. Similarly, in Chapter 4 we proxy for mental health problems with mental healthcare use on the assumption that if individuals seek mental healthcare, they are likely to have experienced some manner of psychological distress.

One thing we do not do, is defining mental health problems by meeting a threshold of diagnostic criteria. While individuals experiencing high rates of psychological distress often meet diagnostic criteria for mental disorders and vice versa (Kessler et al., 2002), meeting a clinical threshold is not a prerequisite for being identified as experiencing high psychological distress. We do not define mental health problems by diagnostic criteria for multiple reasons. Firstly, diagnostic criteria change over time (American Psychiatric Association et al., 2013), and not all individuals who meet a diagnostic threshold get diagnosed or seek care (Kieling et al., 2011; Thornicroft et al., 2017). Hence, large datasets typically do not allow identification of who meets a clinical threshold and who does not. More importantly, however, passing a diagnostic threshold in itself does not generally result in poor outcomes; subclinical mental health problems are also associated with impairment and poorer socioeconomic outcomes (Judd et al., 2000; Luppa et al., 2007; Rothon et al., 2009; Alloway et al., 2010).

1.2 Outline of the thesis

This thesis starts its investigation in childhood, by studying the persistence of child and adolescent mental healthcare using registry data from the Northern Netherlands. How predictive is past mental healthcare use of future mental healthcare use? More importantly, I investigate to what extent persistence of care is associated with underlying, individual time-invariant characteristics and find that these characteristics are likely to be responsible for the majority of persistence of care. This implies that, to a large extent, once children enter care they receive care for many more years.

In the third chapter we leave childhood behind and investigate the lifcycle pattern of mental health. Previous studies have often found a U-shape in mental health, or a midlife nadir, where mental health declines when individuals are relatively young, after which it improves again once individuals have reached middle age. However, studies investigating age-patterns all suffer from the age-period-cohort problem. This fundamental statistical problem posits that it is impossible to completely disentangle cohort effects[3] and period effects[4] from age effects. Consequently, this chapter aims to identify the age-profile of mental health while introducing minimal bias to reach identification. Using mental health data from the US Panel Study of Income Dynamics (PSID) we apply first difference estimation to derive an unbiased estimate of the second derivative of the age effect as well as an estimate up to a linear period trend of the first derivative. Next, we use a battery of estimators with varying restrictions to approximate the first derivative. The Chapter provides conclusive evidence that the age profile of mental health in the US is not U-shaped and tentative evidence that the age-profile follows an inverse U-shape where individuals experience a mental health high during their life course. Further analyses, using German and Dutch data, confirm that these results do not only apply to the US, but also to Germany and to the Netherlands.

Next, we investigate whether mental health problems might cause problematic debts. That is, debts that people fail to repay or for which people default. Problematic debts can have far-reaching consequences for debtors, creditors and society

[3] The effect of being born and raised in a specific generation, e.g., being part of generation X might have resulted in specific experiences that influence individuals for the rest of their lives.

[4] The effect of living during a specific time, e.g., during an economic recession.

as a whole, and there is a strong correlation between mental health and problematic debt, both in the literature and in our data. Using nationwide individual-level panel data of Dutch individuals, we employ a fixed effects instrumental variable approach, using the death of a sibling or child as instruments for mental health problems. The results indicate that there is a causal relationship between mental health problems and the onset of problematic debt for men.

Finally, in the last chapter we build on the fact that mental health appears to follow a lifecyle pattern that is distinctly different from physical health and investigate labour market cost of both poor mental and physical health. Since mental health problems appear to occur earlier in the lifecycle, we specifically include long-term effects on labour-market productivity through human capital in the form of labour market experience. Consequently, we develop a lifecycle model that explicitly models mental and physical health as two different components of overall health and include human capital in the form of labour-market experience to account for potential longterm effects of poor heath early in the lifecycle. We find that poor mental and physical health result in large and comparable losses in individual net lifetime earnings.

1.3 Contribution

The results from this thesis underline that, aside from the burden of disease, there is an economic incentive for providing and developing effective mental health interventions: both in terms of preventive care and curative care. Effective interventions have the potential to reduce the incidence of problematic debts (Chapter 4) and to increase labour market earnings (Chapter 5).

This thesis also provides insights on the nature of these effective interventions. Since mental health might follow an inverse U-shape over the lifecycle (Chapter 3), preventive interventions are likely best targeted at young ages and before individuals reach old age. However, results from Chapter 2 indicate that a large share of persistent mental-healthcare use in children and adolescents is due to time-invariant individual characteristics. If we assume that receiving care is strongly related to children's mental health states, this finding suggests that a substantial amount of care might not have long-term effects but might instead be targeted at alleviating and managing symptoms. Consequently, there might be an imperative for the development of, and research on, more effective interventions.

This thesis also provides some scientific and methodological contributions. Firstly, by using the first difference approach proposed by De Ree and Alessie (2011) and Van Landeghem (2012) and applying it to mental health, Chapter 3 is the first study that investigates the age-pattern of mental health without the necessity of arbitrary assumptions. Additionally, Chapter 3 introduces a relatively new approach regarding cohort restrictions and, in contrast with a large fraction of the literature, presents results from multiple estimation strategies for the linear age-effect. This is important, as different methodological choices appear to lead to different outcomes. Chapter 4 is the first study that provides causal evidence that mental health problems can lead to problematic debts. Additionally, we show that deceased relatives might be a valid instrument for mental health problems. Finally, in Chapter 5 we improve on existing lifecycle models used to study the labour market consequences of poor health, by explicitly modelling mental and physical health as two different processes and by explicitly modelling potential human capital effects of bad health through lost labour-market experience.

More generally speaking, this thesis indicates that mental health is indeed an important aspect of human capital (Chapter 5) and that mental health follows a distinct pattern over the lifecycle (Chapter 3), which provides information on potential future avenues for research on mental health. E.g., since mental health appears to be worse early in life, it is important to understand how it interacts with other processes and occurrences earlier in the lifecycle, such as human capital formation in childhood and early adulthood. Moreover, results from Chapter 4 suggest that when individuals obtain problematic debts due to mental health problems, they do not necessarily experience a drop in assets. This tentatively suggests that the pathway from mental health problems to problematic debt might be behavioural and not due to a lack of liquidity, indicating that more research on how mental health problems affect financial decision-making might be warranted.

Chapter 2

The Persistence of Child and Adolescent Mental Healthcare: Results from Registry Data*

* This chapter is based on Dijk, Freriks et al. (2020). The chapter uses data from the Psychiatric Case Registry-Northern Netherlands (PCR-NN), which is maintained by the Rob Giel Onderzoekscentrum (RGOc). Our special thanks go out to Ellen Visser, for managing and providing the data. Furthermore, earlier versions of this chapter were presented at the Boston 2017 Congress of the international Health Economics Association (iHEA), the 2017 European Network for Mental Health Service Evaluation (ENMESH), the 20th Annual European Congress of the International Society For Pharmacoeconomics and Outcomes Research (ISPOR), and at the CPB Netherlands Bureau for Economic Policy Analysis. We want to thank everyone present for their comments and feedback. Additionally, many thanks for invaluable comments from Erik Buskens, Maarten Postma, Minke Remmerswaal, Talitha Veenstra, Tom Wansbeek and two anonymous reviewers. Finally, the findings and views reported in this paper are those of the authors and should not be attributed to individuals or organisations mentioned here.

2.1 Background

The World Health Organization has categorised mental health problems as among the most disabling clinical diagnoses in the world (OECD, 2014). Around 20% of the working age population in OECD countries are currently suffering from a mental disorder and the lifetime prevalence is even twice as high (OECD, 2012). These disorders often originate from childhood (Knapp et al., 2016; Kessler et al., 2007) and have long-lasting effects throughout the lifespan due to worse health and educational outcomes (Currie & Stabile, 2006; Currie, 2009; Currie et al., 2010; Johnston et al., 2014).

Since mental health problems appear to be highly persistent (Knapp et al., 2016), it is important to understand whether child and adolescent mental healthcare is also persistent. If, in a certain year, there is an increase in the amount of mental healthcare required, knowledge on the persistence of that care provides information about the necessity of budget increases for future years. Consequently, understanding the persistence of care is also an important component of cost-effectiveness research, as it allows for a more accurate prediction of child and adolescent mental healthcare costs.

In addition, knowledge on the nature of the persistence of care in children and adolescents provides insights about the effectiveness of budget increases to reduce future healthcare use. If the persistence of care is largely the result of children's time-invariant underlying characteristics, such as genetic predisposition (Lee et al., 2013), children currently in care are likely to receive care for many years to come, which, assuming the reception of care is strongly related to mental health states, suggests that care is mostly targeted at alleviating and managing symptoms but that it does not have long-term effects. In that case, broad budget increases in mental healthcare are unlikely to yield future reductions in required care, unless they alter the nature of the care provided.

If the role of individuals time-invariant characteristics is small, either mental health problems in themselves dissipate over time, care appears to have long-term effects, or the mechanism at work consists of a combination of both. We will refer to persistence that is not caused by time-invariant individual characteristics as the direct care effect of persistence (true state-dependence).

Only few studies have focused on the persistence of child and adolescent mental healthcare. Farmer et al. (1999) and Shenkman et al. (2007), find presence of persistence in child (mental) healthcare in the US, but do not consider the role of time-invariant individual characteristics in this persistence. Several studies on the persistence of child and adolescent mental health problems found that most of the persistence is likely to be due to time-invariant individual characteristics (Contoyannis & Li, 2017; Roy & Schurer, 2013; Wichstrøm et al., 2017).

One might assume that this time-invariant persistence in mental health translates to time-invariant persistence of mental healthcare. However, not all individuals with mental health problems will automatically receive mental healthcare (Kieling et al., 2011). Additionally, studies on the persistence of all healthcare expenditures of elderly US citizens generally find that for these individuals, time-invariant individual characteristics appear to play a relatively small role in overall persistence of care (Feenberg & Skinner, 1994; French & Jones, 2004). Hence, the mechanism underlying the persistence of child and adolescent mental healthcare remains unclear.

Therefore, this chapter investigates the nature of the persistence of child and adolescent mental healthcare by distinguishing between persistence due to time-invariant individual characteristics and the direct care effect. We do so using Dutch registry data of secondary psychiatric care of more than 80,000 children and adolescents in the Northern Netherlands, who received care between 2000 and 2012. The use of such a unique registry dataset results in a large representative sample of individuals in care in the Northern Netherlands. Furthermore, it circumvents reporting bias that might be present in survey self-reports of healthcare use (Drapeau et al., 2011). Hence, this allows us to obtain estimates of persistence in daily practice, which enhances the generalizability of the results. Additionally, during the period of observation, three major reforms took place of which we analyse the effects.

2.2 Methods

2.2.1 Data

We use a unique registry dataset from the Psychiatric Case Registry Northern Netherlands (PCR-NN), which is a large longitudinal record of care contacts at the largest psychiatric institutions in the Northern Netherlands between 2000 and 2012. The PCR-NN contains year of birth, sex and diagnoses of the individuals in care, as well as entries denoting each care contact an individual received, which contained information on the date of the care contacts and the type of care.

As soon as individuals had their first appointment, or received their first diagnosis, at one of the institutions they entered the PCR-NN. Each separate appointment or diagnosis is a new entry in the dataset. An individual might not be observed in the original sample at a particular point of time for several reasons: (1) the individual did not receive secondary psychiatric care; (2) the individual did receive secondary psychiatric care, but not at a reporting institution; (3) the individual is deceased. This third possibility can be ruled out if at a later point that individual reappears in the set. Additionally, mortality in the Netherlands for the age group 5-25 was continuously below 0.03% for all years 2000-2012 (Statistics Netherlands, 2017b, 2017a). While the mortality rates for the individuals in our sample may be higher than those of the general population, they are unlikely to be so to a problematic degree as the direct mortality for mental illnesses is generally low (OECD, 2014; WHO, 2018). Furthermore, as previously mentioned, the institutions in the dataset accounted for most of the secondary psychiatric care provided in the Northern Netherlands. Consequently, it was assumed that individuals receive no secondary psychiatric care when they are not observed. With these assumptions we transformed the PCR-NN into a panel dataset with time intervals of one year.

The original sample of individuals aged 4 to 23 contains 5,975,096 observations of care contacts and diagnoses corresponding to 106,523 individuals. This sample was restricted to 5,083,812 care contacts and diagnoses from 93,786 individuals for Ordinary Least Squares (OLS) estimation, as a few of these care contacts were logged before January 2000 and estimation of persistence automatically excludes individuals with only one available time period. This data was transformed so that observations represented care contacts per year, leading to 485,072 observations from 93,786 individuals. Furthermore, identification of the direct care effect requires the availability of at least three consecutive time periods per individual. Consequently, the final sample for difference GMM-IV estimation contains a total of 391,286 care contacts per year from 81,525 individuals. Descriptive statistics of the OLS and difference GMM-IV samples are provided in Table 2.1.

Table 2.1. Descriptive statistics

	Mean	SD	Minimum	Maximum
OLS sample (N= 93,786)				
Year of birth	1992.30	5.39	1978	2007
Age	15.74	4.75	5	23
Female	0.41			
Care contacts per year per individual	8.36	36.57	0	764
difference GMM-IV sample (N = 81,525)				
Year of birth	1992.27	5.08	1979	2006
Age	16.14	4.50	6	23
Female	0.40			
Care contacts per year per individual	7.09	34.55	0	764

SD: Standard deviation.

2.2.2 Estimation

We assume that the persistence of care can be described as

$$Care_{i,t} = \beta_1 Care_{i,t-1} + \boldsymbol{\beta}_2 \boldsymbol{X}_{i,t} + c_i + \varepsilon_{i,t}, \tag{2.1}$$

where $Care_{i,t}$ and $Care_{i,t-1}$ denote the number of care contacts individual i receives in year t and $t-1$, respectively, c_i captures unobserved time-invariant individual characteristics and $\boldsymbol{X}_{i,t}$ is a vector of strictly exogenous control variables containing age and year dummies, $\varepsilon_{i,t}$ denotes the error term and β_1 is the parameter of interest, aimed to capture the direct care effect.

Equation 2.1 could be estimated using OLS if time-invariant individual characteristics, c_i, are left out of the model. However, this estimation would yield inconsistent estimates of β_1 and $\boldsymbol{\beta}_2$ because $Care_{i,t-1}$ is correlated with the unobserved time-invariant characteristics c_i. To account for these time-invariant characteristics, we could estimate equation 2.1 using first differencing, effectively estimating:

$$\Delta Care_{i,t} = \beta_1 \Delta Care_{i,t-1} + \boldsymbol{\beta}_2 \Delta \boldsymbol{X}_{i,t} + \Delta\varepsilon_{i,t}, \tag{2.2}$$

where $\Delta Care_{i,t} = Care_{i,t} - Care_{i,t-1}$, $\Delta \boldsymbol{X}_{i,t} = \boldsymbol{X}_{i,t} - \boldsymbol{X}_{i,t-1}$ and $\Delta\varepsilon_{i,t} = \varepsilon_{i,t} - \varepsilon_{i,t-1}$.

Note that the right-hand side variable $\Delta Care_{i,t-1}$ is correlated with the error term $\Delta\varepsilon_{i,t}$ so that OLS estimation of equation 2.2 will yield inconsistent estimates. Additionally, first differencing introduces another source of autocorrelation since $\Delta\varepsilon_{i,t}$ and $\Delta\varepsilon_{i,t-1}$ both depend on $\varepsilon_{i,t-1}$ (Nickell, 1981). To address these problems, we follow the suggestion of Arellano and Bond (Arellano & Bond, 1991) and estimate equation 2.2 with Generalized Method of Moments with Instrumental Variables (GMM-IV) using past levels of care as instruments for $\Delta Care_{i,t-1}$. As excluded instrument, we use the first available lag of $Care_{i,t}$ that does not cause the error term of the first stage to be correlated with $\varepsilon_{i,t}$ (Arellano & Bond, 1991) at a 10 percent significance level. [1]We only use a single lag to prevent problems due to too many, or weak, instruments (Roodman, 2009b).

Since prevalence rates for certain disorders can differ strongly by sex (Merikangas et al., 2009), persistence might also differ by sex. To test this, we perform the estimation separately for males and females. Additionally, we perform a number of sensitivity and robustness analyses. Firstly, we analyse how three different healthcare reforms might have changed the persistence of care over the period of observation. We test for a structural break in the persistence of care due to th Dutch healthcare reform in 2006 and the introduction of Diagnostic Treatment Combinations (DTCs) in 2008. We also assess how results change when we exclude the year 2012 from our analyses, when copayments were introduced for individuals aged 18 plus.

We also test whether our estimations are robust to different definitions of care. First, we re-estimate the model using cost estimates of care instead care contacts, after which we do the same using number of days per year an individual received care instead of care contacts. Additionally, as smaller time intervals might be of interest to policy makers, we vary the time unit of measurement by re-estimating the model again with number of care contacts per quarter - instead of number of care contacts per year - as our variable of interest.

[1] $Care_{i,t-2}$ of $Care_{i,t}$ will be a valid instrument as long as the error term $\varepsilon_{i,t}$ (cf. equation 2.1) is serially uncorrelated. It then holds that $E(Care_{i,t-2}\Delta\varepsilon_{i,t}) = 0$. Note also that $\Delta\varepsilon_{i,t}$ follows a AR(1) process ($cov(\Delta\varepsilon_{i,t}, \Delta\varepsilon_{i,t-1}) < 0$ and $cov(\Delta\varepsilon_{i,t}, \Delta\varepsilon_{i,t-k}) = 0,\ k \geq 2$) if $\varepsilon_{i,t}$ is serially uncorrelated. We will initially run a difference GMM-IV regression with $Care_{i,t-2}$ as excluded instrument for $\Delta Care_{i,t-1}$. We will then carry out a Cumby-Huizinga test to check the validity of the following hypothesis: $\Delta\varepsilon_{i,t}$ follows an AR(1) process, which results in a MA(k) process for the model in equation 2.2. If the test results indicate that there is a higher order process AR(k), we will use $Care_{i,t-(k+1)}$ as excluded instrument for $\Delta Care_{i,t-1}$. We will again perform the Cumby-Huizinga test to assess whether $\Delta\varepsilon_{i,t}$ indeed follows an AR(k) process. In case the Cumby-Huizinga test indicates another autocorrelation process AR(l), $l \neq k$, at a 10 percent significance level, the excluded instrument for $\Delta Care_{i,t-1}$ will be updated following the same procedure.

Since persistence might vary by disorder, we perform separate estimations for individuals with a diagnosis of Attention-Deficit/Hyperactivity Disorders (ADHD), Pervasive Developmental Disorders (PDD), anxiety, and Episodic Mood Disorders (EMD) and any of their subtypes. Lastly, we estimate the persistence of care for the highest care users in 2000, to investigate whether persistence differs based on an individuals' position in the distribution of care contacts. All estimations are performed using `Stata 15`, the GMM-IV estimations are performed using the command `xtabond2` (Roodman, 2009a).

2.3 Results

2.3.1 Main findings

Table 2.2 shows the estimates for β_1 of equation 2.1.[2] According to the Cumby-Huizinga test (Cumby & Huizinga, 1992), the model in equation 2.2 suffers from a MA(1) and a MA(2) process ($p < 0.01$ for both tests) but not from a MA(3) process ($p > 0.10$) (i.e., $\Delta\varepsilon_{i,t}$ is correlated to $\Delta\varepsilon_{i,t-1}$ and $\Delta\varepsilon_{i,t-2}$), suggesting that the model from equation 2.1 suffers from a MA(1) process ($p < 0.01$). In other words, $\varepsilon_{i,t}$ appears to be correlated with $\varepsilon_{i,t-1}$, but not with $\varepsilon_{i,t-2}$. This autocorrelation process is likely the result of the inclusion of a lagged dependent variable. As a result, $Care_{i,t-3}$ is the first valid instrument.

To prevent large reductions in sample size due to the required availability of lags of $Care_i, t-1$, we follow Arellano and Bond (Arellano & Bond, 1991) and replace missing values for $Care_{i,t-3}$ in the first stage equation by zeros. This will not decrease the validity of the results, as it only strengthens the instrument and does not alter the identification of the persistence in the second stage (Arellano & Bond, 1991; Holtz-Eakin et al., 1988).

Since weak instruments might become a problem when using the third lag, we perform an F-test to determine the joint significance of the instruments for $\Delta Care_{i,t-1}$. We find an F-statistic of 1,746.95 ($p < 0.01$) using cluster robust standard errors, which indicates that $Care_{i,t-3}$ is a relevant instrument for $\Delta Care_{i,t-1}$.[3]

[2] The FE estimate, β_1 in equation 2.2, functions as a first check, as the difference GMM-IV estimate should lie between the OLS and FE estimates (Bond, 2002). The results demonstrate that this is the case and, consequently, that the difference GMM-IV is likely consistent.

[3] We also extended the set of instruments by including interactions between year dummies and

Table 2.2. Estimation results

	(1)	(2)	(2)
Care contacts	OLS	FE	d.GMM-IV
Care contacts (-1)	0.539***	0.189***	0.215***
	(0.0064)	(0.0016)	(0.0156)
Age dummies	YES	YES	YES
Year dummies	YES	YES	YES
Observations	485,072	485,072	391,286
R-squared	0.268	0.211	
Number of ID	93,786	93,786	81,525

d.GMM-IV: difference GMM-IV.
YES: included in the estimation, NO: excluded from estimation. Robust standard errors in parentheses.
Inference: *** p<0.01, ** p<0.05, * p<0.1.
Cumby-Huizinga (Cumby & Huizinga, 1992) autocorrelation test results yielded p-valyes of 0.000 {AR(1)}; 0.000 {AR(2)}; 0.215 {AR(3)}; 0.977 {AR(4)}.

The difference GMM-IV estimate only captures the direct care effect and has a value of 0.215, which is smaller than unity, indicating that the process is stable. Hence, if children or adolescents experience a sudden increase in mental healthcare above a certain individual-specific base level of care in a certain year, they will receive an increased number of care contacts for the following years, but this effect will weaken over time so that eventually they will receive a base level of care again, as long as there are no further shocks. Hence, in the absence of further shocks, a sudden increase of 10 care contacts in the present year is associated with an average of less than 3 additional care contacts in the future above an individual's long-term base-level.

In addition, the OLS estimate of equation 2.1 of 0.539 differs substantially from the difference GMM-IV estimate, suggesting that the majority of observed persist-

$Care_{i,t-3}$. The estimation results are barely affected by the inclusion of those extra instruments. Additionally, when we also include $Care_{i,t-4}$ up to $Care_{i,t-10}$ as excluded instruments, results do not change substantially: the direct care-effect ranges between 0.218 ($p < 0.01$) and 0.230 ($p < 0.01$), depending on the number of lags used as excluded instruments.

ence is associated with time-invariant characteristics.[4] In other words, to a large extent, children currently in care appear to receive care for years.[5] If we assume that the reception of care is strongly related to children's mental health states, this finding of the large role of time-invariant characteristics in the persistence of care suggests that a substantial amount of care might not have long-term effects but might instead be targeted at alleviating and managing symptoms.

Since prevalence rates for certain disorders can differ strongly by sex (Merikangas et al., 2009), persistence might also differ by sex. To test this, we perform the estimation separately for males and females. Results can be found in Table 2.3. For 23 individuals, sex was unknown, hence these individuals are excluded from the estimation. Females have a higher persistence of care than males (0.247 and 0.181, respectively). Both the interaction between the sex dummy and the lagged dependent variable and the F-test for the joint significance of all other interactions with the sex dummies are statistically significant ($p < 0.05$). This suggests that the persistence of care is statistically significantly different for males and females. This difference in persistence might be the result of different prevalence rates across different diagnoses between males and females (Kerig et al., 2012).

2.3.2 Policy reforms, definitions of care and decomposition

Policy reforms

We first assess the effects on the persistence of care of several healthcare reforms that took place in the period 2000-2012, using structural breaks. We find that the Dutch healthcare reform of 2006 did not statistically significantly affect persistence of care ($p > 0.10$), whereas the introduction of Diagnosis Treatment Combinations (DTCs) in 2008 appears to be associated with a weakly statistically significant increase in the persistence of care ($p < 0.10$). However, when we perform a combined F-test for 2008 and 2006 of the interactions between the structural breaks and $\Delta Care_{i,t-1}$ we find no statistical significance ($p > 0.10$). The introduction of co-

[4] This result that the OLS estimate is more than double the d.GMM-IV estimate also holds for all further analyses, with the exception of the highest care users and quarterly persistence. OLS results for the further analyses are available upon request.

[5] Since OLS estimation requires less available lags of $Care_{i,t}$ the sample differs slightly from the sample used for difference GMM-IV estimation. Consequently, we have also performed the same OLS estimation using the sample used for difference GMM-IV. This estimation resulted in a very similar coefficient of 0.522 ($p < 0.01$).

Table 2.3. Sex differences

Care conacts	Full sample	Males	Females
Care contacts (-1)	0.181***	0.181***	0.247***
	(0.0207)	(0.0207)	(0.0236)
Care contacts (-1) × female	0.065**		
	(0.0314)		
Age dummies	YES	YES	YES
Year dummies	YES	YES	YES
Interaction terms females	YES	NO	NO
Observations	391,177	235,835	155,342
Number of ID	81,502	46,149	35,353

YES: included in the estimation, NO: excluded from estimation.
Robust standard errors in parentheses.
Inference: *** p<0.01, ** p<0.05, * p<0.1.

payments for individuals aged 18 plus in 2012 does not affect our results: when we perform the estimation with and without the observations from that year the estimates for the direct care effect do not differ statistically significantly ($p > 0.10$). Results can be found in Table 2.4.

Definitions of care

Second, we test whether our estimations are robust to different definitions of care. First, we re-estimate the model using cost estimates of care instead care contacts, after which we do the same using number of days per year an individual received care instead of care contacts. Both results are extremely similar to our initial estimate, indicating that our initial results are robust to different definitions of care. We also vary the time unit of measurement by re-estimating the model again with number of care contacts per quarter - instead of number of care contacts per year - as our variable of interest. The results of this estimation show a coefficient for the direct care effect of persistence of 0.627 ($p < 0.01$). This would indicate that, in the absence of further shocks, a sudden increase of 10 care contacts in the present quarter is associated with less than 17 additional care contacts at some point in the

Table 2.4. The 2006, 2008 and 2012 healthcare reforms

Care contacts	2006	2008	2012
Care contacts (-1)	0.183***	0.186***	0.201***
	(0.0280)	(0.0215)	(0.0170)
Care contacts (-1) × reform	0.047	0.064*	
	(0.0366)	(0.0374)	
Age dummies	YES	YES	YES
Year dummies	YES	YES	YES
Structural breaks	YES	YES	NO
Observations	391,286	391,286	332,907
Number of ID	81,525	81,525	74,259

YES: included in the estimation, NO: excluded from estimation.
Robust standard errors in parentheses.
Inference: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

future. Results can be found in Table 2.5.

Table 2.5. Definitions of care

Care	Number of care days	Cost analysis	Care contacts per quarter
Care (-1)	0.224***	0.231***	0.627***
	(0.0147)	(0.0180)	(0.006)
Age dummies	YES	YES	YES
Year dummies	YES	YES	YES
Observations	391,286	391,286	2,009,510
R-squared			
Number of ID	81,525	81,525	100,515

YES: included in the estimation, NO: excluded from estimation.
Robust standard errors in parentheses.
Inference: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Diagnosis decomposition and highest care users

We also perform separate estimations for individuals with a diagnosis of Attention-Deficit/Hyperactivity Disorders (ADHD), Pervasive Developmental Disorders (PDD), anxiety, and Episodic Mood Disorders (EMD) and any of their subtypes. We find no statistically significant differences in the direct care effect between the different diagnosis groups ($p > 0.10$, both for each diagnosis group independently and a combined F-test). When we estimate the direct care effect of persistence for the highest care users in 2000, we do find a higher of the direct care effect for these individuals, albeit not statistically significantly so ($p > 0.10$). This lack of statistical significance is likely due to the relatively small number of individuals that were identified as highest care users. Results can be found in Table 2.6.

Table 2.6. Diagnosis groups and highest care-users

Care contacts	(1) ADHD	(2) Anxiety	(3) EMD	(4) PDD	(5) Highest care-users
Care contacts (-1)	0.181***	0.183***	0.220***	0.182***	0.364***
	(0.0282)	(0.0334)	(0.0438)	(0.0255)	(0.0966)
Age dummies	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES
Observations	100,609	43,919	17,951	82,783	2,113
Number of ID	19,666	10,175	4,311	14,870	354

YES: included in the estimation, NO: excluded from estimation.
Robust standard errors in parentheses.
Inference: *** p<0.01, ** p<0.05, * p<0.1.

2.4 Discussion

In this chapter we estimated a coefficient of the year-to-year direct care effect of persistence of Dutch secondary psychiatric care of 0.215. In the different sensitivity analyses, this coefficient varied depending on sex and the duration over which care was measured. Results also seemed to indicate that persistence was higher for the highest care users, but lacked statistically significance due to a small sample size.

Future research could investigate further how persistence of care differs among high and low care-users.

Comparison of the OLS and difference GMM-IV results indicate that a substantial part of persistence is due to time-invariant individuals characteristics. These results seem to be in line with previous studies on the persistence of child and adolescent mental health problems (Contoyannis & Li, 2017; Roy & Schurer, 2013; Wichstrøm et al., 2017). For example, Wichstrøm et al. (Wichstrøm et al., 2017) find coefficients of 2-year homotypic persistence that, depending on the disorder, lie between 24% and 56% of estimates of persistence that also include persistence due to time-invariant characteristics.

This study is the first that considers the distinction between persistence of mental healthcare due to time-invariant characteristics and the direct care effect, which provides important information about the nature of care for policy makers and future research. Nevertheless, this study has some limitations, which we will discuss here.

The PCR-NN tracks individuals across institutions in the Northern Netherlands. However, not all institutions are included in the set, and individuals might obtain care at institutions outside the Northern Netherlands or in primary care. Consequently, at some point individuals in the set might have received secondary psychiatric care at institutions outside the set. Since we assume that individuals that are not observed receive no care, the true persistence of care might be underestimated. However, as previously mentioned, the PCR-NN covers most secondary psychiatric care in the Northern-Netherlands. Consequently, this bias is likely to be small.

Additionally, while the PCR-NN contains observations on a large number of individuals between 2000-2012, it lacks information on individual characteristics aside from sex, age and diagnoses. As such, the current study is unable to investigate which time-invariant characteristics in particular are responsible for the persistence of care not explained by the direct care effect. Hence, this is a topic for further research. Literature showing a strong correlation between socioeconomic status and certain mental health problems (Goodman et al., 2003), as well as the probability of receiving care (Daley, 2004; Mandell et al., 2009), might lightly suggests that there might be a link between socioeconomic status and time-invariant persistence of care.

Lastly, in this chapter we perform a number of robustness and sensitivity analyses. It should be noted that the multiplicity problem might arise: the more analyses there are performed, the higher the probability that one or more of the results are generated by random chance.

Additionally, our estimates on the persistence of care should not be conflated with the necessity for care. There might be large groups of individuals with mental health problems who have never been in care and are, therefore, not represented in our sample (Kieling et al., 2011). Hence, budgeting decisions based on our estimates should take important factors in the accessibility of care into account, especially since individuals who might require care but are somehow unable to access it might be among the most vulnerable among society.

2.5 Conclusion

This chapter investigated the persistence of child and adolescent mental healthcare use between 2000 and 2012 with registry data of more than 80,000 Dutch children and adolescents. The results indicate that a substantial part of persistence is due to time-invariant individuals characteristics. Additionally, we find a coefficient for the direct care effect of 0.215 ($p < 0.01$). Specifically, the main result implies that in the absence of further shocks a sudden increase of 10 care contacts in the present year is associated with an average of less than 3 additional care contacts at some point in the future. This result provides essential information about the necessity of budget increases for future years in the case of exogenous increases in healthcare use.

2.6 List of abbreviations

AR = Autoregressive

ADHD = Attention-Deficit/Hyperactivity Disorder

DTC = Diagnosis Treatment Combination

EMD = Episodic Mood Disorders

GMM-IV = General Method of Moments with Instrumental Variables

MA = Moving Average PCR-NN = Psychiatric Case Registry Northern Netherlands

PDD = Pervasive Developmental Disorders

OLS = Ordinary Least Squares

Chapter 3

Mental Health over the Lifecycle: Evidence for a U-Shape?*

* This chapter is based on (Dijk & Mierau, 2019). In this paper use is made of data of the LISS (Longitudinal Internet Studies for the Social sciences) panel administered by CentERdata (Tilburg University, The Netherlands). Additionally we want to thank Rob Alessie, Michele Belloni and Swarnodeep Homroy, as well as participants at the International Association for Applied Econometrics 2019 Annual Conference and the Basel 2019 Congress of the international Health Economics Association (iHEA), for their invaluable comments.

3.1 Introduction

Mental health problems are highly prevalent: approximately 20% of the working age population suffers from a mental disorder at any point in time and lifetime prevalence is estimated to be up to 50% (OECD, 2012). This high prevalence results both in an extremely large burden of disease (Murray et al., 2012; Whiteford et al., 2013), as well as significant societal costs: mental health problems are estimated to be the leading cause of years lived with disability worldwide (Whiteford et al., 2013) and the societal cost of mental disorders is estimated to be 3 to 4% of GDP in OECD countries (OECD, 2012, 2014). Therefore, it is important to know which groups are especially susceptible to mental health problems, so that interventions can be targeted at these groups.

One factor that appears to play a role in the burden of mental health problems is age. A number of studies have investigated the age-pattern of mental health (Bell, 2014; Blanchflower & Oswald, 2008, 2016; Le Bon & Le Bon, 2014; Lang et al., 2011; Page et al., 2013) and the majority of these studies have found that mental health follows a U-shaped pattern in age: young and old individuals generally experience better levels of mental health than individuals in, or close to, middle age (Blanchflower & Oswald, 2008, 2016; Le Bon & Le Bon, 2014; Lang et al., 2011). These results suggest that society would do well to invest more resources targeted at care and prevention of mental health problems among the middle aged.

Of these studies reporting U-Shapes, all except Blanchflower and Oswald (2008) use cross-sectional evidence. However, investigating mental health trajectories over the life course is not without its caveats. By definition age, period and cohort are perfectly collinear (once an individual's age and the current year are known, it is possible to determine which year they were born). As a result, cross-sectional evidence of which age groups currently experience lower or higher mental health provides insufficient knowledge on the age-pattern of mental health, as it provides no evidence on whether the observed differences between age groups can be attributed to age effects or cohort effects. Hence, cross-sectional evidence cannot be generalized to future cohorts and age groups, and can provide no indication of whether interventions should either be targeted at specific cohorts or specific age groups.

Because of the fundamental collinearity between age, period and cohort effects, statistical analysis on the subject requires assumptions with various degrees of arbitrariness that cannot be tested. A number of approaches has been suggested to tackle the problem, especially in the related literature on the age effects of well being and life satisfaction, all with different assumptions and (dis)advantages. Unfortunately, these different approaches often lead to conflicting results. For example, studies assuming cohort effects are negligible consistently report U-shapes in mental health, life satisfaction or well-being (Blanchflower & Oswald, 2016, 2017; Graham & Pozuelo, 2017; Laaksonen, 2018; Le Bon & Le Bon, 2014; Lang et al., 2011), whereas studies on well-being assuming that period effects are negligible consistently report no U-shapes (FitzRoy et al., 2014; Frijters & Beatton, 2012; Kassenboehmer & Haisken-DeNew, 2012). Since the nature of the Age, Period and Cohort (APC) problem prevents formal testing of many of these assumptions the true age-profile remains unknown.

An alternative approach, proposed by De Ree and Alessie (2011) and Van Landeghem (2012) and used by Cheng et al. (2017), stands out because of its lack of need for arbitrary assumptions. By focusing on the first differences of life-satisfaction or well-being[1], these studies can identify age effects up to a linear trend. Hence, while the methods employed in these studies cannot prove the existence of a U-shape in mental health as individuals age (since the linear trend remains unknown), they can provide proof when the U-shape is nonexistent. The studies using this method generally find evidence supporting a U-shaped relationship between well-being (Van Landeghem, 2012; Cheng et al., 2017) or life satisfaction (De Ree & Alessie, 2011) and age.

Nevertheless, the inability of these studies to identify the linear age-trend is troubling, as this means that the true age-profile still remains unkown. Therefore, the current study applies the method proposed by De Ree and Alessie (2011) and Van Landeghem (2012), but aims to provide more information on the linear age-effect by also providing the results of a battery of estimations using varying cohort restrictions.

We use data from three countries: the US Panel Study of Income Dynamics

[1] Using this method they effectively estimate the second derivative with respect to age of a life-satisfaction/well-being equation.

(PSID), as well as the German Socio-Economic Panel (SOEP) and the Dutch LISS panel. Our results indicate that the U-shape is not the dominant functional form in the relationship between mental health and age. In contrast, we find that the age-related profile of mental health likely follows an inverse U-shape, suggesting that the young and the elderly might be particularly at risk of developing mental health problems.

Aside from its relevance to mental healthcare and prevention policy, the methodological contribution of this chapter to the literature is threefold. Firstly, to our knowledge, this study is the first to apply the first difference approach proposed by De Ree and Alessie (2011) and Van Landeghem (2012) to mental health. As such, this study is the first to investigate the age-pattern of mental health without the necessity of arbitrary assumptions. Secondly, this chapter introduces a relatively new approach regarding cohort restrictions. While it is not new to restrict a single cohort when using age, period and cohort effects as control variables, the current adaptation of the method - restricting only a single cohort when age effects are of primary interest and varying this cohort restriction across estimations - is new. Lastly, in contrast with a large fraction of the literature, this chapter presents results from multiple estimation strategies for the linear age-effect. This is important, as different methodological choices appear to lead to different outcomes. Hence, just presenting one estimation strategy based on (a certain set of) arbitrary assumptions does not provide the complete picture.

This chapter is structured as follows. Section 3.2 discusses the existing literature on the age-profile of mental health and well-being as well as the commonly applied methodologies. Section 3.3 provides a detailed explanation of the econometric methods used in this chapter, after which Section 3.4 describes the data used for the main analysis. Results are provided in Section 3.5 and Section 3.6 contains the further analyses. Section 3.7 provides detailed discussion of the main result, after which Section 3.8 provides a conclusion.

3.2 Background

Before delving into the literature on well-being, life satisfaction or mental health and age, it is important to understand the age-period-cohort (APC) problem and the proposed solutions to the problem. A much quoted (Bell & Jones, 2014, 2013, 2015) example of the distinction between age, period and cohort effects is the conversation between a senior worker (A) and a junior worker (B) from (Suzuki, 2012):

> A: I can't seem to shake off this tired feeling. Guess I'm just getting old. [Age effect]
> B: Do you think it's stress? Business is down this year, and you've let your fatigue build up. [Period effect]
> A: Maybe. What about you?
> B: Actually, I'm exhausted too! My body feels really heavy.
> A: You're kidding. You're still young. I could work all day long when I was your age.
> B: Oh, really?
> A: Yeah, young people these days are quick to whine. We were not like that. [Cohort effect] (Suzuki, 2012).

The problem is that every combination of two items of this list perfectly predicts the third. In other words, age, period and cohort effects together exhibit perfect collinearity. As a result, they cannot be estimated in a standard regression equation. Many methodological solutions have been proposed to solve this problem, each with its own caveats.

We will not only report literature regarding the age-profile of mental health, but also the age-profile of life-satisfaction and well-being. These three concepts are closely related, as individuals with low life-satisfaction or well-being are more likely to report lower mental health and vice versa and as such, these strands of literature have been intertwined. Furthermore, the combined literature on life-satisfaction and well-being has been more extensive than the literature that focused exclusively on mental health.

Perhaps the simplest method to circumvent the APC problem is by simply assuming that either period, or cohort effects are negligible and can thus be ignored. Multiple studies have assumed that cohort effects are irrelevant (Blanchflower & Oswald, 2016, 2017, 2019; Graham & Pozuelo, 2017; Laaksonen, 2018; Le Bon & Le Bon, 2014; Lang et al., 2011) and all of these studies report U-shaped age profiles of mental health, life satisfaction or well-being. Others have instead assumed that period effects are irrelevant, which makes it possible to estimate age effects using fixed effects approaches (FitzRoy et al., 2014; Frijters & Beatton, 2012; Kassenboehmer & Haisken-DeNew, 2012; Piper, 2015). Most of these studies argue that there is no U-shaped relation between age and life satisfaction (FitzRoy et al., 2014; Frijters & Beatton, 2012; Kassenboehmer & Haisken-DeNew, 2012). The exception is provided by Piper (2015) whose results suggest that British individuals between 16 and 30 have a lower life satisfaction as they age.

Another method, which requires slightly weaker assumptions, is to assume that age, period and cohort effects are all relevant, but that either age groups, periods or cohorts close together have equal coefficients. E.g., using this assumption, one can run a regression using single-year age dummies, single-year period dummies, but five- or ten-year cohort dummies. Some studies have followed this approach (Blanchflower & Oswald, 2008; Lin et al., 2015; Page et al., 2013), but their results are mixed. Both Page et al. (2013) and Lin et al. (2015) provide no conclusive evidence regarding a U-shape in suicide rates and subjective wellbeing, respectively. Blanchflower and Oswald (2008) find evidence of a U-shape in well-being and rates of depression and anxiety.

Others have used Hierarchical APC (HAPC) models, which require the assumption that cohort and period effects are completely random (Yang, 2008; Bell, 2014; Beja, 2017). Yang (2008) and Bell (2014) use HAPC models and find no evidence of a U-shape in happiness and mental health, respectively. Beja (2017) applies a HAPC model to world wide life satisfaction data and does find a U-shaped relationship between age and life satisfaction for individuals aged 15-69.

The use of parameter restrictions has often been criticized (Bell & Jones, 2013, 2014; Luo & Hodges, 2016; De Ree & Alessie, 2011; O'Brien, 2017). By relying on arbitrary assumptions to reach identification, all of the studies above are likely to suffer from biases of unknown size. For example, by assuming cohort effects are negligible estimated age-effects include cohort effects as well as age effects.

To circumvent this issue, several authors/studies have attempted to identify age effects using only minimal assumptions by focusing on the second derivative of the age profile (Cheng et al., 2017; De Ree & Alessie, 2011; Van Landeghem, 2012). The analyses in these studies can identify age patterns up to a linear trend; they can identify the second derivative of the age profile, but not the first.

This means that the true age-pattern remains unknown. For example, the second derivative of age might indicate the existence of a U-shape, but if the first derivative is sufficiently large, mental health, life statisfaction, or wellbeing is nevertheless continuously increasing over the life course.[2] In such a case, a statistically significant second derivative only means that there is significant curvature in the upward sloping age-trend. Hence, while the methods employed in these studies cannot prove the existence of a U-shape in mental health as individuals age (since the linear trend remains unknown), they can prove that the U-shape is nonexistent.

The studies using this method generally find evidence supporting a U-shaped relationship between well-being (Van Landeghem, 2012; Cheng et al., 2017) or life satisfaction (De Ree & Alessie, 2011) and age. However, these results require caution as the exact functional form remains unknown.[3]

With regard to mental health specifically, four of the six papers cited here do find a U-shaped age profiles of mental health variables (Blanchflower & Oswald, 2008, 2016; Le Bon & Le Bon, 2014; Lang et al., 2011). The fifth study (Page et al., 2013) provides no clear evidence in favour of or against the existence of a U-shape. However, this study only investigates the rather extreme case of suicide and is not necessarily focused on the existence of a U-shape.

The only study cited here that explicitly reports no U-shaped age profile in mental health uses the HAPC model (Bell, 2014). Bell (2014) argues that previous findings of a U-shape are the result from confounding of cohort effects and that, instead, mental health declines as individuals age.

This overview of the literature shows that there is no panacea when it comes to APC estimation. Any method for identifying APC effects either has a large probability of misspecification (parameter restrictions) or is underidentified (only inferring information about the second derivative). As a result, different methods can lead to different outcomes. This is clearly illustrated when studies assuming cohort effects are negligible are compared to studies assuming instead that period effects are negligible. The first category of studies consistently reported U-shapes, while the latter consistently reported no U-shapes. As a result, there is no consensus on the exact age-profile of mental health, life satisfaction and well-being.

[2] Conversely, if the second derivative of age indicates the existence of a U-shape, but the first derivative is sufficiently small, mental health, life statisfaction, or wellbeing is nevertheless continuously decreasing over the life course.

[3] Cheng et al. (2017) claim that they can identify the linear trend in age (i.e. the first derivative). However, their method has certain identification problems, which we explain in detail in the working paper version of this paper (Dijk & Mierau, 2019).

In the sections that follow we investigate the age-profile of mental health using US panel data. To ensure that our results are not the artefacts of methodological choices, we will first estimate the second derivative using first differences, after which we will attempt to approximate the first derivative using a battery of parameter restrictions. Both methods will be explained in more detail below. Our results indicate that there is no U-shape in the relationship between mental health and age and further analyses indicate that this might also be the case for Germany and the Netherlands. In contrast, the relationship might even consist of an inverse U-shape.

3.3 Method

3.3.1 Second derivative

We base our analysis on Van Landeghem (2012) and De Ree and Alessie (2011) who both show that identification of the second derivative can be obtained by taking first differences from the dependent variable and regressing them on age as well as a set of year dummies[4]. That is, assume our Data Generating Process (DGP) is given by:

$$MH_{i,t} = \beta_0 + \beta_1 age_{i,t} + \beta_2 age_{i,t}^2 + \tau year_t + \gamma_t + \sum_{\phi=1905}^{C} \alpha_\phi cohort_i(\phi) + \epsilon_{i,t}, \tag{3.1}$$

where $MH_{i,t}$ denotes the mental health score of individual i in year t, $age_{i,t}$ denotes the age of individuals i in year t, τ is the parameter denoting a linear period-effect and γ_t denotes the deviation from the linear period-effect, $cohort_i(\phi)$ denotes a set of cohort dummies taking value one if ϕ equals the birth year of individual i and zero otherwise and $\epsilon_{i,t}$ denotes the error term. The parameters β_1 and β_2 are the parameters of interest, since they determine whether mental health is U-shaped over the life-course. By first differencing (3.1), and using the fact that

[4] Van Landeghem (2012) uses unaltered year dummies, De Ree and Alessie (2011) use Deaton Paxson year dummies (Deaton & Paxson, 1994). Both methods give equivalent estimates for the second derivative in our case.

$age^2_{i,t} - age^2_{i,t-1} = 2age_{i,t} - 1$,[5] this can be rewritten as:

$$\Delta MH_{i,t} = (\beta_1 - \beta_2 + \tau) + (\gamma_t - \gamma_{t-1}) + 2\beta_2 age_{i,t} + \tilde{\epsilon}_{i,t}, \tag{3.2}$$

where $\tilde{\epsilon}_{i,t} = \epsilon_{i,t} - \epsilon_{i,t-1}$. Hence, we can identify β_2 by using first differences of the mental health scores as dependent variables in a regression analysis with age multiplied by two and a set of year dummies as independent variables. We can only identify β_1 with this method if we are willing to make an assumption about the linear period trend τ.

3.3.2 First derivative

We will use parameter restrictions on cohorts to approximate the first derivative with respect to age. The least restrictive parameter restrictions model that allows for both linear age- and year-effects as well as nonlinear cohort-effects, but is still identified, is one where only two out of all cohorts are expected to have equal coefficients. This model is still biased, but the bias is minimized to the difference between the two cohort effects that are assumed to be equal. Additionally, if the average yearly change in cohort effect approximates zero, on average our estimation of the linear age-effect should be close to the true coefficient.

Therefore, we estimate models of mental health using OLS with cluster robust standard errors with a continuous age variable, age squared, a set of year dummies and a set of (restricted) cohort dummies as independent variables. To reach identification the period dummies start from the second available year and the cohort dummies consist of a full set of cohort dummies minus a reference cohort and with the restriction that one cohort has a coefficient equal to the cohort from the previous birth year.

3.4 Data

We use data from the Panel Study of Income Dynamics (PSID) for the main analysis. The PSID started in 1968 and consists of a nationally representative sample of individuals living in families. From 2001 onwards, with the exception of 2005, the

[5] Since $age_{i,t} = age_{i,t-1} + 1$.

family interviews contained 6 questions belonging the abbreviated Kessler psychological distress scale (K-6) which were asked to the head and/or the partner of head of the household. The K-6 is a broad screener that can be used to assess non-sepcific psychological distress and the prevalence of serious mental illness in the general population (Kessler et al., 2002, 2010) and has been well validated (Prochaska et al., 2012; Furukawa et al., 2008, 2003; Gill et al., 2007). We will use this variable as a measure of mental health. The family interviews were held biennially. Hence, in this study we use data from 9 family interviews, as 2017 data is not yet available and the 2005 interview did not contain the K-6 questions.

The K-6 consists of 6 questions asking how often individuals felt certain negative emotions during the last 30 days (sadness, nervous, restless, hopeless, that everything was an effort, worthless) which they can answer on a scale from 1 (all of the time) to 5 (none of the time) (Kessler et al., 2002). Generally these scores are inverted later so that a score of 0 means 'none of the time' and a score of 4 means 'all of the time' after which the scores from the different questions can be summed into a single score. For convenience, we linearly transformed this single score so that it ranges from 0 to 100, where 0 indicates that an individual answered 'all of the time' to all 6 questions and a score of 100 indicates that an individuals answered 'none of the time' to all 6 questions.[6]

In our sample for analysis we included only the direct respondents of the family interview, as they were the ones answering the K-6 questions. Summary statistics of our final sample can be found in Table 3.1.[7] Our first difference approach requires the presence of at least two consecutive observations of the K-6 for each individual in our set. As a result we lose 3,237 out of 14,378 individuals. However, there is almost no variation between both samples in terms of age, year of birth and K-6 score. Detailed summary statistics of this second sample can be found in Table 3.A.3 in Appendix 3.A.1. Hence, we do not expect this to influence our results.

Figures 3.1, 3.2 and 3.3 provide a graphical analysis of the relation between mental health and age, period and cohort. In the graph, all years are pooled together and age-specific average K6 scores are stratified by 10-year cohort.[8] It is interesting

[6] Using the untransformed data does not alter the results.

[7] When split by gender the summary statistics show no substantial differences between men and women, see Tables 3.A.1 and 3.A.2 in Appendix 3.A.1.

[8] Age groups within each cohort that consisted of less than 100 individuals were left out of the graph as the small samples resulted in volatile K6 scores for those age groups.

Table 3.1. Population summary statistics

	N	Mean	Standard deviation	Minimum	Maximum
Age	14,378	38.7	15.99	16	99
Year of Birth	14,378	1965.84	18.10	1902	1997
Year	14,378	2005.08	4.92	2001	2015
Gender					
Female	7,867	54.72%			
Male	6,511	45.28%			
K-6 score (0-100)	14,378	83.93	17.27	0	100

Summary statistic at first observation (baseline) for each individual

to note that the mental health measure does not show a strong U-pattern and that this is the case for both men and women. Mental health appears to increase at every age until individuals are around 70, after which - at least for women - it declines slightly.

Another interesting observation is that visible cohort- or period-effects appear to be small: values for equal age groups of different cohorts are generally very similar. While this provides no conclusive evidence, it suggests that the patterns that we do see in the graphs might be due to age effects.

3.5 Results

3.5.1 Second derivative

To ensure that our estimates are robust to autocorrelation we have used cluster robust standard errors. Additionally, to reduce any effects of over- or undersampling in the PSID we performed our estimations with PSID family sample weights. Table 3.2 provides the results of the estimation of equation (3.2). It is interesting to note that our estimation results for β_2 do not vary dramatically across genders, both have a statistically significant estimate of -0.009. These negative coefficients indicate that there is no U-shape in mental health over the life course, as a U-shape should have a positive second derivative.

On the contrary, the estimation results for the second derivative with respect to

Figure 3.1. Average scores for: K6 (0-100 scale)

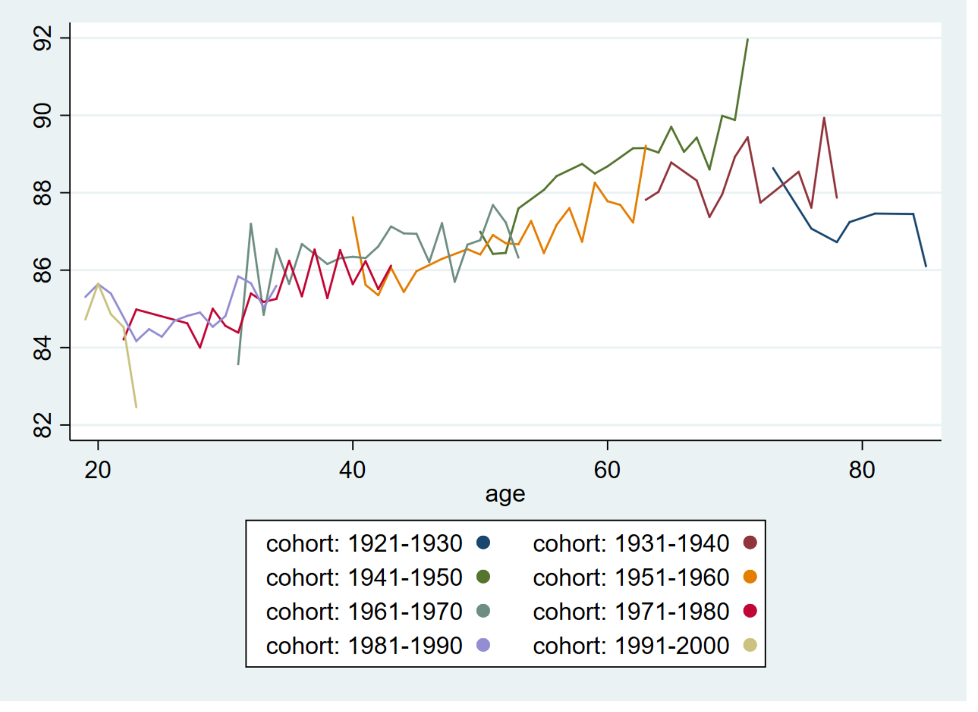


Figure 3.2. Women: K6 (0-100 scale)

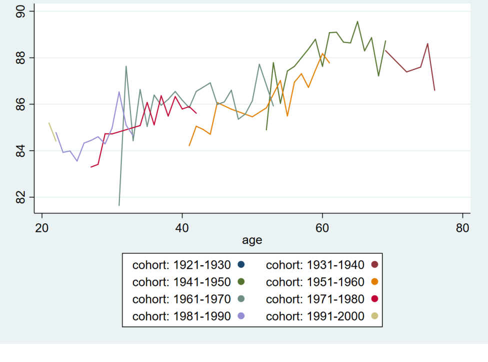


Figure 3.3. Men: K6 (0-100 scale)

Table 3.2. Estimation results: second derivative

	Full sample	Women	Men
Δ K6 (0-100)			
$2age_{i,t}$	-0.009***	-0.009***	-0.009***
	(0.002)	(0.003)	(0.003)
Constant	1.203***	1.545***	0.734
	(0.313)	(0.408)	(0.489)
Clustered SE	YES	YES	YES
Observations	37,292	23,142	14,150
Number of ID	11,141	6,737	4,404

Clustered standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

age (β_2) indicate that there might be an inverse U-shape[9] in mental health over age. However, whether this inverse U-shape truly exists depends on the linear term, which is not identified. If we are, however, willing to assume that there exists no linear time trend ($\tau = 0$), women's mental health would be continuously increasing until they reach old age (they reach their peak mental health[10] at age 83), whereas men would experience a more profound inverse U-shape: given our current estimate, mental health would peak at age 39. Regardless of the size of the linear age-effect, our finding of a negative second derivative disproves the existence of a U-shaped age profile in mental health.

3.5.2 First derivative

Figures 3.4-3.6 provide the estimated coefficients for the linear age-effect for different cohort restrictions. For each restricted year of birth, the coefficient of that cohort is restricted to be equal to the coefficient of the previous cohort. That is, if the restricted cohort is the one born in 1921, then the coefficient for the cohort effect of 1921 is assumed to be equal to that of 1920.[11]

The parameter restrictions result in estimations of the linear age-effect that vary

[9] i.e., a $\cap$-shape.
[10] I.e., their best mental health.
[11] We did not use cohort restrictions on cohorts born before 1920 and after 1993, since these cohorts contain too few individuals (less than 100) to provide accurate results.

Figure 3.4. Estimates for linear age-effect

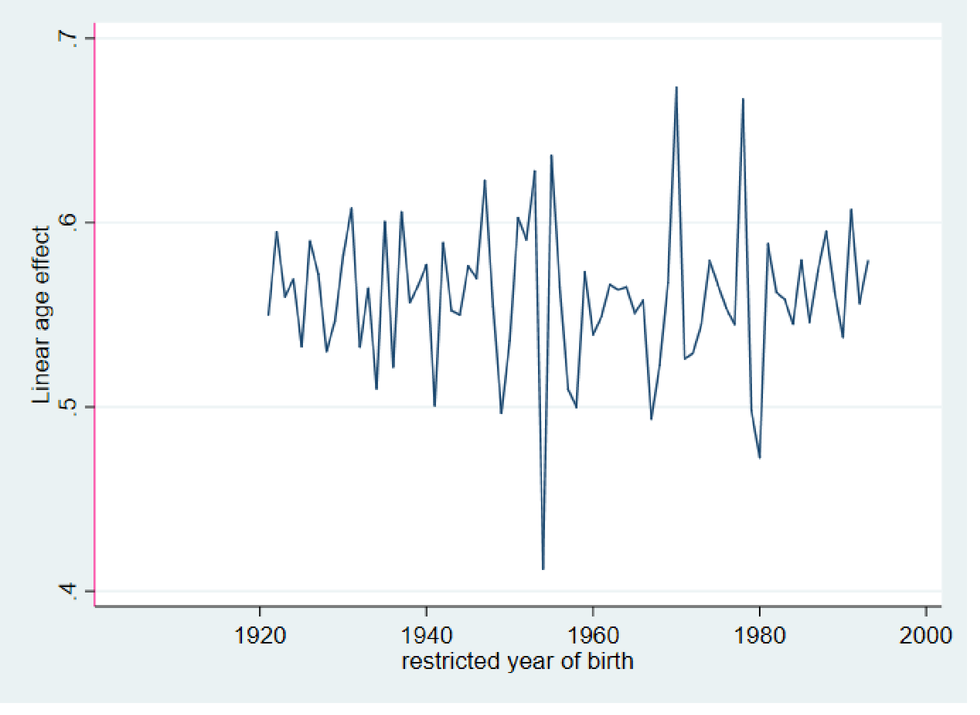


Figure 3.5. Linear age-effect: women

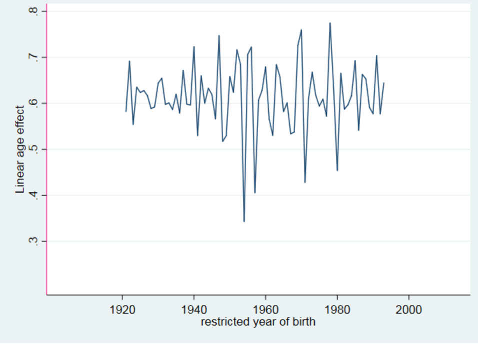
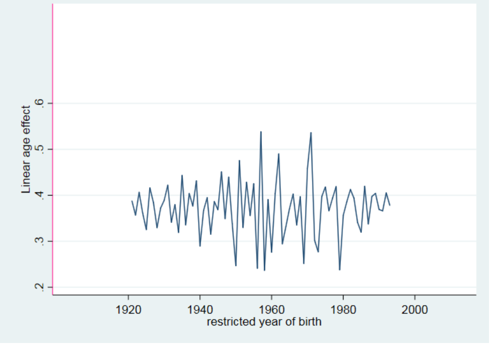


Figure 3.6. Linear age-effect: men



between 0.412 and 0.673. Given these two extremes mental health would either peak somewhere between age 44 (linear age-effect is 0.412) and age 72 (linear age-effect is 0.673).

When we stratify by gender, we find that the estimated linear age-effects for women generally tend to be much higher than the linear age-effects for men, suggesting that women reach their peak mental health later in life. For men, the estimated linear age-effects range from 0.237 to 0.538, suggesting mental health peaks sometime between age 25 and age 58. For women, the estimated coefficients vary between 0.343 and 0.774, suggesting that their mental health peaks sometime between age 37 and age 84. The estimated ages at which individuals reach peak mental health using the varying cohort restrictions approach do not differ substantially from the estimated ages using the second derivative approach with the assumption of no linear period trend.

Consequently, if we are willing to assume that the bias caused by the parameter restrictions is either negligible, or at least close to zero on average, we can conclude that mental health is inversely U-shaped over the life course. This result applies to both men and women.

3.6 Further Analysis

3.6.1 Functional form

It could be that the DGP in this study is too restrictive. It is relatively easy to test this hypothesis by assuming a less restrictive DGP. Following Van Landeghem (2012), we estimate equation (3.2) using a set of dummies for age instead of a single continuous age variable. The age-dependent second derivative is then given by differencing the coefficients of the age dummies. If the initial second order polynomial assumption is correct, the estimated age-dependent second derivative should only exhibit minimal variation around a straight line. If instead the pattern of the age-dependent second derivative is more complicated, this would suggest that our initial assumed DGP is incorrect.

A plot of the age-dependent second order derivatives is given in Appendix 3.A.1. As the graph clearly shows, the age-dependent derivative only shows minimal variation around a straight line. Additionally, a Ramsey RESET test (Ramsey,

1969) of equation (3.2) to assess the null hypothesis for no misspecification provides p-values of 0.035, 0.290 and 0.222 for the entire sample, women and men, respectively. While the small p-value for the entire sample might suggest that the analysis suffers from some form of misspecification, the large p-values of the separate specifications for men and women suggest that this might largely be due to gender differences. Hence, the choice of a second order polynomial for age in equation (3.1) does not appear to cause misspecification. Consequently, the conclusions that the age-profile of mental health is not U-shaped and that it might even follow an inverse U-shape appear to be valid.

3.6.2 Attrition

There might be a possibility that individuals of certain ages with certain mental health levels are more likely to drop out of the sample. If this is the case our estimate of the second derivative would be biased. However, when we add a dummy variable for attrition (indicating whether an individual will have left the panel in the next wave) to our second derivative estimation our results remain relatively unchanged (see Appendix 3.A.1). Additionally, the coefficient for the attrition dummy is statistically insignificant ($p > 0.10$). Similarly, when we perform the second derivative estimation including only those individuals that were present in all waves, we find an estimate for the second derivative that is slightly higher, but still negative and statistically significantly different from zero ($p < 0.05$) and not statistically significantly different from our previous estimations ($p > 0.10$) (see Appendix 3.A.1). Consequently, our results appear to be relatively unaffected by panel attrition.

3.6.3 Period and cohort trend

So far, we have provided two estimation strategies for the linear age-effect. The first estimation strategy (using first differences) required the assumption of a negligible period trend in order to identify the age effect. The second strategy (using varying cohort restrictions) required the assumption of a negligible cohort trend. The degree of certainty about the first derivative hinges on the credibility of these assumptions. In other words, is there reason to believe either a linear period or cohort trend is more or less likely? In Appendix 3.A.1 we provide two graphs: the first provides average K-6 (0-100) scores per year of observation and the second provides average K-6 (0-100) scores per cohort. Note that both provide no conclusive evidence on the linear trend, as the averages are biased with age effects, and period or cohort effects. Nevertheless, average K-6 (0-100) scores show strikingly little variation over time, suggesting that perhaps the assumption of no linear period trend might not be too unrealistic.

3.6.4 Multiple Countries

Our finding that mental health is inversely U-shaped over the life course runs counter to the current literature, which more often than not reports a U-shape in mental health, wellbeing or life satisfaction. It might be though that this is simply due to the fact that we focus on the US, which might be the exception to the U-shaped rule (Blanchflower & Oswald, 2009). To test this assumption, we reperform our analysis of the second derivative on data from the Netherlands and Germany.

For our analysis of the Netherlands, we use data from the Dutch LISS panel[12], which consists of a representative sample of the Dutch population. The LISS panel contains data on individual mental health for the years 2007-2017, with the exception of 2014. Mental health is measured using the abbreviated 5-question version of the Mental Health Inventory (MHI-5) (Ware Jr & Sherbourne, 1992), which is a widely used and well validated instrument, specifically for mood and anxiety disorders (Veit & Ware, 1983; Rumpf et al., 2001; McCabe et al., 1996) . The MHI-5 can be summarized in a score ranging from 0 to 100, where higher scores indicate better mental health.

For Germany we use data from the German Socio-Economic Panel (SOEP). The SOEP is a long-run panel with data on German households from 1984 to 2016. A large number of papers have used SOEP to investigate a U-shape in life-satisfaction and well-being (e.g., Kassenboehmer & Haisken-DeNew, 2012; Frijters & Beatton, 2012; Van Landeghem, 2012; Baetschmann, 2014; FitzRoy et al., 2014; Cheng et al.,

[12] The LISS panel is a representative sample of Dutch individuals who participate in monthly Internet surveys. The panel is based on a true probability sample of households drawn from the population register. Households that could not otherwise participate are provided with a computer and Internet connection. A longitudinal survey is fielded in the panel every year, covering a large variety of domains including work, education, income, housing, time use, political views, values and personality.

2017; Rohrer et al., 2018; De Ree & Alessie, 2011), but, to our knowledge, currently no study has used SOEP to investigate the age-profile of mental health.

For mental health we use the Mental Component Summary scale (MCS), which is computed from answers to the SF-12v2 questionnaire using factor analysis (Andersen et al., 2007). The MCS is calibrated such that the population average is close to 50 and the standard deviation is close to 10, with higher scores implying better mental health. The MCS is available from 2002 onwards, hence we use data from all even years between 2002 and 2016, which resulted in data from 8 different years.[13]

Estimated second derivatives for both datasets can be found in Table 3.A.5 of Appendix 3.A.1. For Germany we find relatively similar results to the US, indicating that the non-existence of the U-shape in mental health in the US is not an isolated case. For the Netherlands we find a statistically insignificant second order derivative of 0.001 (SE: 0.002), indicating that either the second derivative is relatively close to 0 or our current assumed DGP might be misspecified for the Netherlands. We can test this last possibility in the same way as we did previously. Results for the age-dependent second derivative for the Netherlands can be found in Figure 3.A.2 of Appendix 3.A.1. No clear age pattern emerges when looking at the age-dependent second derivative for the Netherlands, suggesting that the second derivative might indeed be close to zero. Additionally, a Ramsey RESET test (Ramsey, 1969) could not reject the null hypothesis of no misspecification with a p-value of 0.174. Consequently, the U-shape in mental health is not only absent when using US data, but also when using German and Dutch data.

3.7 Discussion

Our results consistently indicate that there is no U-shape in mental health over age, and that this finding is not limited to just the US. This is not in line with the literature, which frequently reports a U-shape (Blanchflower & Oswald, 2008, 2016; Le Bon & Le Bon, 2014; Lang et al., 2011), which raises the question why our results differ.

One possible reason for the difference in results is that two of the four studies (Blanchflower & Oswald, 2016; Le Bon & Le Bon, 2014) use some form of mental

[13] 2002;2004;2006;2008;2010;2012;2014;2016

healthcare use as proxies for mental health. The underlying assumption is that if the age profile of mental healthcare use consists of an inverse U-shape, the age profile of mental health must also be U-shaped. However, mental healthcare use might not be an adequate proxy for mental health and the reliability of healthcare use as a proxy might be dependent on age (Clement et al., 2015; Alonso et al., 2007; Wang et al., 2005). This could bias the results.

Additionally, three of the four studies do not control for cohort effects, assuming that these are zero (Blanchflower & Oswald, 2016; Le Bon & Le Bon, 2014; Lang et al., 2011). However, this might not be the case, leading to biased results. Even when cohort effects are taken into account (Blanchflower & Oswald, 2008), all four studies use superfluous parameter restrictions, suggesting that cohort effects are perhaps not adequately controlled for (Bell & Jones, 2013).

Lastly, many of these studies used control variables other than cohort and period variables to estimate the age effects of mental health (e.g. Blanchflower and Oswald (2008) and Lang et al. (2011), and to some extent Blanchflower and Oswald (2016)). This is not problematic per se, but it does beg the question what is being estimated exactly. It is easy to imagine that most of the age effect of mental health is not a direct result of individuals becoming older, but of other factors, physically and in society, that change as individuals age. In that sense adding control variables may seem like a good idea, but there is a vast number of factors that change as individuals age that potentially also affect mental health and it is difficult to asses in an analysis whether all relevant factors have been identified. As a result, when just a few of these factors are included in the analysis as control variables, it is unclear what the residual age-effect found by the analysis consists of and, hence, it is difficult to interpret. Therefore, through the use of control variables, Blanchflower and Oswald (2008) and Lang et al. (2011) measure something fundamentally different (a residual age-effect) from the crude age-effect investigated in this study, which might lead to different results.

Indeed when we perform an anlysis similar to Blanchflower and Oswald (2008), using 10-year cohort dummies and a variety of control variables we do find a U-shape in mental health, albeit a statistically insignificant one (see Appendix 3.A.1). The combination of the two methodological differences (inadequate cohort controls and analysing a residual age-effect) force our previously negative, unbiased estimate for the second derivative to suddenly become positive. There is no clear interpretation that we can provide of this positive estimate, since it is unclear what it entails exactly as it combines both a cohort bias and an unknown residual age-effect.[14]

Moreover, our results are in line with the results of Bell (2014) if we are willing to assume that there is no linear period-effect. Bell (2014) implicitly makes this assumption by using a HAPC model, and just as in this study finds a negative coefficient for the second derivative.

In this chapter we have used a very narrow definition of mental health. The WHO (2014) has defined mental health as 'a state of well-being in which every individual realizes his or her own potential, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to her or his community.' While the questionnaires used in this study capture some of this definition of mental health, they certainly do not encompass all of the definition by the WHO (2014). Specifically, the K-6 focuses more on the presence or absence of psychological distress than the holistic view of mental health proposed by the WHO (2014). On the other hand, non-specific psychological distress is a common symptom in a broad range of mental disorders (Kessler et al., 2002) and all three instruments used in this study have evidence suggesting they can function as valid screening tools in the general population (Gill et al., 2007; Rumpf et al., 2001). Hence, while the current study might not necessarily reflect mental health in its entirety, it does capture important aspects of mental health.

Knowing the crude age pattern of mental health (or psychological distress) is highly important, as it indicates which age groups are at risk for mental health problems. A logical further step then is to see which variables drive this age pattern, so that perhaps specific policies and interventions can be targeted at improving the mental health of at-risk groups. To identify suspect variables, future studies could investigate which variables correlate with the age pattern of mental health, after which researchers can focus on identifying causality. Both of these steps are outside the scope of this chapter.

[14] When we add these same control variables to the second derivative approach used in this chapter, we still consistently find a negative second derivative, although it is no longer significant at a 5% or 1% level (results available upon request). However, it should be noted that these control variables could introduce significant endogeneity bias into the estimate (Glenn, 2009).

From our background section we conclude that there is no panacea when it comes to APC estimation. Any method for identifying APC effects either has a large probability of misspecification or is underidentified. As a result, while we can derive an unbiased estimate for the second derivative, when estimating the first derivative different methods will lead to different biases and different outcomes. Consequently, any study reporting results from an APC analysis should be interpreted with caution. We have tried to circumvent this problem by widely varying the restrictions on cohorts used to reach identification and also reporting the results of an estimation where the linear period-effect is assumed to be zero, assuming that if all these different restrictions give similar results our results are less likely to be the artefact of methodological choices. However, it is almost impossible to know in what direction results from different restrictions might be biased since that requires knowledge on all elements of the APC-problem which are by definition unidentifiable. As a result, we cannot know with certainty that the methods applied in this study do not suffer from biases as a result of a linear period or cohort trend. The only certainty we can provide is that various estimates with different restrictions are at least less likely to all suffer from a similar bias than a study employing just a single set of restrictions.

In other words, while we cannot be completely certain that the true linear age-effect lies within the bounds reported by this study, we have tried to reduce this uncertainty. Moreover, we can be certain that our estimate of the second derivative is unbiased. Hence, we can say with certainty that there is no U-shape in mental health over age and that this study provides tentative evidence that mental health follows an inverse U-shape over the life course. In other words, we provide conclusive evidence that the idea that individuals generally experience their worst mental health during midlife, and better mental health when they are younger or older, is incorrect. Instead, the opposite may be true.

3.8 Conclusion

This chapter investigated how mental health changes over the life-cycle by first employing an unbiased estimator for the second derivative of the age pattern, after which the linear age-effect was estimated by widely varying the restrictions on cohorts to reach identification. While a decent body of literature suggests that the age-profile of mental health might be U-shaped, we find evidence that this U-shape does not exist and might in fact be a methodological artefact. On the contrary, our results suggest that the relationship between mental health and age might actually be closer to an inverse U-shape, where individuals experience a mental health high at some point during their lives. This finding is highly societally relevant as it suggests that the young and the elderly might be particularly at risk for mental health problems. Future research should investigate what the determinants of the age pattern of mental health are.

3.A Appendix

3.A.1 Graphs and Figures

Summary statistics

Table 3.A.1. Summary statistics: women

	N	Mean	Standard deviation	Minimum	Maximum
Age	7,867	38.08	15.99	16	97
Year of Birth	7,867	1965.91	18.19	1903	1997
Year	7,867	2004.55	4.73	2001	2015
K-6 score (0-100)	7,867	83.18	17.39	0	100

Summary statistic at first observation (baseline) for each individual

Table 3.A.2. Summary statistics: men

	N	Mean	Standard deviation	Minimum	Maximum
Age	6,511	39.38	15.97	16	99
Year of Birth	6,511	1965.76	18.00	1902	1997
Year	6,511	2005.72	5.07	2001	2015
K-6 score (0-100)	6,511	84.84	17.08	0	100

Summary statistic at first observation (baseline) for each individual

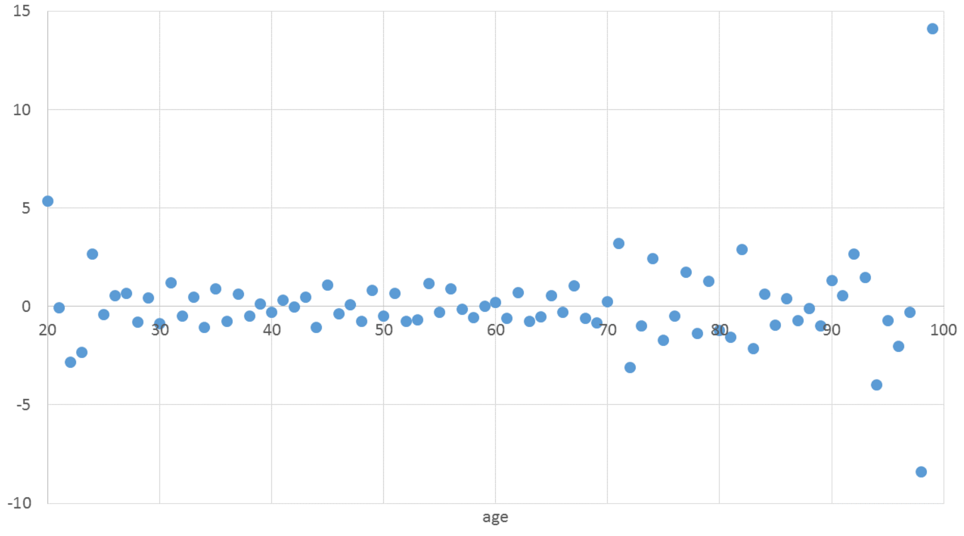
Table 3.A.3. Population summary statistics: individuals with at least two consecutive scores

	N	Mean	Standard deviation	Minimum	Maximum
Age	11,141	38.14	15.50	16	95
Year of Birth	11,141	1965.18	17.52	1905	1995
Year	11,141	2003.90	4.08	2001	2013
Gender					
Female	6,737	60.47%			
Male	4,404	39.53%			
K-6 score (0-100)	11,141	84.53	16.69	0	100

Summary statistic at first observation (baseline) for each individual

Age-dependent second derivative

Figure 3.A.1. Age-dependent second derivative



Attrition

Table 3.A.4. Estimation results: second derivative

	Full sample	Individuals present in all waves
Δ K6 (0-100)		
$2age_{i,t}$	-0.009***	-0.007**
	(0.002)	(0.003)
Constant	1.411***	1.231***
	(0.538)	(0.426)
Attrition_{t+1}	-0.217	
	(0.443)	
Clustered SE	YES	YES
Observations	37,292	19,130
Number of ID	11,141	3,826

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

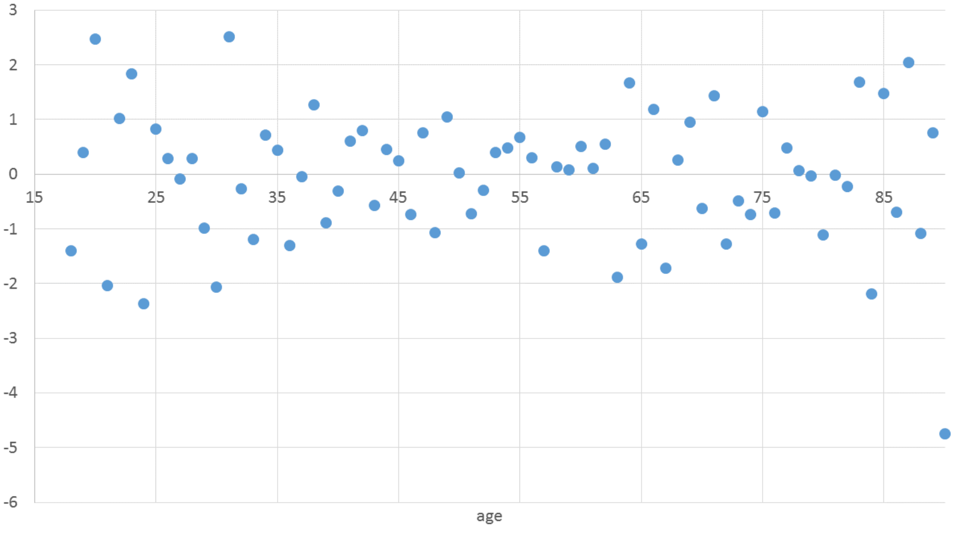
Netherlands and Germany

Table 3.A.5. Estimation results: second derivative

	Netherlands	Germany
$2age_{i,t}$	0.001	-0.006***
	(0.002)	(0.001)
Constant	0.373	0.793***
	(0.267)	(0.137)
Clustered SE	YES	YES
Sample weights		YES
Observations	33,511	111,706
Number of ID	9,250	35,286

Cluster robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 3.A.2. Age-dependent second derivative: Netherlands



Second derivative estimates for individuals aged >90 are not shown due to extreme outliers as a result of limited sample sizes for these age groups.

Residual age-effect with 10-year cohorts

Table 3.A.6. Estimation results: residual age-effect with 10-year cohorts

	K6 (0-100)
$age_{i,t}$	0.007
	(0.096)
$age^2_{i,t}$	0.001
	(0.001)
Cohort dummies	10-year
Year dummies	1-year
Controls	YES
Clustered SE	YES
Sample weights	YES
Observations	40,808
Number of ID	11,695

Control variables consisted of state dummies, the natural log of income, marital status dummies, education level dummies, employment status dummies, race dummies and a dummy variable denoting whether the household included children under 18.
Cluster robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Cohort and period trends

Figure 3.A.3. Average K6 scores per year (0-100)

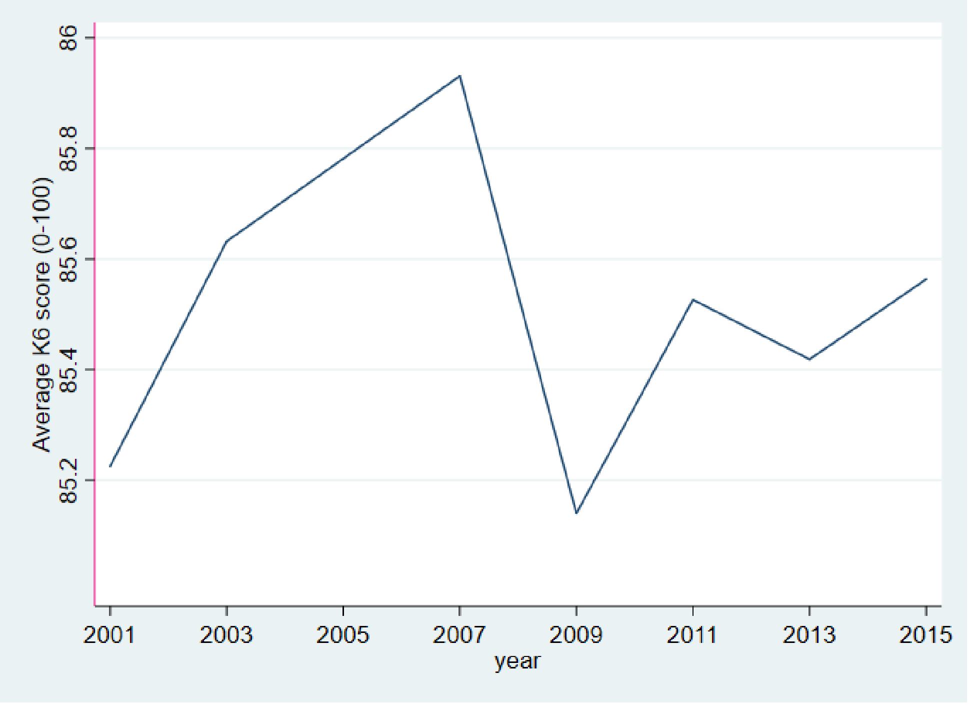
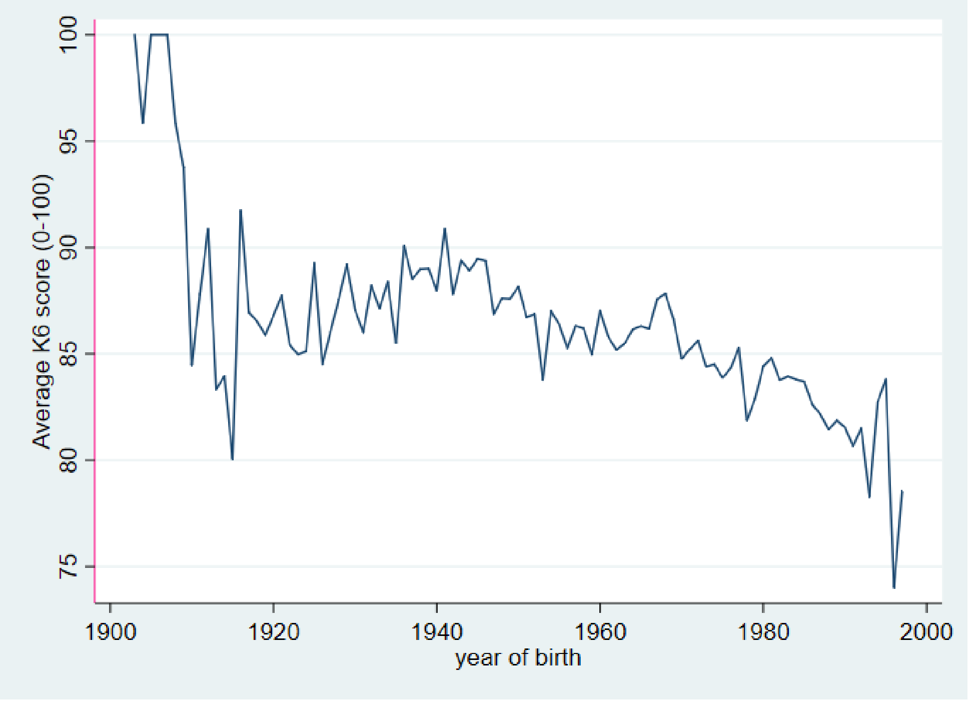


Figure 3.A.4. Average K6 scores per cohort (0-100)



Chapter 4

When Feeling Blue Gets You into the Red: the Effect of Mental Health Problems on the Onset of Problematic Debt*

* This chapter is based on Dijk and Roos (2020). The results in this chapter are preliminary and based on calculations by the authors using non-public microdata from Statistics Netherlands. Under certain conditions, these microdata are accessible for statistical and scientific research. For further information: microdata@cb.nl. The authors would like to thank Statistics Netherlands for providing access to the data. We would furthermore like to thank Viola Angelini, Jochen Mierau, Andrew Bryce, Heike Vethaak, Maaike Diepstraten, Rudy Douven, Jonneke Bolhaar, Gijs Roelofs and Rob Alessie as well as participants at the Essen Economics of Mental Health Workshop 2020, 12th conference of the Lowlands Health Economics Study Group and various seminars for their comments.

4.1 Introduction

A variety of socioeconomic and -demographic variables - including income, education, wealth, occupation, race and ethnicity are found to be associated with health. The causal pathway of the socioeconomic status-health gradient is, however, unclear and seems to differ between different measures of socioeconomic status (SES). The literature has posited several explanations for the association between SES and health (Adler & Ostrove, 1999; Hoffmann et al., 2018). The first is the social causation hypothesis which posits that SES influences health. The second is the health selection hypothesis which states that health influences SES. Third, some third variable, like major life events, family background or genetic endowment, may cause both worse health and SES (Zimmerman & Katon, 2005; Hoffmann et al., 2018).

In this chapter, we focus on the relationship between health status (proxied by healthcare use) and another potentially important socioeconomic variable: problematic debts.[1] Problematic debts constitute an enormous loss not only to debtors and creditors, but also to society as a whole. In the Netherlands, the societal costs of an average household at risk for problematic debt was estimated to be up to €48,283 in 2011, excluding the losses to creditors (Ministerie van SZW, 2019).[2] Moreover, recent literature on the 2008 recession suggests that individual and/or household debt might have far-reaching negative macroeconomic consequences: increases in household debt are associated with future declines in GDP and more severe recessions (Mian et al., 2017; Verner & Gyöngyösi, 2020).

Adequate prevention of problematic debts is therefore of vital importance and high on the political agenda of many OECD countries. In order to design prevention strategies that are effective, knowledge is required on the determinants and causes of the onset of problematic debt. Unfortunately, relatively little is known about the causes of problematic debt. Previous studies on the determinants of problematic debt have mostly focused on financial variables, such as income and expenses, or on money attitudes, financial literacy and time preferences (Webley & Nyhus, 2001; Strömbäck et al., 2017; Gathergood, 2012b). Although financial

[1] Not all debts are problematic. Problematic debts are those debts that people fail to repay or for which people default. Normative debts are managed debts which are paid without difficulty.

[2] The societal costs of problematic debts consist of income losses because of unemployment, absenteeism at the workplace due to illness and legal costs. When taking into account the costs of creditors and local governments, the costs for the average household at risk for problematic debts was estimated to be €103,787 (Ministerie van SZW, 2019)

variables and money attitudes are clearly related to problematic debt, the literature suggests that they are not the only drivers of problematic debt. That is, another body of literature shows a strong association between mental health problems and problematic debt, arrears, or financial strain (Fitch et al., 2011; Richardson et al., 2013; Turunen & Hiilamo, 2014; French & Vigne, 2019).

The vast majority of studies on the problematic debt-mental health relationship are, however, cross-sectional and/or suffer from endogeneity problems (Brown et al., 2005; Zimmerman & Katon, 2005). Also, the focus of these studies has mostly been to show how problematic debt might cause mental health problems (Gathergood, 2012a; Keese & Schmitz, 2014). A few studies find that mental health problems seem to precede problematic debts even if they exacerbate after problematic debt occurs (Gathergood, 2012a; Kidger et al., 2011). However, to our knowledge, no studies explicitly study the health selection hypothesis.

This chapter aims to fill this gap by investigating the effect of mental health problems on the onset of problematic debt. Causal effects can be difficult to establish, especially in cases where the two variables of interest are intertwined. A common approach to overcome the issue of reverse causality is an instrumental variable approach. In the health-problematic debt relationship, the instrument would require and exogenous shock/event that affects individuals' mental health and has no (in)direct financial consequences that might lead to problematic debt. We find that the death of a family member not living in the same household can be an appropriate instrument for mental health problems (section 4.6). Using this instrument allows us to go beyond correlations and say something about the causal effect of mental health problems on problematic debts.

We furthermore contribute to the literature by overcoming two empirical issues that beset current studies on the problematic debt-health relationship. First, most studies are not able to differentiate between normative and problematic debts (Fitch et al., 2011). For this chapter, we obtained a population wide objective measure of a problematic debt: we focus on payment arrears for health insurance premiums in the Netherlands. In the Netherlands, all citizens are obliged to buy standardized individual basic health insurance from a private health insurer. Persons who do not pay their health insurance premium are transferred from the private health insurer to the public National Administration Office (CAK) (section 4.3.1). We use these transfers to measure problematic debts. Because defaulting for health insurance premiums is shown to be positively related to having difficulties to pay mortgage/rent, electricity, gas and water and to pay off debts or payment arrangements (Jungmann & Werksma, 2012; Posthumus et al., 2019), it can serve as a proxy for having other problematic debts.

Second, the vast majority of studies on the problematic debt-health relationship are cross-sectional (Richardson et al., 2013). We, in contrast, use a panel data set which allows us to follow individuals over time. Our data over 2012-2016 allows us to precisely measure the timing of ending up in a problematic debt situation: we observe the exact time when people are transferred from the private health insurer to the public National Administration Office and we have this data available for the full population. We are therefore also able to ensure exogeneity of our instrument by including individual fixed effects (and time variant control variables) to our estimations.

Overall, we find a strong correlation between mental health problems and the onset of problematic debt. Our instrumental variable estimations show that there is a causal relationship between mental health problems and the onset of problematic debt for men, but we find no evidence of such a relationship for women. We perform several robustness checks to test for the sensitivity of our results. Our study indicates that interventions aimed at reducing and preventing problematic debts might be more effective if they include effective strategies for improving mental health and that effective mental health interventions might have long-term societal savings in the form of prevented problematic debts.

The chapter proceeds as follows. Section 4.2 summarizes previous literature on the problematic debt-health relationship. Section 4.3 outlines the institutional context of the chapter and Sections 4.4 and 4.5 present methodology and the data. The results are shown in Section 4.6. Sections 4.7 and 4.8 discuss and conclude on the results.

4.2 Background

A large body of literature shows that worse mental health and debt are related (Fitch et al., 2011; Richardson et al., 2013; Turunen & Hiilamo, 2014; Downing, 2016;

French & Vigne, 2019). Of the mental disorders investigated in the literature, major depression as well as its symptoms, seems to be the most researched and is consistently associated with high, or problematic debt (Sweet et al., 2013; Gathergood, 2012a; Hojman et al., 2016), debt/financial worries (Reading & Reynolds, 2001) and financial strain (Szanton et al., 2010; Zimmerman & Katon, 2005). Although Bridges and Disney (2010) state that the relationship between depression and problematic debt that is so consistently found, may be due to reporting bias –individuals who are depressed are more likely to mark a debt as problematic, regardless of the size or severity of the debt– others still find a relationship after accounting for reporting bias (Gathergood, 2012a), or when using a measure that should be less sensitive to this type of bias (Zimmerman & Katon, 2005).

While the association between problematic debt and mental health has been firmly established, only few studies have focused on determining whether mental health problems may cause problematic debt. A causal relationship from mental health problems to problematic debt does seems likely as mental health problems are associated with problems in daily functioning. For example, major depression is associated with cognitive impairment and deficits (Evans et al., 2014; Lee et al., 2013) and might be associated with abnormalities in financial reward processing (Pulcu et al., 2014). Additionally, individuals with mental disorders are less likely to be employed (OECD, 2012) and often have lower incomes (OECD, 2012). All of these factors might lead to a higher probability of accruing problematic debt.

Indeed, Gathergood (2012a) notes that individuals with more problematic mortgage debt already reported worse mental health before the onset of this debt, a finding which is corroborated by the work of (Roos et al., 2020) for the Netherlands. Similarly, (Kidger et al., 2011) report that patients who are admitted to an emergency department after an attempted suicide are more likely than other patients to experience bankruptcy in the following two years. This timing of events suggests that mental health problems might also cause the onset of problematic debt, instead of merely being a consequence of problematic debt. However, these studies do not provide proof for a causal relationship, as forward-looking individuals might already experience the distress resulting from problematic debt or bankruptcy before they occur.

Causal effects can be difficult to establish, especially when the variables of interest are so intertwined and difficult to measure as debts and mental health. The number of studies studying causal effects in the problematic debt-mental health relationship is low. The few papers that try to establish a causal relationship all focus on the effect of debts on mental health. The studies use instrumental variables to determine causal effects of problematic mortgage debt (Gathergood, 2012a), secured and unsecured debt (French & McKillop, 2017) or financial strain (Zimmerman & Katon, 2005) on mental health (Zimmerman & Katon, 2005; Gathergood, 2012a) or feeling depressed or anxious (French & McKillop, 2017). While Gathergood (2012a) and French and McKillop (2017) do find statistically significant causal effects, Zimmerman and Katon (2005) do not.

4.3 Institutional context

4.3.1 Problematic debt

In this chapter, we investigate the effect of mental health problems on the onset of problematic debt. Many studies on the debt-mental health relationship do not differentiate between types of debt, and whether the debt was problematic or unproblematic (Fitch et al., 2011). In this chapter, presence of individual problematic debt will be determined by whether individuals have failed to pay for their basic health insurance premium for at least 6 months.

In the Netherlands, by law all individuals are required to purchase a government mandated basic health insurance policy from a private health insurer.[3] The standardized basic benefits package includes, amongst others, hospital care, GP services, mental healthcare, prescription drugs and maternity care. In addition to basic health insurance, people are free to buy supplementary health insurance, which provides coverage for benefits that are not included in the basic benefits package. There is a fixed mandatory annual deductible which ranged between €350 and €385 between 2013-2016, but individuals may choose to supplement this mandatory deductible with a voluntary deductible of up to €500 in exchange for a lower premium.

[3] With the exception of individuals in military service, in detention, and individuals who wish not to be insured based on religious grounds (together these groups, however, make up less than 0.07 percent of total Dutch population (Ministerie van VWS, 2019)).

To prevent people from defaulting for their basic health insurance policies, Dutch health insurers are obliged to send out payment notices and to offer payment arrangements and debt assistance as soon as the enrollee fails to pay for his health insurance. After several months of defaulting, the health insurer terminates any supplementary health insurance and voluntary deductible.

Insured who fail to pay their basic insurance premium for (more than) six consecutive months are transferred from the private health insurer to the public National Administration Office (CAK), which is a government owned organization that then provides these individuals with a government mandated basic health insurance (wanbetalersregeling). CAK charges and collects an administrative premium from the defaulter for the basic insurance policy, which is higher than the nominal premium that health insurers charge. The defaulter also has to pay additional costs related to debt collection and interest. It is important to note that defaulting only introduces a different payment regime and does not, in any way, affect access to care covered under the basic benefit package.

Only when the defaulter pays off his debt at the health insurer and CAK, the defaulter will flow out of CAK and his basic health insurance policy will be transferred back to the health insurer. Any debts resulting from a failure to pay for premiums of supplementary health insurance or deductibles have to be settled by the health insurer with the defaulter (without inference of CAK).

In the period 2012-2016, the annual number of Dutch health insurance defaulters registered on December 31 ranged between 277.000 and 325.000 (Ministerie van VWS, 2018). For the majority of defaulters the debt at the health insurer, which does not include the administrative premium of CAK, (well) exceeded €750 (Ministerie van VWS, 2018). The majority of defaulters remains under the CAK regime for over 24 months (Ministerie van VWS, 2018). Defaulting for health insurance premiums is shown to be positively related to other problematic debts: in 2018, 79% of households who had defaulted on their health insurance premium also had other problematic debts (Statistics Netherlands, 2020).[4,5] Conversely, of the households with

[4] This percentage is constructed using the number of households with at least one individual who had defaulted on their health insurance in 2018 but had no other registered problematic debts from Statistics Netherlands (2020) and the total number of households with at least one individual who had defaulted on their health insurance in 2018 from the online appendix of Statistics Netherlands (2020), available from `https://dashboards.cbs.nl/v3/SchuldenproblematiekInBeeld/` (accessed July 29, 2021).

[5] Not all problematic debts are centrally registered. In this case, 'other problematic debts' consist of defaulting for over 12 months at the Tax and Customs Administration; arrears at the Education Execut-

problematic debts, health insurance debt is among the main reasons for problematic debts (Statistics Netherlands, 2020). In fact, Posthumus et al. (2019) find that among households with the highest problematic debts, more than 40% defaults on their health insurance premiums. Therefore, failure to pay for health insurance premiums also serves as a proxy for having other problematic debts.

4.3.2 Mental health problems

In this chapter, we start by estimating a simple OLS model with the use of mental healthcare as the independent variable (section 4.4.1). Although identifying mental health problems through mental healthcare use may underestimate mental health problems, it is preferred over self-rated health as the latter is well known to be prone to biases (Richardson et al., 2013; Bridges & Disney, 2010).

In the Dutch healthcare system, short-term (i.e. less than one year) curative mental healthcare is divided into primary and secondary mental healthcare services. Primary mental healthcare is provided to patients with mild mental disorders in an ambulatory setting. Patients may use primary mental healthcare without a referral by a general practitioner. Secondary mental healthcare includes ambulatory curative mental healthcare and inpatient curative mental healthcare up to one year. A referral from a primary care physician is needed for patients to use secondary mental care. Secondary mental healthcare is mostly provided by independent psychotherapists or psychiatrists and mental healthcare organizations. Both primary and secondary mental healthcare are part of the standardized basic benefits package.

In the instrumental variable approach that we estimate after the OLS equation, we instrument for mental health problems by bereavement (section 4.4.2). For those left behind, bereavement is associated with the onset of depression-like symptoms and an increase in the prevalence of major depressive disorder even one to two years after the death occurred[6] (Zisook & Kendler, 2007) as well as other psycho-

ive Agency of the Dutch Ministry of Education, Culture and Science; arrears for payments on loans and credit over €250 registered at the Central Credit Information system of the Credit Registration Office (BKR); arrears for traffic fines; and/or the registration of at least one household member as a participant in a (lawful) debt restructuring program (WSNP or as registered at BKR) or as being under a conservatorship because of irresponsible spending/problematic debts.

[6] APA distinguishes between 'normal' grief and Major Depressive Disorder (MDD). According to APA in grief, painful feelings often come in waves, are focused on the deceased and may be accompanied by positive emotions and humor. Feelings of self-esteem are generally preserved and if suicidal ideation

pathologies, such as bereavement-related depression, or anxiety and traumatic or complicated grief (Boelen et al., 2003). Especially bereavement-related depression does not appear to differ much from non-bereavement-related major depression (Kendler et al., 2008). Dutch individuals in need of mental care because of bereavement could use both primary as well as secondary mental healthcare.

4.4 Empirical approach

4.4.1 Ordinary least squares estimation

In this chapter, we investigate the effect of mental health problems on the onset of problematic debt. We start our empirical approach with an Ordinary Least Squares (OLS)/Linear Probability Model (LPM) estimation with a mental health indicator (mental healthcare use), i.e. we estimate the following regression equation:

$$D_{i,t} = \beta_0 + \beta_1 M_{i,t} + \beta_2 X_{i,t} + \varepsilon_{i,t}, \tag{4.1}$$

where $D_{i,t}$ is an indicator variable denoting whether at time t individual i experienced problematic debt ($D_{i,t} = 1$) or not ($D_{i,t} = 0$), $M_{i,t}$ is an indicator variable denoting whether the individual received mental healthcare at time t (1= use; 0 = no use), $X_{i,t}$ is a vector of control variables consisting of a set of year dummies and a third-degree polynomial for age (see section 4.4.2 for a detailed description of the covariates), and β_0, β_1 and β_2 are parameters to be estimated, where β_1 is the parameter of interest, and $\varepsilon_{i,t}$ denotes the error term.

4.4.2 Instrumental variables estimation

Although indicative of the health-problematic debt relationship, the OLS estimation does not provide causal evidence of the effect of mental health problems on the incidence of default, since the estimates might suffer from two sources of

is present it often stems from thoughts of joining the deceased. In depression, mood and ideation are almost constantly negative, accompanied by feelings of worthlessness and self-loathing, and individuals' preoccupations are often extremely self-critical and pessimistic. If present, suicidal ideation often stems from feeling worthless and undeserving of life, or an inability to cope with the pain of depression (American Psychiatric Association et al., 2013).

endogeneity bias: reverse causality bias and omitted variable bias. First, financial distress/problematic debts might cause mental health problems (Gathergood, 2012a). If individuals suspect that they might be unable to pay their bills or to repay their debt in the future, mental health problems that result from this financial distress might take place before the default occurs. Second, factors such as employment status (Drydakis, 2015; Marcus, 2013), divorce (Amato, 2010; McManus & DiPrete, 2001; Wilmoth & Koso, 2002) or, more broadly, socioeconomic status (Rai et al., 2013) might affect both mental health and the probability of default. If these variables are not accounted for, we might erroneously conclude that mental health problems cause default. including these variables as controls might, however, also lead to a bad control situation, as, here too, there can be reverse causality. That is, mental health problems might cause changes in marital (Butterworth & Rodgers, 2008) and employment status (Schmitz, 2011), which in turn might cause the onset of problematic debt, while the opposite may also be true.

A common approach to overcome the issue of endogeneity is an instrumental variable (IV) approach in which there is an instrument for the independent variable of interest (in this case: mental health). Unbiased and effective IV estimation requires an exogenous shock or event that affects individuals' mental health but has no other indirect or direct financial consequences that might lead to problematic debt. We find that the death of relative can be an appropriate instrument for mental health problems. As previously discussed, bereavement is associated with the onset of mental health problems (Stroebe et al., 2007; Zisook & Kendler, 2007). At the same time, the death of a child or sibling is likely to be an exogenous event, not caused by the individuals' mental health problems or problematic debts.[7]

To maximize exogeneity of the instrument to problematic debts, we use as instruments the death of a sibling or an adult child, not living in the same household as the individual under observation. That is, in the Netherlands, parental financial responsibility legally ends when children are 21; hence the focus on adult children. The focus on siblings or adult children is to ensure that we minimize the (positive or negative) financial effects of bereavement by inheritance. Namely, according to Dutch law, parents and siblings will only inherit in case there are no spouses, chil-

[7] Homicides may be endogenous (Martone et al., 2013; Oram et al., 2013). Homicide rates are, however, quite low in the Netherlands (¡0.001% (Statistics Netherlands, 2019)) and it is therefore unlikely that homicides obscure our IV estimation.

dren or grandchildren, or when specifically mentioned in a will. By focusing on adult children or siblings we thus limit the potential for direct inheritances. Furthermore, the individuals under observation are parents and siblings that do not live in the same household as the deceased to minimize the risk of financial effects as a result of changes in household composition because of the death of one of the family members. With our robustness tests, we test the sensitivity of our results to these selections (section 4.4.3).

We estimate the following regression model:

$$D_{i,t} = \beta_i + \beta_1 M_{i,t} + \boldsymbol{\beta}_2 \boldsymbol{X}_{i,t} + \varepsilon_{i,t}, \tag{4.2}$$

and use the following first stage equation to determine the causal effect of mental health problems on the onset of problematic debt:

$$M_{i,t} = \gamma_i + \gamma_1 C_{i,t-1} + \gamma_2 S_{i,t-1} + \boldsymbol{\gamma}_3 \boldsymbol{X}_{i,t} + \nu_{i,t}, \tag{4.3}$$

Where, as in equation 4.1, $D_{i,t}$ is an indicator variable denoting whether at time t individual i experienced problematic debt and $M_{i,t}$ indicates whether individual i received mental healthcare in year t. $X_{i,t}$ denotes a vector of control variables. This vector includes a third degree polynomial for age, as mortality increases with age, and so also the incidence of bereavement will increase with age. Furthermore, to account for time-trends in mortality, mental healthcare use and/or incidence of default, as well as policy changes affecting mortality, mental healthcare use and/or incidence of default, we add a set of year dummies.[8] To account for the possibility that the incidence of bereavement might be higher due to certain family characteristics that in turn might be related to either mental health problems or problematic debt, we use individual fixed effects, denoted by β_i (equation 4.2) and γ_i (equation 4.3).[9]

[8] The inclusion of year dummies together with an individual fixed effect results in a problem of perfect collinearity for the linear age effect, due to the age-period-cohort problem. Hence, we exclude the linear term in age. This does not affect our results.

[9] Since we focus on the incidence of problematic debt, as opposed to the prevalence, the individual fixed effect moslty control fort he possibility that the death of a child or sibling might occur more or less for parents or siblings that have more years of mental healthcare use.

Additionally, $C_{i,t-1}$ is a dummy variable denoting whether the individual lost an adult child not living in the same household in the previous year (1 = yes; 0 = no) and $S_{i,t-1}$ is a dummy variable denoting whether the individual lost a sibling not living in the same household in the previous year (1 = yes; 0 = no).[10] We use lagged bereavement instead of level bereavement to allow for enough time for mental health problems and default to arise. More importantly, using lagged bereavement ensures that the bereavements used in the analysis take place before the use of mental healthcare and the incidence of problematic debts.[11]

To ensure robustness against heteroskedasticity due to the use of a linear probability model and to account for the panel structure of the data, all estimations are performed with robust standard errors clustered at the individual level. Estimation is performed using `xtivreg2` in `STATA`.

4.4.3 Robustness tests

To ensure that the results that we find by applying the approach discussed in section 4.4.2, are not merely the result of confounding factors and that the instrument is appropriately exogeneous, we perform a number of robustness checks.

First, in section 4.4.2 we explained that we focus on bereavement after losing an adult child or siblings to minimize the potential of a financial effect by inheritance. If individuals receive an inheritance after the death of their relatives, their financial situation may be (temporarily) improved, which could reduce the probability of default. This may cause a downward bias in our results. According to Dutch law, spouses, registered partners, children and grandchildren inherit before parents and siblings. As a result, an individual in our analysis will not inherit after the death of a child or sibling if at the time of death the child or sibling had living children, grandchildren, or a registered partner or spouse, and there was no will that specifically mentioned the individual under study as an heir. Focusing the main analysis on parents and siblings thus minimizes the probability of direct inheritances. To further improve our analysis, in robustness test 1, we again perform the IV estim-

[10] Since loss of a child or sibling not living in the same household is uncorrelated with losing a sibling or child living in the same household, following the Frisch-Waugh-Lovell theorem, we do not need to control for these losses in our estimation strategy.

[11] If we were to use level, instead of lagged, bereavement we might in the first stage regress bereavement that took place in, for example, December of year t, on mental healthcare use that took place in June of year t and, in the second stage, on default that took place in January of year t.

ation of equation (4.2) and (4.3) where we change the definition of $C_{i,t-1} = 1$ and $S_{i,t-1} = 1$ so that it only includes the deceased who had relatives (i.e. children or grandchildren) or partners who, according to Dutch law, would be the first in line to inherit, so that the probability that the individual under study (i.e. the parent or the siblings) would inherit is small.

Second, we perform the main analysis on a sample containing only the observations of individuals that had to pay their health insurance deductible in a given year. In all analyses in this chapter, we identify mental health problems through individuals' mental healthcare use. This means that all individuals identified to have mental health problems in our analyses have incurred some healthcare cost, since the Dutch healthcare system contains a mandatory annual deductible which ranged between €350 and €385 over the years 2013-2016. These healthcare cost might increase individuals' probability of incurring problematic debts, especially as we identify these debts through defaults on health insurance payments. In practice, not all individuals with mental health problems might receive mental healthcare (Kieling et al., 2011; Thornicroft et al., 2017) and, as a result, not all individuals with mental health problems would necessarily incur (higher) healthcare cost. As such our main analysis might overestimate the effect of mental health problems on the onset of default. Consequently, by performing a robustness analysis where we restrict the sample to observations of individuals who have had to pay some share of the deductible in a given year, we control for this potential bias. In other words, in this robustness analysis we change the counterfactual in our analysis from individuals that did not require mental healthcare and thus might not have had to pay their deductible, to individuals who did not require mental healthcare but had to pay a deductible for some other type of healthcare (robustness test 2).[12]

Third, although parents and siblings may not receive inheritances, they may receive financial or social support from friends and family after the death of a family member. If so, this may bias our results downwards as it mitigates the potential effects of mental health problems on defaulting. That is, relatives may experience

[12] We cannot add the deductible as a control variable, since that would introduce biases to the first stage (equation 4.3). Since we identify mental health problems by mental healthcare use, all individuals identified as having mental health problems have to pay some (or all) of their deductible. Hence, in equation 4.3, adding the deductible on the right-hand side would entail adding an endogenous control variable, resulting in a weak instrument problem. By selecting a sample conditional on paying some of the deductible we circumvent this problem.

significant mental health problems, which could result in default if it were not for the financial or social support from friends and family. It seems reasonable to assume that siblings are likely to experience less financial and social support after the death of a (adult) sibling than parents (Breen & O'Connor, 2011). We re-estimate equation (4.2) using deceased siblings as instrument for mental health problems only (robustness test 3).

Fourth, in the main analysis we restrict the sample to individuals who have either siblings or adult children (section 4.5.2). We do this because instrumented mental healthcare use of individuals who have neither siblings nor adult children will always be zero and, therefore, including these individuals in our sample would lead to biases if they have heterogeneous incidence rates of problematic debts. This sensitivity may also be present, albeit to a lesser extent, if we include individuals who either have siblings but no adult children, or who have adult children but no siblings, since, by definition, for these individuals one of the instruments will always equal zero. We investigate the sensitivity of our results to this bias by performing the IV analysis on a sample of individuals who have both children aged over 20 and siblings (robustness test 4).

Fifth, individuals are marked as defaulters if they fail to pay their basic insurance premium for (more than) six consecutive months. This means that, in practice, they accrued problematic debts months before we observe it in the data. Assuming that there is a relationship between mental health problems and defaulting, depending on how long it takes for mental health problems to actually result in problematic debts, the difference in timing may influence our results. In the fifth sensitivity test, we therefore define defaulting as they year in which the individual first stopped paying their health insurance bills (i.e. transfer date to CAK minus six months). This allows for a larger lag between the death of the (adult) child or sibling and the occurrence of arrears. We only observe the exact transfer date to CAK from 2013 onwards. Hence, we can only perform this analysis on data from 2014 to 2016.

Additionally, to investigate the exogeneity of our approach we also perform the IV estimation with the log of the second lag of household assets (i.e., the level of assets before bereavement occurred) as an additional control variable. Potentially, the individuals experiencing mental health problems and default after bereavement were already more likely to struggle financially before the loss occurred. Additionally, individuals in worse financial situations might be more likely to experience bereavement. If the individual fixed effects adequately controlled for individual characteristics that affect both the probability of bereavement and the onset of default this should not bias the results. To assess whether the fixed effects did adequately control for these characteristics, we add the log of the second lag of household assets (i.e., individuals' financial situation before bereavement) as a control variable. Due to limited data availability for household assets, this analysis is performed for the years 2014-2016 with regard to the onset of problematic debt and 2012-2014 with regard to household assets (robustness test 6).

Lastly, we perform an analysis to determine how individuals get to defaulting. Two possible pathways from mental health to problematic debt might be defined. First, by affecting individuals' cognitive abilities and discount rates (Evans et al., 2014; Lee et al., 2013; Pulcu et al., 2014), mental health problems might directly affect financial decisions and individuals' abilities to meet financial obligations regardless of income and expenses. That is, financially speaking individuals might still be able to pay their health insurance, but their mental health problems prevent them from doing so. We will refer to this pathway as the behavioral pathway. Second, mental health problems might affect individuals' income (for example, due to reduced labor participation (OECD, 2012)) and expenses (for example, due to mental healthcare cost) as a result of which they might not have the financial means to pay their health insurance, regardless of cognitive ability and discount rates. We will refer to this pathway as the liquidity pathway. In the liquidity case, default should co-occur with a drop in assets, whereas in the behavioral pathway it might not. By adding level log assets to the IV estimation we investigate whether the onset of problematic debt coincides with a general drop in household assets. Since asset data is not available for the year 2016, we perform this analysis on default data from 2013-2015.

4.5 Data

4.5.1 Data sources

We combine several nationwide individual-level administrative datasets. The data consists of administrative records of all individuals living and registered in the Netherlands. As such, the data in this chapter is representative of the Dutch population and has external validity. Depending on the variables, data is available for different periods. Overall, records ranged from 2010-2016.

Data on problematic debts are obtained from the National Administration Office (CAK). People who are registered at CAK are classified as defaulters. The dataset includes all defaulters registered at December 31 of each year, their (past) entry and (future) exit dates from CAK.

Of each individual, we have data on healthcare use (1 = use, 0 = no use) from the Dutch data warehouse of insurers (VEKTIS). From the same dataset, we obtain the individuals' deductible costs (in e). We furthermore use data from the Dutch population register on individuals' gender, date of birth and, when applicable, their date of death, and data from the tax authority and the Education Executive Agency of the Dutch Ministry of Education, Culture and Science (DUO) to measure individuals' gross total household assets at January 1st of each year.

Because not all relevant registers used in this chapter contain data for all years between 2010-2016, the final set used for analysis contained data on mental healthcare use and the onset of problematic debt from 2013-2016 and data on bereavement from 2012-2015.

4.5.2 Sample selection

In this chapter, we use the death of an adult child or sibling, not living in the same household as the individual under observation, as an instrument for mental health problems (Section 4.4.2).

Our population registry data allows us to link parents to their lawful children to determine, parent-child, sibling and (for the robustness analysis) grandparent-grandchild relationships. Because, in our setup, the instrumented mental healthcare use of individuals who have neither siblings nor adult children will always be zero, we restrict our sample to individuals who have siblings or adult children not living in the same household.[13] Individuals were considered to be siblings if they shared the same legal mother.

To determine whether individuals did or did not share the same household, we used population level registry data tracking households. We use date of birth to construct a variable for age at December 31st of a given year and date of death to identify if any siblings or adult children died in a given year. Since the registry contained records from 2011-2016 for individuals who were officially registered at a municipality at December 31st of any of those years, we can only track year of death from 2012-2016. Moreover, since we use lagged bereavement in our analyses (and level mental healthcare use and problematic debt), we use data on bereavement from 2012-2015.

Our data consists of 14,897,447 individuals (57,028,317 observations) aged 18+ registered in the Netherlands over the period 2013-2016. Of these individuals, 594.952 (0.96%; 4,164,916 observations) did not appear in the health insurance records (because these individuals did not have health insurance during that period), or had incomplete health insurance records for the purpose of our analysis. Additionally, since we are interested in the onset of default, we exclude individuals that are known to have previously defaulted or once they have defaulted (i.e. not registered previously at CAK during the total period 2011-2015) (137,892 individuals and 1,133,103 observations). This also reduces the potential for reverse causality bias. Since our empirical approach requires individuals to either have siblings, or children over age 20, not living in the same household in the previous year, we excluded another 3,074,372 individuals and 10,905,295 observations of individuals who had neither siblings nor children aged over 20 not living in the same household. Lastly, since the fixed effects estimations required at least 2 observations between 2013-2016 per individual, another 373,640 individuals and 373,640 observations were excluded from the sample. As a result, our sample for analysis contained 10,716,591 individuals and 41,584,766 observations between 2013-2016. Our final sample includes 71.9% of the adult population registered at a municipality in the Netherlands during that period.

[13] Note that this may only lead to biased estimations if these individuals also have different incidence rates of problematic debt.

Table 4.1. Summary statistics

General population	Observations	Individuals	Mean	SD
Age	58,166,569	14,897,447	49.383	19.104
Default: prevalence	58,166,569	14,897,447	0.019	
Default: incidence	57,028,317	14,776,313	0.005	
Any mental healthcare use	53,996,804	14,302,495	0.052	
Household assets	40,644,770	14,137,700	€155,255.00	€575,376.60

Sample for analysis	Observations	Individuals	Mean	SD
Age	41,584,766	10,716,591	52.340	17.495
Default	41,584,766	10,716,591	0.004	
Any mental healthcare use	41,584,766	10,716,591	0.050	
Deceased sibling$_{-1}$	41,584,766	10,716,591	0.009	
Deceased child$_{-1}$	41,584,766	10,716,591	0.001	
Household assets	31,211,479	10,701,369	€165,389.30	€589,102.20
Men				
Age	20,059,713	5,185,983	51.632	17.005
Default	20,059,713	5,185,983	0.005	
Any mental healthcare use	20,059,713	5,185,983	0.042	
Deceased sibling$_{-1}$	20,059,713	5,185,983	0.009	
Deceased child$_{-1}$	20,059,713	5,185,983	0.001	
Household assets	15,047,299	5,176,607	€170,760.30	€607.824.00
Women				
Age	21,525,053	5,530,608	53.001	17.914
Default	21,525,053	5,530,608	0.003	
Any mental healthcare use	21,525,053	5,530,608	0.057	
Deceased sibling$_{-1}$	21,525,053	5,530,608	0.009	
Deceased child$_{-1}$	21,525,053	5,530,608	0.002	
Household assets	16,164,180	5,524,762	€160,389.50	€571.077.30

SD: Standard deviation

4.6 Results

4.6.1 Summary statistics

Table 4.1 provides an overview of the summary statistics for the general Dutch adult population, the entire sample used for estimation, as well as summary statistics separated by gender. As can be seen in the table, the sample for analysis is slightly older on average than the general population (52.3 years old versus 49.4 years old, respectively), which is to be expected, since we select part of our sample on individuals with children aged over 20. Additionally, the incidence of default in the sample for analysis is relatively similar to that of the general population (0.4% and 0.5% annually, respectively). While this may seem low, we know that once individuals accrue problematic debt, they often remain in a situation with problematic debt for years (Ministerie van VWS, 2017). Consequently, the actual prevalence of default is much higher: 1.9% in the general population.

4.6.2 Main analyses

Table 4.2 provides an overview of the main results.[14] As can be derived from Table 4.2, we find a strong positive correlation between mental healthcare use and problematic debt for the overall population ($p < 0.01$), as well as for men ($p < 0.01$) and women separately ($p < 0.01$).[15] This positive correlation remains for men even when we include individual fixed effects ($p < 0.01$) and when we instrument for mental health using deceased siblings or children ($p < 0.05$). The correlation for women is positive and comparable in magnitude to the one for men if we only include fixed effects ($p < 0.01$). However, for women, the correlation between mental healthcare use and default turns negative once we introduce both individual fixed effects and instruments for mental healthcare use ($p < 0.10$).

These results suggest that mental health problems, or at least those resulting from bereavement, cause problematic debts in men but not for women. That the coefficients for the IV estimations are larger than those of the fixed effects estimation, might be due to the fact that our instrumental variable estimation targets a

[14] Estimation results of equation 4.3 are provided in Table 4.A.1 in Appendix 4.A.1.

[15] In addition to the OLS/LPM, we also performed a logit estimation for the overall sample and men and women separately and find results that are in line with the OLS estimation results. These results are available upon request.

Table 4.2. Estimation results

	All:			Women:			Men:		
	OLS	FE	IV	OLS	FE	IV	OLS	FE	IV
Default									
Mental healthcare	0.0048***	0.0008***	0.0101	0.0028***	0.0002**	-0.0233*	0.0080***	0.0015***	0.0997**
	(0.0001)	(0.0001)	(0.0134)	(0.0001)	(0.0001)	(0.0123)	(0.0013)	(0.0002)	(0.0393)
Fixed effects	NO	YES	YES	NO	YES	YES	NO	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Age controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Hansen J-statistic (p-value)			0.231			0.385			0.817
KP LM statistic			217.3			164.8			54.6
individuals	10,716,591	10,716,591	10,716,591	5,530,608	5,530,608	5,530,608	5,185,983	5,185,983	5,185,983
observations	41,584,766	41,584,766	41,584,766	21,525,053	21,525,053	21,525,053	20,059,713	20,059,713	20,059,713

Clustered standard errors in parentheses

*** $p< 0.01$, ** $p< 0.05$, * $p< 0.10$

very specific population, namely one that is more likely to suffer from depression-like symptoms (according to the literature (Section 4.3.2)). More specifically, our estimation approach only allows us to identify the Local Average Treatment Effect (LATE) (Angrist & Pischke, 2008).

Additionally, the low incidence of default combined with the low incidence of the death of a child or sibling (0.1% and 0.9% for the overall sample, respectively) means that the instrumental variable analysis requires a very large sample for effects to be statistically significant. Even if the causal effect of mental health problems on the incidence of default is relatively large, it would still mean that of the small share of individuals in our IV estimation who lose a child or sibling in a given year likely only a small number will also default. Consequently, despite the large sample size, the power of our instrumental variable analysis is relatively low, resulting in larger p-values. Nevertheless, despite the lower power of the IV-estimations, we still find statistically significant results at the 5 and 10 percent level for men and women, respectively.

Furthermore, the Hansen J-statistics and Kleibergen-Paap LM statistics for all IV estimations indicate that the analyses are unlikely to suffer from weak instruments and endogeneity of the instruments.

4.6.3 Robustness analyses

To ensure that the results from the previous section are not merely the result of confounding factors, we perform a number of robustness checks. The results from these robustness analyses are presented in Appendix 4.A.2.

Inheritances (robustness test 1)

The coefficients for these analyses do not greatly alter our main conclusions. We find an effect of mental healthcare use on problematic debt of 0.0170 ($p > 0.10$), 0.1184 ($p < 0.05$) and -0.0166 ($p > 0.10$) for the overall sample, men and women, respectively (Table 4.A.2). The fact that the coefficient for women is smaller and no longer statistically significant at the 10% level, suggests that perhaps the previous negative coefficient might be at least partially due to the reception of inheritances after bereavement. However, p-values might have also increased due to fewer instances of bereavement, as we restricted the definition of $S_{i,t-1}$ and $C_{i,t-1}$ to only include the deceased who had relatives, other than the individual under study, or partners who would inherit.

Out-of-pocket expenses (robustness test 2)

To find out whether our findings on the effect of mental health problems on the onset of default is sensitive to copayments, we performed the IV estimation of equation (4.2) on a sample containing only those individuals who had paid the deductible in a given year (Table 4.A.3). In this analysis, we find coefficients of 0.0090 ($p > 0.10$), 0.0855 ($p < 0.05$) and -0.0197 ($p < 0.10$) for the overall sample, men and women, respectively. These results are comparable to our main results, both in sign and in magnitude. Hence, these results do not alter our previous conclusions.

Social and financial support (robustness test 3)

To account for the fact that parents may receive financial or social support from friends and family, we re-estimated equation (4.2) using only deceased siblings as instrument for mental health problems (Table 4.A.4). In this analysis, we find a coefficient of 0.0415 ($p > 0.10$), 0.112 ($p > 0.10$) and -0.0006 ($p > 0.10$), for the overall sample, men and women, respectively. While removing one instrument from the estimation results in larger p-values, the coefficient does not change substantially for men and, hence, does not alter the previous conclusions. For women, however, the effect is more volatile: i.e., the coefficient does change substantially (from -0.0233 in the main analysis to -0.0006 here). That means that a large portion of the coefficient in the main analysis is driven by women who seek mental healthcare use after the loss of an adult child.

Both children and siblings (robustness test 4)

We account for the potential bias resulting from individuals who have neither siblings nor adult children, by re-estimating equation (4.2) on a sample of individuals who have both children aged over 20 and siblings (Table 4.A.5). For this analysis we find (non-significant) coefficients of 0.0023 ($p > 0.10$), 0.0687 ($p > 0.10$) and -0.0214 ($p > 0.10$) for the overall sample, men and women, respectively. These findings do not alter the main conclusions. The increased p-values that we find in this analysis are likely the result of the reduced sample size.

First occurrence of arrears (robustness test 5)

Because individuals are marked as defaulters if they fail to pay their basic insurance premium for (more than) six consecutive months, they accrued, in practice, problematic debts months before we observe it in the data. In this analyses, we therefore defined defaulting as the year in which the individual first stopped paying their health insurance premium (Table 4.A.6). We find coefficients of -0.0037 ($p > 0.10$), 0.0706 ($p > 0.10$) and -0.0299 ($p < 0.10$) for the overall sample, men and women, respectively. If we, however, re-perform the main analysis on a sample limiting ourselves to the same years of data (2014-2016) we obtain coefficients of 0.0088 ($p > 0.10$), 0.0898 ($p < 0.10$), -0.0200 ($p > 0.10$) for the overall sample, men and women, respectively (Table 4.A.7).[16] Hence, the results do not seem to differ substantially depending on the timing in the analysis.

Endogeneity (robustness test 6)

To investigate the exogeneity of our approach, we also perform the IV estimation with the log of the second lag of household assets (i.e., the level of assets before bereavement occurred) as an added control variable (Table 4.A.8). Due to limited data availability for household assets, this analysis could only be performed for the years 2014-2016 with regard to the onset of problematic debt (2012-2014 with regard to household assets). We find coefficients of 0.0118 ($p > 0.10$), 0.0460 ($p > 0.10$) and -0.0003 ($p > 0.10$). While these estimates are different from those of the main analysis, performing the main analysis on years 2014-2016 only, resulted in coefficients of 0.0118 ($p > 0.10$), 0.0459 ($p > 0.10$) and -0.0002 ($p > 0.10$) for the overall sample, men and women, respectively (Table 4.A.9). This suggests that the change in coefficients is likely due to a reduction in sample size and number of years under study, instead of omitted variable bias affecting assets, bereavement and onset of problematic debt.

[16] Note: in Table 4.2 we present results of the analyses on years 2013 to 2016. Because in this sensitivity test we do not only restrict our analysis to a different sample, but we also had to restrict our data to 2014 and 2016 as we only observe the exact transfer date to CAK from 2013 onwards, we also re-performed the main analyses on these years.

Why defaulting? (robustness test 7)

Lastly, we investigate whether the onset of problematic debt coincides with a general drop in assets by adding the level log household assets to the IV estimation (Table 4.A.10). We find coefficients of -0.0049 ($p > 0.10$), 0.0186 ($p > 0.10$) and -0.0130 ($p > 0.10$) for the overall sample, men and women, respectively. Again, because our data on household assets is limited to 2013-2015, we also re-perform the main analysis on these years. We then obtain coefficients of -0.0052 ($p > 0.10$), 0.0177 ($p > 0.10$) and -0.0131 ($p > 0.10$) for the overall sample, men and women, respectively (Table 4.A.11). This finding suggests that the different results are resulting from a change in the sample size rather than the addition of the log of household assets as a control variable.

4.7 Discussion

In this chapter we investigate the effect of mental health problems on the onset of problematic debt. We do so by exploiting an exogenous shock as an instrument for mental health problems. We estimate a fixed effects model where we use the death of an adult child or sibling, not living in the same household as the individual under observation, as an instrument for mental health problems. Our results indicate that there is indeed a causal link from mental health problems to problematic debt for men. While results vary slightly across different robustness analyses, our main findings hold.

For women, we find that mental health problems as a result of bereavement lead to a lower probability of default on health insurance payments. However, this results is only significant at a 10-percent level. Additionally, it is important to note that the instrument for mental health in this chapter, bereavement, is associated with a specific set of symptoms, not representative of all possible mental health problems. Hence, while this chapter shows that some mental health problems can cause the onset of problematic debt in men, it does not provide proof that this would be the case for all mental health problems. Conversely, while the results of this chapter might tentatively suggest that for women mental health problems lead to a reduced probability of onset of default, it is important to note that these results only hold for mental health problems associated with bereavement and that they provide no information on the effect of other mental health problems on the onset of default.

Moreover, the results in this chapter potentially suffer from a downward bias that might explain the negative causal relationship found for women in the IV analyses. For example, the reception of inheritances after bereavement might lower the possibility that individuals incur problematic debts. If, at the same time, individuals who receive inheritances are more likely to develop mental health problems after bereavement, this might result in negative correlations between bereavement and defaulting. Similarly, help from friends or family after bereavement might also, in itself reduce the probability of default. If individuals with mental health problems after bereavement are more likely to receive help, this would result in a downward bias of the IV estimates. For women, especially, the latter might have been the case, as our analysis where we only used deceased siblings as instruments resulted in a coefficient for women extremely close to zero (Table 4.A.4; column (3)). Assuming individuals are more likely to receive help from family and friends after the loss of a child than after the loss of a sibling, this result tentatively suggests that the negative coefficient for women in the main analysis might be explained by gender-related differences in receiving support. This gender difference in receiving help might not be unlikely, as women are generally also more likely to seek mental healthcare than men, even after controlling for symptom severity (ten Have et al., 2004; Oliver et al., 2005).

Nevertheless, while the robustness analyses were aimed to address downward biases, we cannot be certain that they did so completely, since we are only able to indirectly control for the reception of help or inheritances. While this potential endogeneity of the instrument might explain the results found for women, it does not affect the qualitative reliability of the result for men. Since, if this bias exists, it would mean that, for men, the true causal effect of mental health problems after bereavement on the onset of problematic debt would be even larger than the one already found.

There may also be an upward bias of our results. While we have attempted to ensure that the instruments used in this chapter are exogenous, by including fixed effects, making sample adjustments, testing the exogeneity of the instruments using the Hansen J-statistic, and by performing various robustness analyses, our instrument may, to a certain degree, nevertheless be endogenous, resulting in an upward bias of the coefficient.

First, deceased individuals may have provided vital social and financial support before their death to the individuals under study. In that case, loss of a sibling or child may lead to mental health problems and problematic debts simultaneously. However, if financial support was that vital, the addition of the second lag of log household assets in the robustness checks would likely have affected the results, which did not happen. Hence, loss of social support following the death of a relative resulting in cessation of bill payments cannot fully explain the results of this chapter. This potential source of upward bias is therefore considered to be negligible.

Second, individuals could have accrued debt by providing end-of-life care to their deceased child or sibling (e.g., reduced labor market participation). Our robustness checks tackled this problem in two ways. First, we estimated the IV on a sample which only included deceased children and siblings who still have a living heir. Hence, we use the deaths of family members that likely still had another relative apart from the one under study that could have taken on a large portion of informal care. Second, in another robustness check we only used death of a sibling as an instrument. Assuming that individuals are more likely to provide informal end-of-life care to their child than a sibling, end-of-life care should pose less of a problem in this analysis. Both robustness checks provided comparable coefficients as the main analysis and, therefore, did not change the main conclusions. Hence, our results are unlikely to be the consequence of financial consequences of informal end-of-life care.

Consequently, it is unlikely that the estimates suffer from these sources of upward bias. As such, the results in this chapter indicate a causal relationship between mental health problems and the onset of problematic debt. To our knowledge, this is the first study investigating whether mental health problems cause the onset of problematic debt. Therefore, the results in this chapter provide important knowledge for policy makers, and organizations providing mental healthcare and/or social aid or support.

Our results show that, at least for men, mental health problems can cause problematic debts. As such, interventions aimed at reducing and preventing problematic debts might be more effective if they include effective strategies for improving mental health. Simultaneously, this result highlights that, from a societal perspective, it could be worthwhile to inquire about the financial situation of individuals receiving mental healthcare and to provide resources to help prevent problematic debts to these individuals. Moreover, from a policy perspective, the results from this chapter indicate that effective mental health interventions might have long-term societal savings in the form of prevented problematic debts. Additionally, the results of this chapter open up avenues of further research into the mechanisms of how mental health problems lead to problematic debt. The causal pathway from mental health problems to problematic debts did not appear to be associated with a drop in assets. This suggests that mental health problems directly affect financial decisions and individuals' abilities to meet financial obligations regardless of income and expenses. However, these results are not conclusive as the robustness test focused on a measure of household assets - not individual assets - and did not explicitly include income, expenses, or possible explanators for the behavioral pathway, such as cognitive ability and discount rates. Knowing which of these pathways plays a larger role is important, since it provides information on the potential effectiveness of preventive and reactive measures against problematic debts for individuals with mental health problems. If the liquidity pathway is more important, financial transfers and measures targeting individuals' income and expenses (e.g., career counselling) might be more effective. Since the behavioral pathway appears to be more important, measures targeting income and expenses might be ineffective. Instead, measures easing the cognitive load of payment might be more effective, such as automizing payments. Consequently, in order to design effective interventions and policies based on these results, future research should investigate this potential mechanism from mental health problems to problematic debts.

4.8 Conclusion

Many individuals struggle with problematic debts, which can have far-reaching consequences for debtors, creditors and society as a whole. Many studies have noted a (positive) correlation between mental health problems and problematic debt, however, as of yet there has been no conclusive evidence that mental health problems cause the onset of problematic debts.

This chapter investigated the causal effect of mental health problems on the onset of problematic debt, using administrative records of all individuals living and registered in the Netherlands, by instrumenting mental health problems with the lagged death of a sibling or an adult child, not living in the same household. Our results indicate that there is indeed a causal link from mental health problems to problematic debt for men, where mental health problems can cause the onset of problematic debt. For women, the results tentatively suggest that mental health problems might lower the probability of onset of problematic debt, but these results are only statistically significant at the 10 percent level and might be the result of downward biases on the coefficient. The results from this chapter indicate that interventions aimed at reducing and preventing problematic debts might be more effective if they include effective strategies for improving mental health and that effective mental health interventions might have long-term societal savings in the form of prevented problematic debts.

4.A Appendix

4.A.1 First stage

Table 4.A.1. First stage estimation results

Mental healthcare	All	Men	Women
Deceased children	0.0111***	0.0078***	0.0128***
	(0.0009)	(0.0014)	(0.0012)
Deceased siblings	0.0024***	0.0019***	0.0029***
	(0.0003)	(0.0004)	(0.0004)
Fixed effects	YES	YES	YES
Year dummies	YES	YES	YES
Age controls	YES	YES	YES
individuals	10,716,591	5,185,983	5,530,608
observations	41,584,766	20,059,713	21,525,053

Clustered standard errors in parentheses.
All analyses performed using individual fixed effects, year dummies and a third degree polynomial in age.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

4.A.2 Robustness analyses

Table 4.A.2. Instrument with siblings & children with heirs present

Default	All	Men	Women
Mental healthcare	0.0170	0.1184**	-0.0166
	(0.0193)	(0.0605)	(0.0182)
Hansen J-statistic (p-value)	0.139	0.695	0.283
KP LM statistic	109.196	24.1	85.0
individuals	10,716,591	5,185,983	5,530,608
observations	41,584,766	20,059,713	21,525,053

IV-estimation. Clustered standard errors in parentheses.
All analyses performed using individual fixed effects, year dummies and a third degree polynomial in age.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 4.A.3. Individuals with deductible> 0

Default	All	Men	Women
Mental healthcare	0.0090	0.0855**	-0.0197*
	(0.0126)	(0.0360)	(0.0117)
Hansen J-statistic (p-value)	0.373	0.696	0.746
KP LM statistic	214.8	53.5	163.3
individuals	9,667,801	4,459,206	5,208,595
observations	34,456,351	15,511,890	18,944,461

IV-estimation. Clustered standard errors in parentheses.
All analyses performed using individual fixed effects,
year dummies and a third degree polynomial in age.
*** $p< 0.01$, ** $p< 0.05$, * $p< 0.10$

Table 4.A.4. Instrument only with deceased siblings

Default	All	Men	Women
Mental healthcare	0.0415	0.112	-0.0006
	(0.0324)	(0.0718)	(0.0310)
Hansen J-statistic (p-value)	NA	NA	NA
KP LM statistic	71.1	24.0	47.7
individuals	10,716,591	5,185,983	5,530,608
observations	41,584,766	20,059,713	21,525,053

IV-estimation. Clustered standard errors in parentheses.
All analyses performed using individual fixed effects,
year dummies and a third degree polynomial in age.
*** $p< 0.01$, ** $p< 0.05$, * $p< 0.10$

Table 4.A.5. Individuals who have both children aged > 20 and siblings

Default	All	Men	Women
Mental healthcare	0.0023	0.0687	-0.0214
	(0.0182)	(0.0495)	(0.0173)
Hansen J-statistic (p-value)	0.126	0.260	0.498
KP LM statistic	99.3	27.3	72.642
individuals	2,623,978	1,189,012	1,434,966
observations	9,932,408	4,480,862	5,451,546

IV-estimation. Clustered standard errors in parentheses. All analyses performed using individual fixed effects, year dummies and a third degree polynomial in age.
*** $p< 0.01$, ** $p< 0.05$, * $p< 0.10$

Table 4.A.6. Default defined by first occurrence of arrears

Default	All	Men	Women
Mental healthcare	-0.0037	0.0705	-0.0299*
	(0.0182)	(0.0509)	(0.0178)
Hansen J-statistic (p-value)	0.335	0.755	0.478
KP LM statistic	98.3	23.7	75.6
individuals	10,497,956	5,064,146	5,433,810
observations	31,023,746	14,944,469	16,079,277

IV-estimation. Clustered standard errors in parentheses. Analyses for the years 2014-2016 only. All analyses performed using individual fixed effects, year dummies and a third degree polynomial in age.
*** $p< 0.01$, ** $p< 0.05$, * $p< 0.10$

Table 4.A.7. Main analysis for the years 2014-2016

Default	All	Men	Women
Mental healthcare	0.0088	0.0898*	-0.0200
	(0.0158)	(0.0467)	(0.0151)
Hansen J-statistic (p-value)	0.586	0.564	0.678
KP LM statistic	98.3	23.7	75.6
individuals	10,497,956	5,064,146	5,433,810
observations	31,023,746	14,944,469	16,079,277

IV-estimation. Clustered standard errors in parentheses. Analyses for the years 2014-2016 only. All analyses performed using individual fixed effects, year dummies and a third degree polynomial in age.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 4.A.8. Control for log of assets

Default	All	Men	Women
Mental healthcare	-0.0049	0.0186	-0.0130
	(0.0139)	(0.0416)	(0.0127)
Hansen J-statistic (p-value)	0.768	0.695	0.876
KP LM statistic	77.6	16.9	61.9
individuals	7,987,577	3,786,835	4,200,742
observations	22,949,880	10,857,318	12,092,562

IV-estimation. Clustered standard errors in parentheses. Analyses for the years 2013-2015 only. All analyses performed using individual fixed effects, year dummies and a third degree polynomial in age and the natural log of household assets.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 4.A.9. Main analysis for sample with log of assets

Default	All	Men	Women
Mental healthcare	-0.0052	0.0177	-0.0131
	(0.0139)	(0.0415)	(0.0127)
Hansen J-statistic (p-value)	0.760	0.696	0.866
KP LM statistic	77.6	16.9	61.9
individuals	7,987,577	3,786,835	4,200,742
observations	22,949,880	10,857,318	12,092,562

IV-estimation. Clustered standard errors in parentheses. Analyses for the years 2013-2015 for indivdiduals with available asset data only. All analyses performed using individual fixed effects, year dummies and a third degree polynomial in age.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 4.A.10. Control for second lag of log assets

Default	All	Men	Women
Mental healthcare	0.0118	0.0460	-0.0003
	(0.0116)	(0.0348)	(0.0098)
Hansen J-statistic (p-value)	0.028	0.253	0.065
KP LM statistic	93.8	23.0	71.5
individuals	7,990,366	3,791,980	4,198,386
observations	22,926,139	10,858,351	12,067,788

IV-estimation. Clustered standard errors in parentheses. Analyses for the years 2014-2016 only. All analyses performed using individual fixed effects, year dummies and a third degree polynomial in age and lag 2 of the natural log of household assets.
*** $p< 0.01$, ** $p< 0.05$, * $p< 0.10$

Table 4.A.11. Main analysis for sample with second lag of log assets

Default	All	Men	Women
Mental healthcare	0.0118	0.0459	-0.0002
	(0.0116)	(0.0348)	(0.0098)
Hansen J-statistic (p-value)	0.028	0.253	0.065
KP LM statistic	93.8	23.0	71.5
individuals	7,990,366	3,791,980	4,198,386
observations	22,926,139	10,858,351	12,067,788

IV-estimation. Clustered standard errors in parentheses. Analyses for the years 2014-2016 for indivdiduals with available lag 2 asset data only. All analyses performed using individual fixed effects, year dummies and a third degree polynomial in age.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Chapter 5

Health and Labour Supply over the Lifecycle: Mental and Physical Health and the Role of Labour Market Experience*

* This chapter is based on (Dijk, Groneck & Mierau, 2020). In this paper use is made of data of the LISS (Longitudinal Internet Studies for the Social sciences) panel administered by CentERdata (Tilburg University, The Netherlands). We want to thank participants from the 2019 Viennese Vintage Workshop on Heterogeneous Dynamic Models of Economic and Population Systems for their comments.

5.1 Introduction

Poor health is associated with major reductions in labor supply and losses in lifetime earnings. For example, De Nardi et al. (2017) estimate that individuals can lose on average $1,243 in annual earnings due to bad health. Similarly, Capatina (2015) shows that poor health is particularly detrimental to non-college labour supply: poor health leads to a reduction of labour supply of 11%. French (2005) suggests that 10% of the drop in employment for US individuals aged 55-70 can be explained by poor health.

As health is generally considered to be declining with age, many lifecycle models investigating the consequences of poor health have focused more on later stages in the lifecycle, such as retirement (French, 2005; French & Jones, 2011) or saving behaviour of the elderly (De Nardi et al., 2010; Palumbo, 1999). Studies that look at younger ages generally also model health as declining with age (Capatina, 2015; De Nardi et al., 2017; Capatina et al., 2018). Additionally, they generally investigate the effects of poor health on individual savings and labour market decisions through channels such as individual labour market productivity, disutility[1] of poor health, survival rates, medical cost and insurance (Capatina, 2015; French, 2005; De Nardi et al., 2017) and social security (Pashchenko & Porapakkarm, 2017).

These lifecycle models generally view health problems as a broad composite by using individual's subjective health rating into categories as poor, fair, good and excellent (e.g., Capatina, 2015; De Nardi et al., 2017), which, like physical health tends to show a pattern of declining health with age (Capatina, 2015; De Nardi et al., 2017; Capatina et al., 2018). However, by using one overall score, previous studies might have ignored potential dichotomies in health, particularly between mental and physical health.

Mental health problems constitute a major component of overall health impairment: approximately 20% of the working age population suffers from a mental disorder at any point in time and lifetime prevalence is estimated to be up to 50% (OECD, 2012). This high prevalence results both in an extremely large burden of disease[2] (Murray et al., 2012; Whiteford et al., 2013), as well as significant estim-

[1] Or time cost.

[2] Burden of disease is determined by adding the number of years of life lost due to a disease to the number of years lived with disability due to a disease.

ated societal costs: mental health problems are estimated to be the leading cause of years lived with disability worldwide (Whiteford et al., 2013) and the societal cost of mental disorders is estimated to be 3 to 4% of GDP in OECD countries (OECD, 2012, 2014).

Mental health problems are also associated with substantial reductions in labour supply. In OECD countries, employment rates for individuals with mental health problems are approximately 10 to 15% lower (OECD, 2012). In the Netherlands, social benefit recipients (excluding pension payments) receive mental healthcare three times more often than working individuals (Einderhand & Ravesteijn, 2017). This indicates that poor mental health might play an important role in the overall labour market consequences of poor health.

Importantly, mental health appears to follow a lifecycle pattern that is distinctly different from physical health. Whereas physical, and subjective, health generally appears to worsen with age, the majority of mental health problems start early in life: before age 14 (Kessler et al., 2005). Studies investigating the lifecycle pattern of mental health suggest that mental health, unlike physical health, does not follow a simple decline as individuals age, but that instead individuals might be vulnerable to poor mental health at younger ages compared to the ages at which most physical health problems occur (Bell, 2014; Blanchflower & Oswald, 2008, 2016; Dijk & Mierau, 2019; Lang et al., 2011; Le Bon & Le Bon, 2014). Since mental health problems generally appear to occur earlier in the lifecycle than physical or subjective health problems, the labour market consequences of poor mental health, in terms of reductions in labour supply and productivity, might occur earlier in the lifecycle as well.

Ignoring these differences in lifecycle patterns could lead to an underestimation of labour market costs. Especially, since absences from the labour market earlier in life can have wage effects later in life through loss of experience (Attanasio et al., 2008; Blundell et al., 2016; Bronson & Mazzocco, 2019). This channel, through which poor health might affect later labour market supply and productivity has not been previously investigated. Even studies that focus on lifetime cost of poor health (Capatina, 2015; De Nardi et al., 2017) do not take mental health and the potential effect it might have due to loss of labour market experience into account.

Consequently, this chapter considers the consequences of explicitly modelling mental and physical health problems as two different processes in an individual lifecycle model to assess the labour costs of poor health. This way, we can assess the effects of poor physical and mental health, both separately and combined. Additionally, we can assess how much of the overall cost of bad health previous studies might have potentially missed by viewing health as a singular process that can be summarized by subjective health. To account for the fact that mental health problems might generally occur earlier in the lifecycle, we explicitly model potential human capital effects of bad health through lost labour market experience.

To ensure that the results from this study are also informative about previous literature, we mostly follow previous lifecycle models that study the labour market consequences of poor health (i.e., French, 2005; Capatina, 2015). In the model, individuals choose their consumption level and labour market participation, subject to potential mental and physical health shocks that affect both utility levels and individual wages. In turn, labour participation choices affect future wages through the accumulation and depreciation of labour market experience. Both mental health and physical health affect individuals through three channels. Firstly, individuals in poor health earn lower wages. Secondly, individuals in poor health have a health-state specific disutility, that shifts preferences for leisure and labour. Thirdly, if individuals decide not to work in a certain period due to their health problems, future wages will be lower due to the loss of labour market experience.

We calibrate the model for Dutch men aged 30-85 using data from the LISS panel.[3] We find that the labour market losses, in terms of net lifetime earnings, due to poor mental health are substantial and comparable to those from poor physical health: €153,446.5 and €166,487.1 per individual, respectively. Additionally, we find that not taking human capital in terms of labour market experience into account might potentially lead to an overestimation of lost earnings due to poor health.

The effect of explicitly modelling the effects of labour market experience results in a two-sided tale. On one hand, the inclusion of labour market experience in our model results in persistent losses in net earnings for those individuals that decide

[3] The LISS panel is a representative sample of Dutch individuals who participate in monthly Internet surveys. The panel is based on a true probability sample of households drawn from the population register. Households that could not otherwise participate are provided with a computer and Internet connection. A longitudinal survey is fielded in the panel every year, covering a large variety of domains including work, education, income, housing, time use, political views, values and personality.

not to work due to poor health, as a result of lost labour market experience. On the other hand, the inclusion of a labour market experience mechanism provides an alternative form of precautionary savings: instead of assets, individuals can also accumulate human capital to reduce the risk of future low labour market earnings due to future health shocks. Additionally, individuals have an incentive to keep working, even if they are in poor health, to prevent future losses in earnings. As such, lifecycle models assessing the consequences of poor health and health risk might, therefore, potentially overestimate the negative effect of health risk on employment rates if they do not take this mechanism of labour market experience into account.

We start our analysis by a series of stylized facts (Section 5.2), after which the model and the calibration and estimation of model parameters is described in Sections 5.3 and 5.4. Section 5.5.1 contains an investigation of counterfactuals to assess to lifetime labour market consequences of poor mental and physical health, as well as an investigation of the importance of the different channels through which health can influence individuals' choices. Lastly, Section 5.6 provides a conclusion.

5.2 Stylized facts

We start our investigation by assessing whether the patterns and concepts described above are also visible in the LISS data. For a detailed overview of the data and measures used, see Appendix 5.A. In the introduction we stated that 1) mental health follows a lifecycle pattern that is distinctly different from physical and subjective health and 2) mental and physical health problems are both associated with lower employment and wages. If these statements hold true, then a lifecycle model considering health as a singular process that can be modelled using a Markov process for subjective health (e.g., Capatina, 2015; De Nardi et al., 2017; Capatina et al., 2018) will likely ignore much of the labour market effects of poor mental health. Consequently, in such a case, a life cycle model in which both the lifecycle pattern of mental and physical health are explicitly modelled as separate states/processes is warranted.

To assess whether mental and physical health indeed follow two distinct patterns we start our analyses by plotting both over the lifecycle. Figures 5.1a and 5.1b show the different patterns for mental health and physical health. While physical health declines as individuals age, mental health seems to first increase and later decline in old age. These effects appear to be mostly age effects, as different cohorts seem to have similar scores at similar ages.

Does subjective health reflect one of these patterns more than the other? For this we construct indices of both mental and physical health scores and a create an index for a subjective health score. Figure 5.2 provides a plot of the index of subjective health next to those for physical and mental health. While both subjective and physical health decline as individuals age, mental health shows the pattern described above. [4]

The combination of the different lifecycle patterns for mental and physical health and the fact that subjective health more closely follows physical health does not need to be a problem for lifecycle models that investigate the interaction between labour and health if mental health shows no significant interactions with the labour market. Consequently we assign individuals to health states and plot employment and log wages in Figures 5.3a and 5.3b. For more details on the states and wage data see Appendix 5.A. While the correlation between mental health and log wages seems unclear from the graph, mental health problems do appear to be associated with a moderate decline in employment.

Consequently, our data appears to confirm that mental health follows a lifecycle pattern that is distinctly different from physical and subjective health and mental and physical health problems are associated with lower employment. As a result, physical and mental health cannot be adequately modelled by only using a Markov-process for subjective health.

5.3 Model

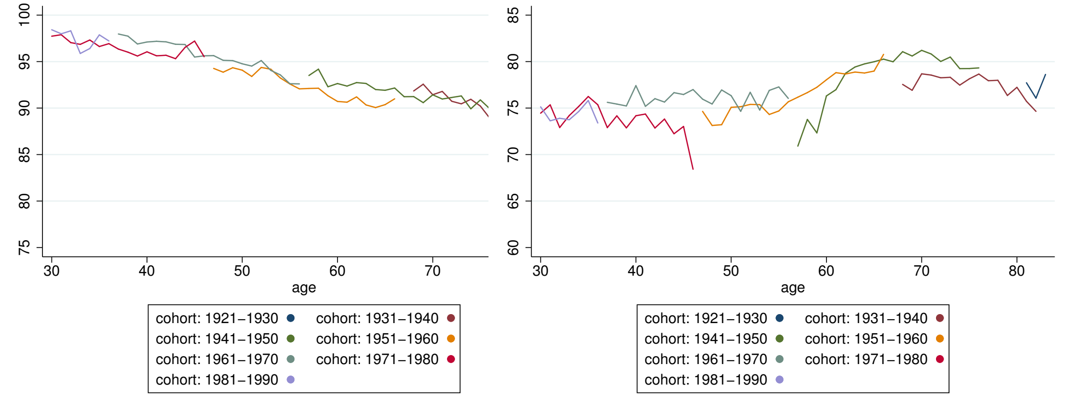
To abstract from education choices, we model individuals from age 30 to age 85. All individuals work until age 65 after which we assume that individuals retire.[5] Each

[4] While qualitatively all scales are comparable, as in lower scores mean worse health, they are not necessarily quantitatively comparable: we cannot be sure that a 5% decline in one scale is equivalent to a 5% decline in another scale. Hence, it is not surprising that subjective health declines more than physical health in Figure 5.2.

[5] Before 2013, the statutory retirement age in the Netherlands was 65. From 2013 onwards the statutory retirement age has gradually increased to 65 years and 1 month in 2013; 65 years and 2 months in 2014; 65 years and 3 months in 2015; 65 years and 6 months in 2016; 65 years and 9 months in 2017; 66 years

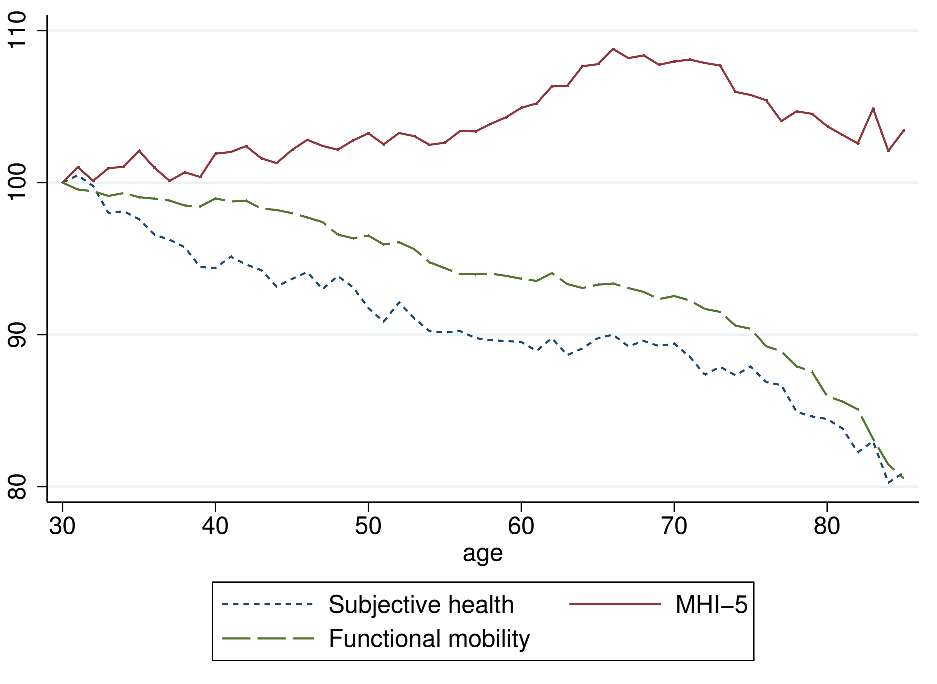
Figure 5.1. Age-health profiles

(a) Average scores for physical health (b) Average scores for Mental Health



Average health scores by age and 10-year cohort. Higher scores indicate better health. For a detailed description of the data used for the construction of the graphs see Appendix 5.A. Age-cohort groups with fewer than 50 observations are excluded.

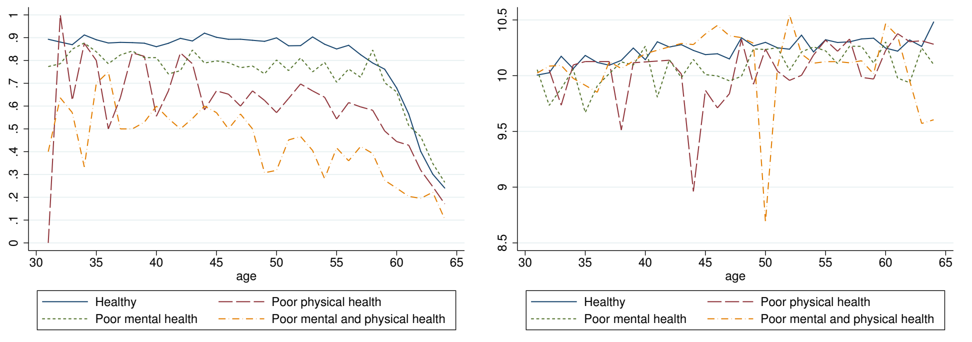
Figure 5.2. Indices for mental, physical and subjective health, age 30=100



Indices of average health scores by age. For a detailed description of the data used for the construction of the graphs see Appendix 5.A.

Figure 5.3. Employment and earnings by health states

(a) Employment (b) Log earnings



period (t), an individual's health state is determined through an age- and gender-dependent Markov process. To account for the distinct lifecycle-patterns of physical and mental health, we model four health states: good health, poor physical health, poor mental health, and both poor physical and mental health. Age-dependent transition-probabilities between health states ensure that both physical and mental health follow the lifecycle patterns observed in the data.

Depending on their health state (h) individuals incur a disutility, or time cost, ϕ_h.[6] After observing their health state individuals choose whether to work, through which they can earn a wage (W_t), but incur a time cost (θ). Wages depend on labour market experience, the current health state and an individual fixed effect. Additionally, each period, individuals choose their levels of consumption and their savings subject to a borrowing constraint of 0. Consequently, health affects individuals in three possible ways. Firstly, it affects an individual's direct labour market productivity, affecting W_t. Secondly, poor health comes with a time cost, or equivalently a disutility. Lastly, since individuals' human capital is affected by their labour market experience, previous labour market participation decisions (affected by previous health states) affect current labour market productivity.

in 2018. The average age at which individuals retired rose from 61.7 in 2007 to 64.8 in 2018. Between 2011-2017 the modal age of retirement was 65, before then the modal age was lower (60-62 years), in 2018 the modal age was 66 (Statistics Netherlands, 2021).

[6] Introducing a health-state dependent time-cost in the utility function is roughly equivalent to a health-state dependent disutility.

5.3.1 Preferences

Each period (t), individuals derive utility from consumption of non-medical goods (c_t) and leisure (l_t):

$$U_t(c_t, l_t) = \frac{1}{1-\sigma}\left(c_t^{\alpha} l_t^{1-\alpha}\right)^{1-\sigma}, \tag{5.1}$$

where

$$l_t = 1 - \theta L_t - \sum_{h \in [P,M,MP]} \Phi_h I_h. \tag{5.2}$$

In equation 5.1, σ is a preference parameter that accounts for the degree of substitution between leisure and consumption, as well as the degree of relative risk-aversion. $I_{h=P}$, $I_{h=M}$ and $I_{h=MP}$ are indicator variables indicating whether an individual suffers from poor physical health, poor mental health, or both poor physical and mental health, respectively. L_t indicates whether individual is working ($L_t = 1$) or not ($L_t = 0$). Consequently, θ, Φ_P, Φ_M and Φ_{MP} represent the time cost of working, poor physical health, poor mental health, and both poor physical and mental health, respectively.

5.3.2 Budget Constraint

To account for the Dutch social security system, there is an income floor $\bar{y}$ below which individuals, regardless of labour participation, are reimbursed until they reach $\bar{y}$. Hence, income is determined by

$$y_t = \max\{W_t, \bar{y}\}, \tag{5.3}$$

where W_t denotes the individual's earnings if he decides to work in period t. Consequently, assets evolve according to

$$a_{t+1} = (1+r)a_t + y_t - c_t, \tag{5.4}$$

where a_t denotes the amount of assets at the beginning of period t.

5.3.3 Earnings

For the wage equation, we combine the earnings processes employed by Bronson and Mazzocco (2019) and Capatina (2015). Earnings depend on labour market experience similarly to Bronson and Mazzocco (2019). When individuals work in every period, the wage equation reverts back to the wage equation used by Capatina (2015), with the exception that, in that case, our wage equation contains a second order polynomial in age, whereas Capatina (2015) uses a third degree polynomial.

Labour earnings at age t are given by:

$$\ln(W_{t,h}) = w(e_t, h_t) + \bar{\mu} + \lambda_t + u_t, \tag{5.5}$$

where $\bar{\mu}$ is an individual fixed effect with $\mu \sim \mathcal{N}(0, \sigma_\mu^2)$, λ_t is an idiosyncratic transitory shock where $\lambda_t \sim \mathcal{N}(0, \sigma_\lambda^2)$ and u_t is an idiosyncratic shock following an AR(1) process with $u_t = \rho u_{t-1} + \eta_t$, $u_{i,0} = 0$ and $\eta_t \sim \mathcal{N}(0, \sigma_\eta^2)$. The deterministic component of labour earnings $w(e_t, h)$ is a function of (latent) previous labour market experience e_t, health and health interacted with labour market experience.

$$\begin{aligned} w(e_t, h_t) = &\beta_0 + \beta_1 e_t + \beta_2 e_t^2 + (\beta_3 + \beta_4 e_t) I_{h=P} + (\beta_5 + \beta_6 e_t) I_{h=M} \\ &+ (\beta_7 + \beta_8 e_t) I_{h=MP}, \end{aligned} \tag{5.6}$$

where e_t evolves according to

$$e_t = e_{t-1} + L_{t-1} + \delta(1 - L_{t-1}), \tag{5.7}$$

where L_{t-1} is a dummy variable taking value 1 if the individual worked in the previous period and 0 when the individual did not work in the previous period. I.e., when individuals work in a given year, experience increases by 1 in the next year, but when individuals do not work, experience depreciates by δ. Furthermore, we assume $e_0 = 0$ and $L_0 = 0$. In other words, when individuals enter the model, they are assumed to have no labour market experience.

5.3.4 Health status, medical expenses and insurance

Health shocks follow an age-, and gender-, dependent Markov process, where individuals can switch between four different health states: good mental and physical health ($h = H$), poor mental health and good physical health ($h = M$), poor physical health and good mental health ($h = P$), and poor mental and physical health ($h = PM$). Individuals cannot actively invest in their health, which is common in the literature (e.g., French, 2005; French & Jones, 2011; De Nardi et al., 2017).

We abstract from health-insurance decisions and out-of-pocket expenditures, which is in line with the Dutch healthcare system. The Dutch Health Insurance Act mandates that every individual has to purchase a basic health insurance plan whose coverage is extensive and largely government mandated. Consequently, individual insurance decisions are limited. Additionally, co-payments in this basic plan are small and almost non-existent and the government mandated deductible is low: €350 in 2018. [7] As such, out-of-pocket payments are relatively small and unlikely to drive model outcomes.

5.3.5 Retirement

We model a retirement phase from age 65 to 85. When individuals retire at age 65, they receive a pension based on the average earnings potential at age 64, regardless of whether they worked in that period, and a replacement rate of retirement income, the latter of which is constant across individuals and health and income states. I.e.,

$$\ln(W_{t>64}) = R\big(w(\bar{e}, h_{t=64}) + \bar{\mu} + \lambda_{t=64} + u_{t=64}\big), \tag{5.8}$$

where R denotes the replacement rate of net retirement income and $\bar{e}$ is the average experience at age 64. Additionally, once retired, individuals remain in their previous health states. I.e., heterotypic transition probabilities are set to zero, and homotypic transition probabilities are set to unity. In retirement, individuals decide on their consumption level, but they can no longer participate in the labour market.

[7] Individuals can opt for a higher deductible plan, but even then deductibles remain relatively low: the maximum deductible was €850 in 2018.

5.3.6 Individual's problem

Individuals solve

$$\begin{aligned} V(h_t, t, a_t, e_t, \bar{\mu}, \lambda_{t+1}, u_t) =& \max_{c_t, L_t,} [U(c_t, L_t, h) \\ &+ \beta \mathrm{E} V(h_{t+1}, t+1, a_{t+1}, e_{t+1}, \bar{\mu}, \lambda_{t+1}, u_{t+1})], \end{aligned} \tag{5.9}$$

s.t. equations 5.4, 5.7, 5.5, 5.8 and 5.2. β denotes the discount factor and $t = 1$ when individuals are aged 30 and terminal age is at $t = 55$ (age 85). We abstract from survival probabilities, since mortality is not observed in LISS. Additionally, the ages of interest in the model are 30 to 65, at which mortality is low.

5.4 Calibration and estimation

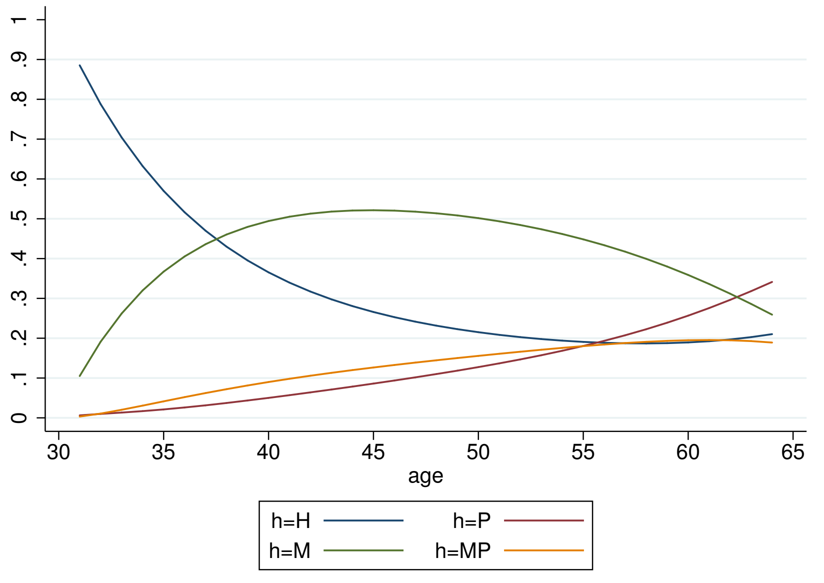
We simulate a population of men from age 30-85. Table 5.4 provides parameter inputs, as well as their source. The model is calibrated to match Dutch men in the period 2007-2018, who are either employed or not employed, but not self-employed. Our strategy is threefold, some parameters are estimated directly from the data, some parameters are selected from the literature and all other parameters are calibrated targeting specific moments from employment observed in the data. Calibrated parameters are the disutilities of labour (θ) and health (Φ_P, Φ_M and Φ_{MP}). Estimated parameters consist of health state transition probabilities, parameters detailing the stochastic and deterministic component of wages and the income floor. Parameters selected from the literature consist of the coefficient of relative risk aversion (σ), the discount factor (β), the consumption weight (α), the interest rate (r) and the replacement rate of retirement income (R).

The model period is set to one year and we model individuals from age 30 onwards with terminal age 85.

5.4.1 Health state transitions

For a description of the health states see Appendix 5.A. State transitions are estimated, similarly to Capatina (2015), using logistic regression models with a third

Figure 5.4. Health states by age



Proportion of the population in predicted health states by age, starting with a completely healthy population.

degree polynomial for age:

$$
\begin{aligned}
Logit(\tilde{h}_{i,t}|\mathbf{x_{i,t}}) =& \xi_0 + \xi_1 M_{i,t-1} + \xi_2 P_{i,t-1} + \xi_3 (M_{i,t-1} \times P_{i,t-1}) + \xi_4 t_i + \xi_5 t_i^2 \\
&+ \xi_6 t_i^3 + \eta_{i,t},
\end{aligned}
$$

where ξ_0 to ξ_6 are the parameters to be estimated. We refrain from using an ordered logistic regression model since the two dimensions of physical and mental health make an objective ordering of the states impossible. Hence, we treated transitions as sequential: we first estimated a logistic regression model for the probability of transitioning to good or poor mental health, after which we estimated logistic regressions conditional on the current mental health state. Results for these models are provided in Table 5.1. Using these logit results we can construct an age-dependent Markov-process for the four different health states.

Table 5.1. Results logistic regressions health state transitions

	$h = M, MP$	$h = P$	$h = MP$
Counterfactual†	$h = H, P$	$h = H$	$h = M$
Constant	2.970	-0.111	-9.150
	(3.678)	(9.644)	(13.531)
$h_{-1} = M, MP$	2.349***	0.842***	0.279
	(0.065)	(0.211)	(0.225)
$h_{-1} = P, MP$	0.785***	6.062***	5.691***
	(0.094)	(0.137)	(0.383)
$h_{-1} = MP$	0.135	-0.634*	0.199*
	(0.134)	(0.332)	(0.480)
age	-0.352	-0.385	0.392
	(0.238)	(0.607)	(0.869)
age^2	0.008	0.009	-0.009
	(0.005)	(0.012)	(0.018)
age^3	-6.04e-05*	-6.65e-05	7.05e-05
	(3.46e-05)	(8.36e-05)	(1.24e-04)
Observations	12,238	10,104	2,134

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

†: health state when the dependent variable equals zero

5.4.2 Estimation of the wage parameters

Since the LISS data only contains observations between 2007 and 2018 we do not know the complete labour market history of all individuals and thus we cannot construct a measure of e_t for all individuals. Consequently, we estimate the deterministic component of wages with LISS data using a sample of men aged 30-65 that in a 2009 survey have indicated to have never been out of the labour force for more than six months since starting their first job, for years after 2009 we include these same individuals as long as they have indicated to be employed for at least 16 hours per week in each previous, starting from 2009. Additionally, we include individuals who were aged 30 at some point between 2007-2018 and, in the given year, have indicated to be employed for at least 16 hours per week in each previous period, starting from age 30.

For these individuals, the deterministic component of wages at period t is equivalent to

$$\begin{aligned} w(t, h_t) =& \beta_0 + \beta_1 t + \beta_2 t^2 + (\beta_3 + \beta_4 t) I_{h=P} + (\beta_5 + \beta_6 t) I_{h=M} + (\beta_7 \\ &+ \beta_8 t) I_{h=MP}. \end{aligned} \tag{5.10}$$

We first estimate this deterministic component of labour earnings $w(t, h_t, j)$ combined for all years to obtain parameter estimates for β_0-β_8 using ordinary least squares (OLS).

We then perform the same estimation separately for each year to extract the stochastic component of wages from the residuals. From these residuals estimates we construct a variance-covariance matrix of residual wages for different years. Using this variance-covariance matrix we estimate $\hat{\sigma}^2_\mu$, $\hat{\sigma}^2_\lambda$, $\hat{\sigma}^2_\eta$ and $\hat{\rho}$ using GMM. Estimation results of these parameters can be found in Table 5.2. These estimation results are similar to Capatina (2015), with the exception of $\hat{\rho}$, which is considerably lower in our estimation (0.36 compared to 0.89 to 0.97 in (Capatina, 2015)).

While the limited number of years of LISS data does not allow for the construction of individual values for e_t in the data, we can estimate average experience at age 64, by computing average lifetime employment at age 64. I.e., we take the average of average employment by age for ages 30 to 64, and compute $\bar{e}$ using equation

Table 5.2. Estimation results labour earnings equation from data

Parameter	Description	
$\hat{\sigma}^2_\mu$	Variance of individual fixed effect	0.1177
$\hat{\sigma}^2_\lambda$	Variance of transitory shocks	0.2403
$\hat{\sigma}^2_\eta$	Variance of the innovation	0.0571
$\hat{\rho}$	Autoregressive coefficient	0.3604

Table 5.3. Estimation results labour earnings equation from data

Parameter	
β_0	10.0148***
	(0.0545)
β_1	0.0192***
	(0.0066)
β_2	-0.0004**
	(0.0002)
β_3	-0.2155
	(0.2608)
β_4	0.0028
	(0.0106)
β_5	-0.2843***
	(0.0833)
β_6	0.0077*
	(0.0043)
β_7	0.0019
	(0.2971)
β_8	-0.0033
	(0.0125)
Observations	2,143

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.7.[8]

5.4.3 Income floor

The income floor is estimated using the average net monthly income of individuals aged 30-65 that are not in in paid employment for 16 hours or more, or self-employed. We assume income floors are equal for men and women. To obtain a yearly income floor, the monthly income floor was multiplied by 12.

5.4.4 Calibration of utility parameters

The disutilities of labour (θ) and health (Φ_P, Φ_M and Φ_{MP}) are identified using age-employment profiles by health state from age 30-64 from the data and model. θ is calibrated, as opposed to being an equivalent of hours worked, so that it also includes non-productive time and utility losses from work, such as travel time or utility losses due to stress.[9] For the data moments, individuals are considered to be employed when they work 16 hours or more per week on average and are not self employed or employed in a family business.

The calibration minimizes the sum between the squared differences between the data moments, $\mathcal{M}^D$, and the corresponding model outcomes, $\mathcal{M}^S(\gamma)$, for the set of parameters $\gamma' = [\theta, \Phi_P, \Phi_M, \Phi_{MP}]$. All calibration targets are weighted equally. As specific calibration targets we use employment profiles by health state. More formally, the algorithm solves the problem:

$$\min_{\gamma}\Big(\mathcal{M}^D - \mathcal{M}^S(\gamma)\Big)'\Big(\mathcal{M}^D - \mathcal{M}^S(\gamma)\Big), \tag{5.11}$$

where $\mathcal{M}^D$ and $\mathcal{M}^S(\gamma)$ are vectors containing employment rates by age and health state from the data and model, respectively. We start all calibrations and simulations with a healthy population at age 30.

5.5 Model outcomes

[8] We find a lifetime employment rate of 76.675%. Consequently, given equation 5.7 and the value for δ (see Table 5.4), $\bar{e} = (0.76675 - 1.076(1 - 0.76675)) * 35 = 18.052$.

[9] On the other hand, individuals might very much enjoy their work. In that case the disutility of labour migth actually be lower than its equivalent time cost.

Results from a preliminary calibration are presented in Table 5.5. Figures 5.5 and 5.6 show model and data employment and wage rates for different health states. The disutilities from poor health are slightly larger for poor physical health than poor mental health: 0.18 for poor physical health, 0.12 for poor mental health and 0.38 for the combination of poor physical and mental health.

Table 5.4. Exogenous model parameters

Parameter	Description	Values	Source
σ	Coefficient of relative risk aversion	2.8	(Capatina, 2015)
α	Consumption weight (utility)	0.4	(Capatina, 2015)
β	Time discount factor	0.974	(Capatina, 2015)
δ	Depreciation rate of labour market experience	1.076	(Bronson & Mazzocco, 2019)
$\bar{y}$	Income floor	11309.54	LISS data
$\bar{e}$	Average experience at retirement	18.052	LISS data
r	Interest rate	1.04	(Capatina, 2015)
R	net replacement rate of retirement income	1.05	(Knoef et al., 2017)

δ was constructed by averaging high-school and college estimates from Bronson and Mazzocco (2019)

Table 5.5. Exogenous model parameters

Parameter	Description	Values
θ	Time cost of work	0.24
Φ_P	Time cost of poor physical health	0.18
Φ_M	Time cost of poor mental health	0.12
Φ_{MP}	Time cost of poor physical and mental health	0.38

Table 5.6. Counterfactual analyses: baseline

Description	Net lifetime earnings	Employment
Cost of poor health	€187,870.8	13.3 p.p.
Cost of poor mental health	€153,446.5	10.6 p.p.
Cost of poor physical health	€166,487.1	12.3 p.p.

p.p.: percentage points

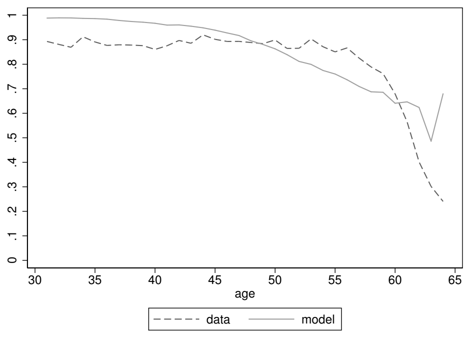
Table 5.7. Counterfactual analyses: model without experience

Description	Net lifetime earnings	Employment
Cost of poor health	€171,035.4	13.8 p.p.
Cost of poor mental health	€140,376.2	11.3 p.p.
Cost of poor physical health	€154,513.7	12.8 p.p.

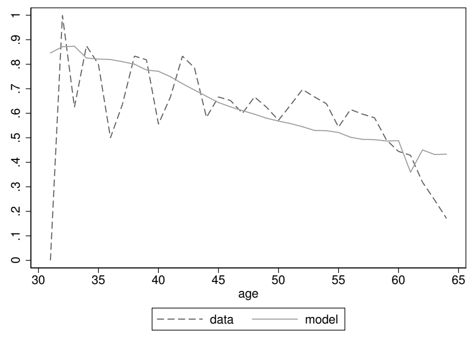
p.p.: percentage points

Figure 5.5. Employment rates from data and calibrations

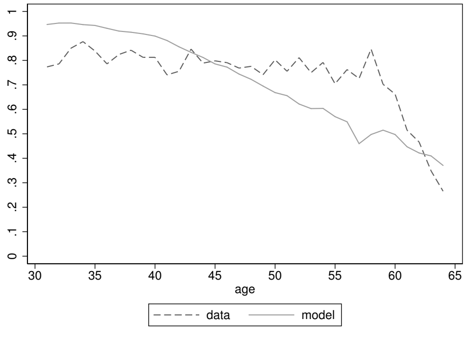
(a) Employment rates men when $h = H$



(b) Employment rates men when $h = P$



(c) Employment rates men when $h = M$



(d) Employment rates men when $h = MP$

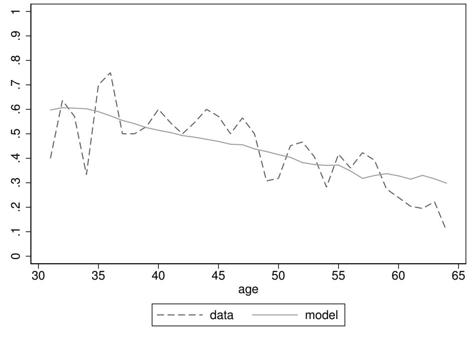
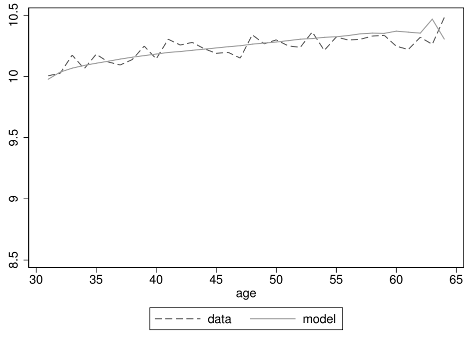
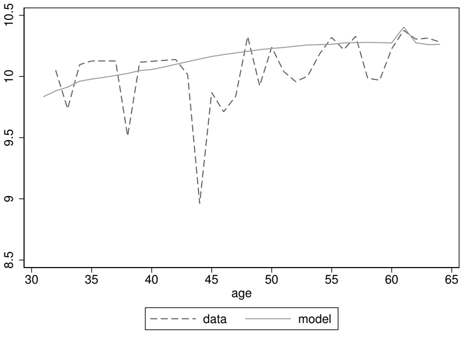


Figure 5.6. Log earnings from data and calibrations

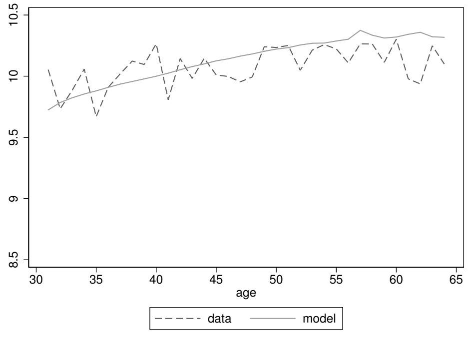
(a) Log earnings men when $h = H$



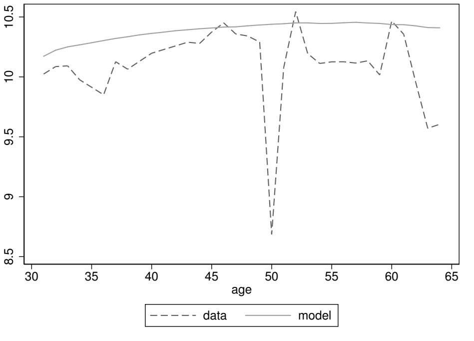
(b) Log earnings men when $h = P$



(c) Log earnings men when $h = M$



(d) Log earnings men when $h = MP$



5.5.1 The effect of poor health on earnings and employment

We assess the effects of poor health by simulating a population without health risk, where all individuals remain healthy. Poor health results in an average of €187,870.8 in lost individual net lifetime earnings, excluding retirement income, both due the direct loss of earnings by not working, direct losses in productivity when individuals do work when in poor health and loss of future wages due to reduced human capital as a result of not working due to poor health. Poor health leads to a lower overall employment rate of 72.2% as opposed to 85.5%. The specific loss due to poor physical health consists of an average of €166,487.1 in lost individual net lifetime earnings and average yearly employment over ages 30-65 is higher if individuals cannot suffer from physical health problems (84.4% as opposed to 72.2%).[10] The specific loss due to poor mental health consists of an average of €153,446.5 in lost individual net lifetime earnings and mental health problems lead to a decrease in the average yearly employment rate over the lifecycle from 82.8% to 72.2%.[11] The fact that these separate numbers due to poor mental or physical health do not sum to the total loss due to poor health is due to composite effects of both health states

We also consider the role of the different channels through which health can influence model outcomes. These analyses are graphed in Figure 5.7. Firstly, we shut down the role of human capital depreciation by setting $e_t = t$ for all individuals, regardless of whether they worked in previous periods or not. Unsurprisingly, this leads to higher average log earnings. Additionally, employment is much lower due to the fact that current employment no longer affects future earnings. Consequently, while poor health might lower employment through the other chan-

[10] We obtain this result by assuming that all individuals in the baseline calibrations that would have been in the poor mental health state are now in good health and that all individuals in the health state with both poor physical and mental health are now in the poor physical health state. I.e., we construct new transition probabilities ($\pi^*_{h_t,h_{t+1}}$) for just the states $h = H, P$ from the probabilities used in the baseline model ($\pi_{h_t,h_{t+1}}$) according to

$$\pi^*_{h_t=H,h_{t+1}=H} = \pi_{h_t=H,h_{t+1}=H} + \pi_{h_t=H,h_{t+1}=M}, \tag{5.12}$$

$$\pi^*_{h_t=H,h_{t+1}=P} = \pi_{h_t=H,h_{t+1}=P} + \pi_{h_t=H,h_{t+1}=MP}, \tag{5.13}$$

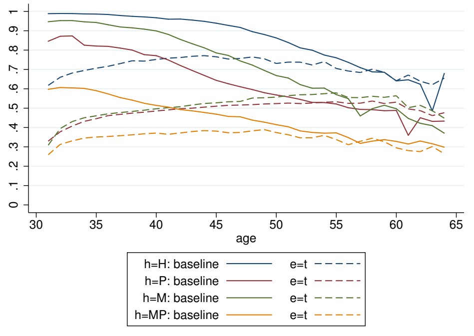
$$\pi^*_{h_t=P,h_{t+1}=H} = \pi_{h_t=P,h_{t+1}=H} + \pi_{h_t=P,h_{t+1}=M}, \tag{5.14}$$

$$\pi^*_{h_t=P,h_{t+1}=P} = \pi_{h_t=P,h_{t+1}=P} + \pi_{h_t=P,h_{t+1}=MP}. \tag{5.15}$$

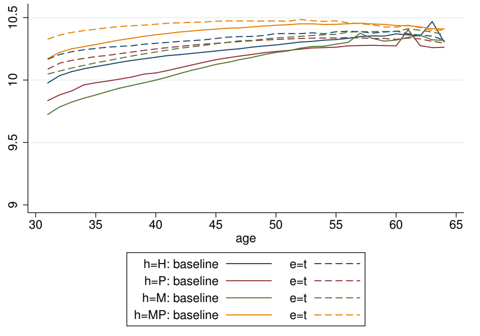
[11] This result is obtained in a similar fashion as the result for the cost of poor physical health.

Figure 5.7. Effects of different channels

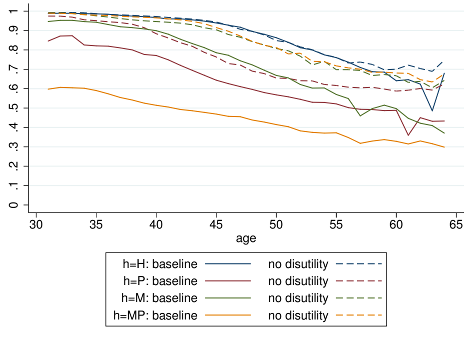
(a) Experience: employment



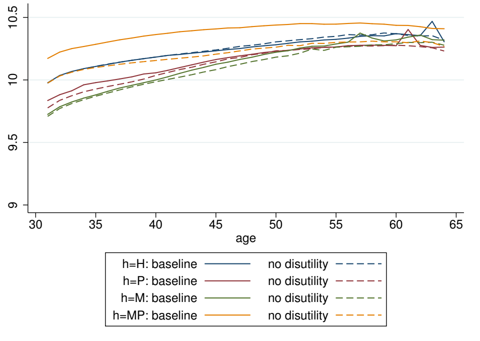
(b) Experience: log earnings



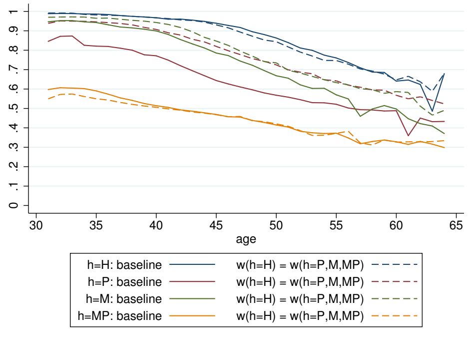
(c) Disutility: employment



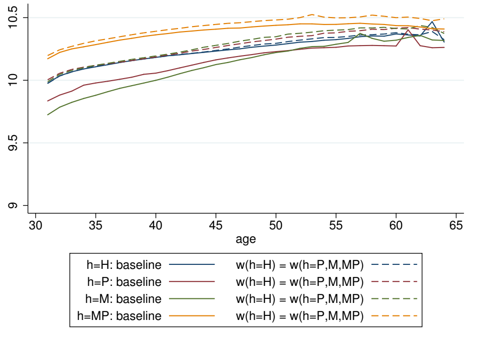
(d) Disutility: log earnings



(e) Direct productivity cost: employment



(f) Direct productivity cost: log earnings



nels, the accumulation of human capital (or the avoidance of loss of human capital) provides a powerful incentive to work regardless of health status. This also appears to be confirmed if we analyse the employment effects of poor health in this counterfactual model (see Table 5.7 for results). Without the human capital mechanism, poor health reduces overall employment slightly more, both relatively and in percentage points.

Secondly, we model a world where individuals derive no direct disutilities from poor health. When individuals derive no disutilities from poor health, labour participation in the poor health states increases, especially for individuals who suffer from both poor physical and mental health. Labour participation of healthy individuals remains relatively unchanged when there are no disutilities from poor health.

Lastly, we model a world without direct productivity losses due to poor health (i.e., $\beta_3 - \beta_8$ are set to zero). Unsurprisingly, this leads to generally higher wages and generally higher employment rates. While the direct productivity cost of poor health appear to have a substantial effect on employment for individuals in poor mental health and poor physical health, it plays almost no role for the employment rate of individuals in good health or both poor mental and physical health. For these individuals, the disutility channel of poor health appears to play the most important role.

5.6 Conclusion

Mental health problems are highly prevalent and appear to be associated with high societal cost. However, despite its relevance, current lifecycle models generally model health in such a way that mental health is largely ignored. Hence, in this chapter we investigated the distinct effects of mental and physical health on net lifetime earnings and employment. We find that poor mental and physical health both result in large and comparable losses in net lifetime earnings. Additionally, we find that individuals attempt to avoid human-capital related future reductions in earnings, leading to higher employment rates, regardless of their health state. Consequently, not taking human capital in terms of labour market experience into account might potentially lead to an overestimation of lost earnings due to poor health.

5.A Appendix

Data

For our preliminary anlyses and to estimate and calibrate the lifecycle model we use data from the LISS panel.[12] The LISS panel consists of a representative sample of the Dutch population. The questionnaires used in this study are the longitudinal health, income, housing, asset, work and schooling and the background questionnaires as well as the WageIndicator survey that was issued only once during the study period in 2009. The health, income and work and schooling questionnaires were held annually, while the asset and housing questionnaires were completed biennially, and the background questionnaires were updated monthly by the participants. The eventual dataset follows individuals between 2007 and 2018.[13]

Mental health

Mental health is measured using the abbreviated 5-question version of the Mental Health Inventory (MHI-5), which is a widely used (Ware Jr & Sherbourne, 1992) and well validated instrument, specifically for mood and anxiety disorders (Veit & Ware, 1983; Rumpf et al., 2001; McCabe et al., 1996).[14] The MHI-5 consists of five questions asking individuals how they felt during the past month (very anxious, so down that nothing could cheer me up, calm and peaceful, depressed and gloomy, happy) which individuals can answer on a scale from 1 to 6, where a 1 indicates that the individual never felt that way and a 6 indicates that the individual continuously felt that way during the last month. A composite score is calculated by inverting the answers on the negative questions and summing all separate item scores, so that higher scores indicate better mental health. This score, which ranges from 5 to 30, can then be converted by linear transformation into a score that ranges from 0 to 100, as is conventional.

[12] The LISS panel is a representative sample of Dutch individuals who participate in monthly Internet surveys. The panel is based on a true probability sample of households drawn from the population register. Households that could not otherwise participate are provided with a computer and Internet connection. A longitudinal survey is fielded in the panel every year, covering a large variety of domains including work, education, income, housing, time use, political views, values and personality.

[13] While in most instances the health questionnaire was issued yearly, the interval between questionnaires was not always constant.

[14] The MHI-5 is heavily focused on affective disorders. It is likely relatively insensitive to externalizing disorders

Physical health

For physical health we require a variable that does not accidentally capture mental health too. Hence, we use a set of Function mobility questions aimed at assessing mobility limitations, which are also used in the SHARE health questionnaires[15]. These questions ask respondents about ten activities whether they can perform them without any trouble, with some trouble, with a lot of trouble or only with the help of others. Activities range from walking 100 metres, to walking several stairs without resting in between and picking up a small coin lying on a table. To make the scores on these questions easier to compare to the MHI-5 scores, individual question scores are added and then linearly transformed so that a score of 0 means that the respondent answered 'only with the help of others' to all questions and a score of 100 means that the respondent answered 'without any trouble' to all questions. We refer to this variable as Functional Mobility (FM).

Indices for mental, physical and subjective health

For Figure 5.2 we construct a subjective health measure from the question: "How would you describe your health, generally speaking?" Individuals could answer on a five-point scale from poor (=1) to excellent (=5). These scores were averaged by age and then indexed average score ate age 30 set to 100. The MHI-5 scores and FM scores were similarly indexed to obtain indices for mental and physical health, respectively.

Health states

Individuals are considered to have poor mental health when they belong to the lowest overall quintile of MHI-5 scores. This quintile comprises individuals with a score of 60 or lower on the MHI-5. Incidentally, a score of 60 has also been proposed as a clinical cutpoint for a case of common mental disorder (Kelly et al., 2008).[16] Individuals are considered to have poor physical health when they belong to the lowest overall tertile of FM scores, which corresponds to a score below 87.5. Together, these different mental and physical health states translate into four pos-

[15] http://www.share-project.org/home0.html

[16] However, others have recommended different cutpoints. Nevertheless, these other cutpoints are generally close to 60 (Rumpf et al., 2001; Strand et al., 2003).

sible overall health states: good mental and physical health ($h = H$), poor physical and good mental health ($h = P$), poor mental and good physical health ($h = M$), poor mental and physical health ($h = PM$).

Net earnings and employment

Net earnings were constructed by adding annual individual self-reported net earnings over all employers that an individual had and included holiday allowance, 13th month and profit-sharing schemes. Individuals were considered employed if they had indicated that they spent on average 16 hours or more per week in paid emloyment during a given year, including (paid and unpaid) overtime. Individuals were considered not to be employed when they indicated that their primary occupation consisted of seeking a job following a job loss, being a first time job seeker, being exempted from job seeking following job loss, attending school or studying, taking care of the housekeeping, being a pensioner or with early retirement, being out of the labout force due to a work disability, or performing unpaid work/volunteering.

Assets

To determine a starting distribution of assets at the beginning of age 30. We take self-reported assets from the biennial asset questionnaires and combine them with data on housing wealth from the housing questionnaires of the same respective years. When individuals were uncertain of specific amounts or refused to answer they could indicate to which category the amount belonged. In these cases their answers were imputed by assigning the midpoint of the chosen catgory. E.g., if an individual refused to provide the exact sum of all his/her bank accounts, but indicated that the amount was between €1,000 and €2,500 the imputed sum of the individual's bank accounts was $(€2,500 + €1,000)/2 = €1,750$. The eventual asset variable consists of real estate (whether individuals live in it or not), the net balance on all bank accounts, equity shares of private limited companies, partnerships or one-man companies, the value of stocks and bonds, outstanding loans to others, inventory such as motorcycles, cars and boats and miscellaneous assets such as jewelry and art, minus outstanding (student) debt and mortgages. Individuals that shared assets with a partner were assigned half of the shared assets as well as their individual assets. In line with the borrowing constraint, negative net individual asset values are converted to zeros. The asset data from individuals age 30 is matched one-to-one to the asset grid, assigning each data point to the closest value on the grid.

Estimation of the stochastic earnings parameters

We estimate the stochastic component of wages with LISS data using a sample of men and women aged 30-65 that in the WageIndicator survey in 2009 have indicated to have never been out of the labour force for more than six months since starting their first job, for years after 2009 we include these same individuals as long as they have indicated to be employed for at least 16 hours per week in each previous period, starting from 2009. We extract the stochastic component of wages by running OLS regressions of the deterministic component for each year of data and predicting the residuals. We then use these predicted stochastic components of wages to construct a variance-covariance matrix of residual wages for different years. Using this variance-covariance matrix we estimate $\hat{\sigma}^2_{\mu}$, $\hat{\sigma}^2_{\lambda}$, $\hat{\sigma}^2_{\eta}$ and $\hat{\rho}$ using GMM. We assume that the stochastic component of earnings is equal for men and women, whereas the parameters for the deterministic component of earnings might differ by gender. Hence, in the GMM estimation we include data from both genders.

Model dimensions

We discretize the u_t into a 4-state Markov process using Tauchen's method. Similarly, we construct grids with a state-space of 4 for μ and λ.[17] We use a 30-state asset grid, with the lowest possible asset level set to zero in each period to account for the borrowing constraint. The experience grid consists of 20 grid points, with the lowest level of experience set to zero in each period. The individual's problem is solved using a grid search along a consumption grid with 40 grid points.

[17] Without a Markov process.

Chapter 6

Conclusion

6.1 Why mental health matters

Mental health problems are highly prevalent, associated with a large burden of disease and associated with lower socioeconomic outcomes. However, up until recently, mental health has been largely ignored by economists. This is problematic because mental health might differ from physical health on some key aspects: mental health problems often start early in life, in contrast to most physical health problems, and mental health problems might affect decision-making in ways distinct from physical health problems. Consequently, this thesis investigated mental health and its consequences at different points in the lifecycle.

6.2 Summary of findings

In Chapter 2, we investigated the persistence of child and adolescent mental healthcare using registry data from the Northern Netherlands. How predictive is past mental healthcare use of future mental healthcare use? More importantly, we investigated to what extent persistence of care is associated with underlying, individual time-invariant characteristics and find that these characteristics are likely to be responsible for the majority of persistence of care. This implies that, to a large extent, once children enter care they receive care for many more years. Moreover, if we assume that the reception of care is strongly related to children's mental health states, this finding suggests that a substantial amount of care might not have long-term effects but might instead be targeted at alleviating and managing symptoms.

Chapter 3 investigated the lifcycle pattern of mental health. Previous studies have often found a U-shape in mental health, or a midlife nadir, where mental health declines when individuals are relatively young, after which it improves again once individuals have reached middle-age. However, studies investigating age-patterns all suffer from the age-period-cohort problem. This fundamental statistical problem posits that it is impossible to completely disentangle cohort effects[1] and period effects[2] from age effects. Consequently, this chapter aimed to identify the age-profile of mental health while introducing minimal bias to reach identification. Using mental health data from the US Panel Study of Income Dynamics (PSID) we applied first difference estimation to derive an unbiased estimate of the second derivative of the age effect as well as an estimate up to a linear period trend of the first derivative. Next, we approximated the first derivative using a battery of estimators with varying restrictions. We found conclusive evidence that the age profile of mental health in the US is not U-shaped and tentative evidence that the age profile follows an inverse U-shape where individuals experience a mental health high during their life course. Further analyses, using German and Dutch data, confirmed that these results do not only apply to the US, but also to Germany and to the Netherlands.

In Chapter 4 we investigated whether mental health problems might cause problematic debts. That is, debts that people fail to repay or for which people default. Problematic debts can have far-reaching consequences for debtors, creditors and society as a whole, and there is a strong correlation between mental health and problematic debt, both in the literature and in our data. Using nationwide individual-level panel data of Dutch individuals, we employed a fixed effects instrumental variable approach, using the death of a sibling or child as instruments for mental health problems. The results indicate that there is a causal relationship between mental health problems and the onset of problematic debt for men.

In Chapter 5 we built on the result from Chapter 3 that mental health appears to follow a lifecyle pattern that is distinctly different from physical health and investigated labour market cost of both poor mental and physical health. We developed

[1] The effect of being born and raised in a specific generation, e.g., being part of generation X might have resulted in specific experiences that influence individuals for the rest of their lives.

[2] The effect of living during a specific time, e.g., during an economic recession.

a lifecycle model that explicitly models mental and physical health as two different components of overall health and include human capital in the form of labour-market experience to account for potential longterm effects of poor heath early in the lifecycle. We found that poor mental and physical health result in large and comparable losses in net lifetime earnings.

6.3 Implications for research and policy

The results from this thesis underline that there is an economic incentive for providing and developing effective mental health interventions: both in terms of preventive care and curative care. Effective interventions have the potential to reduce the incidence of problematic debts (Chapter 4) and to increase labour market earnings (Chapter 5).

This thesis also provides insights on the nature of these effective interventions. Since mental health might follow an inverse U-shape over the lifecycle (Chapter 3), preventive interventions are likely best targeted at young ages and before individuals reach old age. However, results from Chapter 2 suggest that potentially a substantial amount of care might not have long-term effects but might instead be targeted at alleviating and managing symptoms. Consequently, there might be an imperative for the development of, and research on, more effective interventions.

The results from this thesis indicate that mental health is indeed an important aspect of human capital (Chapter 5) and that mental health follows a distinct pattern over the lifecycle (Chapter 3), which provides information on potential future avenues for research on mental health. E.g., since mental health appears to be worse early in life, it is important to understand how it interacts with other processes and occurrences earlier in the lifecycle, such as human capital formation in childhood and early adulthood. Moreover, results from Chapter 4 suggest that the pathway of mental health problems to problematic debt is not necessarily associated with a drop in assets, indicating that more research on how mental health problems affect financial decision-making might be warranted.

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Samenvatting

Geestelijke gezondheidsproblemen komen veel voor en gaan gepaard met een grote ziektelast en lagere sociaaleconomische uitkomsten. Tot voor kort was er binnen de economie echter weinig oog voor mentale gezondheid. Dit is problematisch omdat mentale gezondheid op een aantal belangrijke aspecten kan verschillen van lichamelijke gezondheid: geestelijke gezondheidsproblemen beginnen vaak vroeg in het leven, in tegenstelling tot de meeste lichamelijke gezondheidsproblemen, en geestelijke gezondheidsproblemen beïnvloeden mogelijk financiële besluitvorming van individuen op een manier die verschilt van lichamelijke gezondheidsproblemen. Daarom onderzoek ik in dit proefschrift mentale gezondheid en de gevolgen daarvan op verschillende punten in de levensloop.

In hoofdstuk 2 onderzoek ik de persistentie van de geestelijke gezondheidszorg voor kinderen en jongeren met behulp van registerdata uit Noord-Nederland. Hoe voorspellend is het gebruik van de geestelijke gezondheidszorg in het verleden voor toekomstig gebruik van geestelijke gezondheidszorg? Daarnaast onderzoeken we in hoeverre persistentie van zorg samenhangt met onderliggende, individuele kenmerken die niet veranderen over tijd en concluderen we dat deze kenmerken waarschijnlijk verantwoordelijk zijn voor het grootste deel van de persistentie van zorg. Dit houdt in dat kinderen die in zorg komen, grotendeels nog jaren in zorg blijven. Bovendien, als we aannemen dat het ontvangen van zorg sterk verband houdt met de mentale gezondheidstoestand van kinderen, suggereert deze bevinding dat een aanzienlijke hoeveelheid zorg wellicht geen langetermijneffecten heeft, maar in plaats daarvan wel eens gericht zou kunnen zijn op het verlichten en beheersen van symptomen.

In hoofdstuk 3 onderzoek ik hoe mentale gezondheid verloopt over de levensloop. Eerdere studies vonden vaak een U-vorm voor mentale gezondheid (ofwel een dieptepunt op middelbare leeftijd), waarbij mentale gezondheid afneemt zo lang mensen relatief jong zijn en weer verbetert zodra mensen middelbare leeftijd hebben bereikt. Studies die dit soort leeftijdspatronen onderzoeken, zijn echter allemaal onderhevig aan het leeftijd-periode-cohortprobleem. Dit fundamentele statistische probleem stelt dat het onmogelijk is om cohorteffecten volledig te ontwarren van leeftijd- en periode-effecten. Daarom tracht dit ik in dit hoofdstuk om het leeftijdsprofiel van de mentale gezondheid te identificeren door zo min mogelijk bias te introduceren voor identificatie. Met behulp van data over mentale gezondheid van de US Panel Study of Income Dynamics (PSID) passen we een first-differenceschatting toe om zonder vertekening (bias) de de tweede afgeleide van het leeftijdseffect, evenals de eerste afgeleide tot op een lineaire periodetrend, te schatten. Vervolgens benader ik de eerste afgeleide met behulp van een grote reeks schatters met verschillende beperkingen. De resultaten geven overtuigend bewijs dat het leeftijdsprofiel van de mentale gezondheid in de VS geen U-vorm volgt en een voorzichtige indicatie het leeftijdsprofiel mogelijk een omgekeerde U-vorm volgt waarbij individuen tijdens hun leven een mentale gezondheidspiek ervaren. Verdere analyses met Duitse en Nederlandse data bevestigen dat deze uitkomsten niet alleen gelden voor de VS, maar ook voor Duitsland en Nederland.

In Hoofdstuk 4 onderzoek ik of geestelijke gezondheidsproblemen problematische schulden kunnen veroorzaken. Dat wil zeggen: schulden die mensen niet terugbetalen of waarvoor mensen in gebreke blijven. Problematische schulden kunnen verstrekkende gevolgen hebben voor schuldenaren, schuldeisers en de samenleving als geheel en er is een sterke correlatie tussen geestelijke gezondheid en problematische schulden, zowel in de literatuur als in onze data. Met behulp van landelijke individuele paneldata van alle in Nederland woonachtige individuen onderzoeken we of dit ook een oorzakelijk verband is. We passen een fixed-effect instrumentele variabeleschatting toe, waarbij het overlijden van een broer, zus of kind gebruikt wordt als instrument voor geestelijke gezondheidsproblemen. De resultaten geven aan dat geestelijke gezondheidsproblemen bij mannen problematische schulden kunnen veroorzaken.

In Hoofdstuk 5 bouw ik voort op het resultaat uit hoofdstuk 3 dat mentale gezondheid een levenslooppatroon lijkt te volgen dat duidelijk verschilt van fysieke gezondheid. Ik onderzoek de arbeidsmarktkosten van zowel een slechte mentale als fysieke gezondheid door middel van een levensloopmodel. We modelleren mentale en fysieke gezondheid als twee afzonderlijke componenten van de algehele gezondheid. Bovendien onderzoeken we hoe slechte gezondheid in het begin van de levensloop langetermijneffecten kan hebben op menselijk kapitaal door gemiste arbeidsmarktervaring. De resultaten laten zien dat een slechte mentale en fysieke gezondheid resulteren in een groot en vergelijkbaar verlies van individuele netto inkomsten over de levensloop.

De resultaten van dit proefschrift laten zien dat er een economisch argument is voor effectieve interventies in de geestelijke gezondheidszorg: zowel preventief als curatief. Effectieve interventies kunnen de incidentie van problematische schulden verminderen (hoofdstuk 4) en het inkomen op de arbeidsmarkt verhogen (hoofdstuk 5).

Dit proefschrift geeft ook inzicht in de aard van deze effectieve interventies. Aangezien geestelijke gezondheid gedurende de levensloop mogelijk een omgekeerde U-vorm volgt (hoofdstuk 3), kunnen preventieve interventies het best gericht worden op mensen van jongere leeftijd of voordat mensen een hoge leeftijd bereiken. De resultaten van hoofdstuk 2 suggereren echter dat een aanzienlijke hoeveelheid zorg mogelijk geen langetermijneffecten heeft, maar in plaats daarvan gericht kan zijn op het verlichten en beheersen van symptomen. Daarom is het wellicht noodzakelijk dat er effectievere interventies ontwikkeld en onderzocht worden.

Daarnaast geven de resultaten van dit proefschrift aan dat mentale gezondheid inderdaad een belangrijk aspect is van menselijk kapitaal (Hoofdstuk 5) en dat mentale gezondheid een duidelijk patroon volgt gedurende de levenscyclus (Hoofdstuk 3), wat informatie verschaft over toekomstige mogelijkheden voor onderzoek naar mentale gezondheid. Aangezien mentale gezondheid gemiddeld slechter lijkt te zijn op jonge leeftijd, is het bijvoorbeeld belangrijk om te begrijpen wat de wisselwerking is tussen mentale gezondheid en andere processen en gebeurtenissen die vroeg in de levensloop plaatsvinden, zoals de vorming van menselijk kapitaal in de kindertijd en jongvolwassenheid. Bovendien suggereren de resultaten van hoofdstuk 4 dat het pad van psychische problemen naar problematische schulden niet noodzakelijkerwijs verband houdt met een daling van bezittingen, wat aangeeft dat meer onderzoek naar de invloed van geestelijke gezondheidsproblemen op de financiële besluitvorming gerechtvaardigd kan zijn.