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DISCUSSION PAPER SERIES

IZA DP No. 17143

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Guido Cozzi
University of St. Gallen

Noemi Mantovan
University of Liverpool

Robert M. Sauer
University of London and IZA

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

How Important Are Mental and Physical Health in Career and Family Choices?*

We present a dynamic life-cycle model of women's labor supply, marriage, and fertility choices that explicitly incorporates mental and physical health. Correlated mental and physical health production functions are simultaneously estimated, including the endogenous decisions to seek psychotherapy and smoke cigarettes as health accumulation factors. The model is estimated by the Simulated Method of Moments with Indirect Inference using data from the British Household Panel Study. Results indicate that mental health has a stronger impact on labor supply than physical health. At the same time, estimates show that working part-time and full-time aect both mental and physical health. Moreover, we nd dierences in the interaction of the two forms of health on other life dynamics, with better mental health having stronger impacts on marriage and fertility outcomes than physical health. Counterfactual simulations reveal that not only permanent, but also temporary shocks to health and employment have long-lasting eects on life decisions, life satisfaction, and income due to their interaction with fertility. Finally, policy experiments show that lower costs for psychotherapy and increased costs of cigarettes would substantially increase fertility but decrease employment, while a decrease in childcare costs for employed women would increase both fertility and labor supply, supporting women's overall health.

JEL Classification: I12, J12, J13, J16, J22

Keywords: female labor supply, marriage, fertility, career, family, mental health, physical health, psychotherapy, smoking, discrete choice dynamic programming models, structural estimation, simulated method of moments, indirect inference

Corresponding author:
Robert M. Sauer
Royal Holloway College
University of London
Egham, Surrey TW20 0EX
United Kingdom

E-mail: robert.sauer@rhul.ac.uk

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1 Introduction

Mental and physical health are the primary reasons for absenteeism at work and can significantly impact marital and fertility choices throughout a person's lifetime. Latest figures show that in the UK there were 36.8 million workdays lost due to health issues each year, with mental health being the most substantial contributor (HSE, 2023). Policymakers are increasingly focusing on mental health, which is unsurprising given that an estimated one in six people in England experiences mental health problems in any given week (McManus et al., 2016), and that recent years have witnessed a further decline in average mental health following the Covid-19 pandemic. While there is an extensive body of literature examining the effects of physical health on employment across the life cycle (see, for example, Pelgrin and St-Amour, 2016, De Nardi et al., 2016), there is currently no research on how physical and mental health intersect with life cycle decisions and outcomes.

This paper is the first attempt to model the two-way interaction between physical and mental health and life cycle decisions, including employment, marital status, and fertility. Our goal is to contribute to a deeper understanding of the mechanisms connecting mental and physical health trajectories with individual life stati. In our research, similarly to the pioneering work of Jolivet and Postel-Vinay (2024), mental health influences employment in a two-way interaction. However, we distinguish between the impacts of mental and physical health by introducing a separate physical health variable and different sources of health investments to discern between the two: smoking and psychotherapy. Additionally, rather than concentrating on occupational choices for men, our focus is on women, encompassing marital and fertility decisions, with learning about the compatibility of partners. The emphasis on women arises from two key factors: firstly, women are disproportionately affected by psychological issues like anxiety and depression compared to men (McLean et al., 2011). Secondly, women's employment stati tend to be more variable compared to men's, and they are closely linked to marital status and fertility, allowing the analysis to investigate the mechanisms that guide life trajectories.

While the complementarity of mental and physical health is well-documented (Vreeland, 2007), this study seeks to investigate also the substitutability of investment between them by examining their relative impacts, which links to important policy questions, given the substantial pressure that public health services are under (WHO, 2022). When it comes to mental health support, in particular, availability becomes much less consistent across countries and even within the same country. For example, in the UK the National Institute for Health and Care Excellence (NICE) dictates rules for assessment and treatment times for physical health, while there is very little with regards to mental health provision, resulting in about a quarter of emergency mental health patients waiting more than 12 weeks to start any form of treatment (Royal College of Psychiatrists, 2022), and the availability of treatment being akin to a "postcode lottery" (British Psychological Society, 2023). Analyzing mental and physical health also helps with identifying more conservative parameters, making sure that coefficients are not inflated by the absence of the other form of health in either case. We not only empirically estimate this substitutability but also shed light on the underlying mechanisms, encompassing a two-way effect between health and multidimensional life-cycle decisions.

As a result, our model can be used for treatment evaluation and can answer questions such as: What is the impact of a permanent or temporary shock on health? What is the impact of a temporary productivity shock? As well as policy questions on the impact of greater availability of psychotherapy, higher cost of cigarettes, and childcare affordability. In our framework, these questions can be answered by identifying the mechanisms on both mental and physical health.

In order to measure mental health, the estimates rely on the 12 questions composing the General Health Questionnaire (GHQ), which is an established measure in the literature (see for example Blanchflower and Bryson (2024) and Jolivet and Postel-Vinay (2024)) and is used by General Practitioners to detect psychiatric disorders. Finding a measure of physical health that is as reliable is a more challenging task: while mental health has a stronger subjective component, physical health has subjective and objective components and there is not an overall screening measure that is considered reliable. To overcome this impasse, we follow the technique developed by Blundell et al. (2023) and used also by Salvati (2020) dynamically, that consists of instrumenting the principal components of multiple measures of subjective physical health by using an extensive battery of questions on objective physical health stati. This allows the calculation of an unbiased measure of physical health (Blundell et al. (2023)). Our primary findings from the estimation of the two indicate that mental health plays a crucial role in income and employment, particularly dependent on psychotherapy and marital status.

Using data from the British Household Panel Survey (BHPS), which ran from 1991 to 2008, we simulate and estimate a dynamic model of female life-cycle choices. Employing a Discrete Choice Dynamic Programming (DCDP) technique with full-backward recursion of the expected maximum (EMAX), we are able to match 152 moments through a Method of Simulated Moments (MSM), containing several Indirect Inference components, estimating a total of 93 parameters. In each period, respondents' self-reported levels of income, partner's income, and mental and physical health are also observed. We analyze the choices and outcomes for women between the ages of 21 and 50. At each age, women make one of 48 available decisions that represent combinations of possibilities with regards to employment, marital status, fertility, smoking, and psychotherapy. Women are heterogeneous in their levels of education and abilities and received job offers for part-time and full-time work, which in turn affect next period's mental and physical health. Similarly to Jolivet and Postel-Vinay (2024), we find that employment can have a stress factor that negatively affects health.

As in Brien et al. (2006) and Anderberg et al. (2023), women make initial decisions about partnership with partial information about their partner's nature. We develop a model of learning using Bayesian updating under which women discover the true compatibility with their partner over time. Marital status, which encompasses cohabiting with a partner, needs to be carefully considered in this context as it is a very important component of the puzzle due to its links to fertility, employment and health. In the model, being divorced is treated differently than being single because of the unequal and long-lasting impacts on mental and physical health of divorce (Lorenz et al. (2006)).

Fertility has a pivotal role in this project for multiple reasons: first of all, especially for women, fertility has a strong impact on employment and can therefore change the career trajectory of women. Second, having children has a multifaceted effect on well-being: psychological research shows that having children has a negative impact on mental health because women encounter greater negative emotions, including greater financial problems, sleep deprivation, and increased marital stress. At the same time, mothers tend to experience greater meaning in life, satisfaction, and enhanced social roles (see Nelson et al. (2014) for a meta-analysis of the literature). We are able to capture both these aspect by introducing a negative impact of having children on women's mental health while allowing fertility to have a positive impact on utility[1].

[1]It would be important to study the impact that primary and secondary infertility, miscarriages and still-

Women make health investments in the form of psychotherapy and smoking. One of the main challenges of this work is to differentiate and disentangle mental and physical health, and these decisions help identify the two forms of health at play in the model. While both can have an indirect effect on mental and physical health, it is safe to assume that psychological treatment has a direct impact on mental health which in turn can affect income and other outcomes (Cozzi et al. (2018), Layard (2017)). It is also safe to assume that smoking has a direct impact on physical health. In an ideal world, we would be able to introduce more choices that affect health, such as alcohol consumption and dietary choices (see Griffith et al. (2018) and Griffith et al. (2019)), but for computational limits it is necessary to reduce to one measure of health and smoking has a clear direct impact on physical health and has been successfully and extensively used in dynamic models of health (Darden (2017), Khwaja (2010), Arcidiacono et al. (2007)), as well as being correlated with drinking alcohol other forms of negative health investment (Cutler and Glaeser (2005)).

A significant advantage of the approach used here is its capacity to perform counterfactual scenarios, including policy experiments. After the estimation by SMM and Indirect Inference, it is possible to compare the new moments obtained from the simulated scenario to the baseline estimation, thus observing the effects of changes in various parameters on the final partial equilibrium as well as investigating the mechanisms that bring to those differences. We perform counterfactual experiments that focus on health shocks (both permanent and temporary), employment shocks, and policy analysis. Results from these experiments show that a permanent negative average mental health shock has a more substantial impact than an equivalent physical health shock on fertility and full-time employment. A negative mental health shock shifts women away from full-time employment by 14% compared to the baseline estimates, with an increase in part-time employment and unemployment of 25% and 4% respectively. It also leads to a 4% reduction in fertility, and causes a 15% decrease in wages, significantly affecting lifetime utility. In contrast, a negative physical health shock of the same magnitude reduces fertility by 2.6% while increasing unemployment by 10%.

More surprisingly, temporary shocks to employment, mental, and physical health also affect the overall life choices trajectory, with life outcomes moving to different long-term equilibria.

births have on women's well-being. While we are unable to do this with currently available data, we plan to focus future research on this.

This is not usually case in the literature (see Jolivet and Postel-Vinay (2024)), where after a period of shocks, choices and states tend to converge back to the baseline. The main reason for our different results is the interaction that fertility has with the other variables, and how a change in the timing and prevalence of fertility moves women to a different employment and health path. A one-off drop in mental health at 20 increases fertility by 1.6% and lifetime unemployment by 6%. The same shock for physical health has lower but still persistent results with a -0.6% decrease in fertility and 0.8% increase in unemployment. A negative technological shock that decreases wages at age 20 and pushes women into unemployment, moves them permanently away from employment (a 16% overall reduction over their lifetimes), changing their life trajectory by increasing and anticipating fertility. A byproduct of the decrease in full-time and part-time work is the improved physical health by 18%.

Policy experiments are trifold and focus on the provision of therapy, cost of cigarettes, and childcare support for working mothers. First, simulations show that increasing the provision of subsidized psychotherapy results in a 1% increase in mental health on average only, but that target impact causes a 2.6% increase in fertility and a 2.8% increase in employment. Second, an increase in the cost of cigarettes has a strong intended effect on physical health with a 77% improvement, and a 17% increase in fertility, but perversely decreases employment by 12%, due to a decrease in expenditure. Finally, introducing support for working mothers in the form of a 30% reduction in the cost of childcare has strong effects on the components of the model: it boosts substantially labor force participation (increasing it by 54%) and fertility (38%), with an improvement in both mental and physical health.

This work contributes to two main strands of literature. First, it builds on the established literature studying the family and employment jointly determined life-cycle decisions of women (van der Klaauw (1996), Francesconi (2002), Keane and Wolpin (2010)). As in Keane and Wolpin (2010), we examine the life-cycle choices in terms of fertility, marital status, and employment for prime-aged women. Moreover, this work relates to Anderberg et al. (2023) and Brien et al. (2005) by introducing a learning curve with Bayesian updating regarding the quality of couples' matches, which enables the exploration of marital and divorce dynamics in a richer environment.

Second, this work contributes to the literature focusing on the dynamics of both physical and mental health. There is a substantial body of work exploring investment choices in physical health (De Nardi et al. (2016), French and Jones (2011), Khwaja (2010), Pelgrin and St-Amour (2016), Darden (2017), Arcidiacono et al (2007), Salvati (2020)), which focuses also on savings and retirement, which is beyond the scope of this project but is going to be the next step for future research.

Work on the dynamics of mental health, on the other hand, is much sparser, and to the best of our knowledge the only body of research that studies the dynamics of employment and mental health is the recent work by Jolivet and Postel-Vinay (2024), which focuses on a two-way interaction between various types of occupation and mental health for men. Our research adds to this new and emerging exploration on the dynamics of mental health by focusing on women, adding fertility, marital status, smoking and psychotherapy decisions, as well as, for the first time to our knowledge, making a first step towards the study of the dynamic components of the substitutability and complementarity of mental health and physical health.

The remainder of the paper is structured as follows. The next section describes the BHPS data used in the estimation. Section 3 presents the model and outlines the solution method. Section 4 describes the estimation procedure and discusses the identification of structural parameters. Section 5 highlights key parameter estimates and presents the counterfactual analysis. Section 6 provides a summary and discusses model extensions reserved for future research.

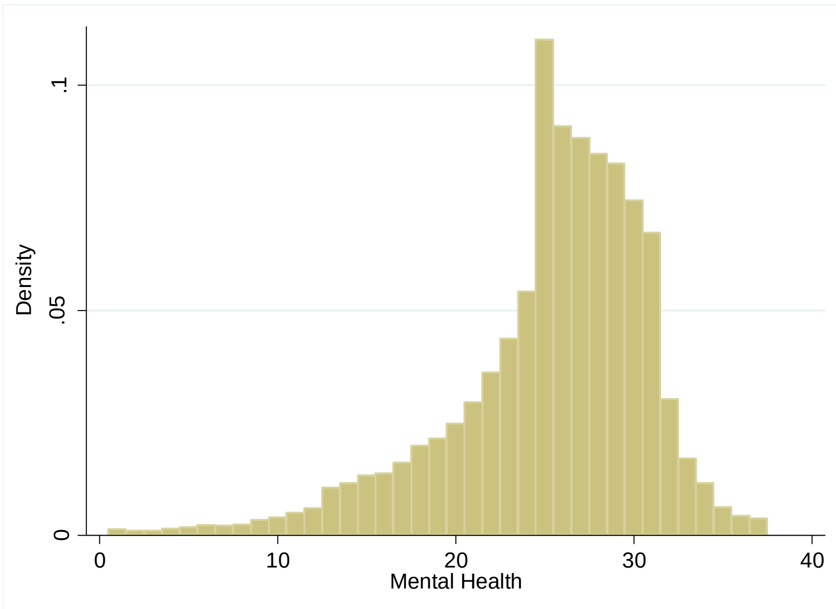
2 Data

The data used in estimation are drawn from the British Household Panel Survey (BHPS). The BHPS began in 1991 and followed the initial sample of respondents for up to 18 years. The first wave of the survey included 5,500 households and 10,300 persons from 250 different areas in Great Britain. An additional 1,500 households from Scotland and Wales were added in 1999. In 2001, 2,000 households from Northern Ireland were appended to the survey.

The BHPS interviewed individuals annually until 2008. The sample used in this study is taken from all waves between 1991 and 2008 and is composed of prime-aged white women between the ages of 21 and 50. Non-white women are excluded in order to abstract from race differences. Examining prime-aged women only avoids the added complexity from incorporating education and retirement decisions. Women who report being retired, long term sick, disabled, on maternity leave, or offer no information about their labor force or mental and physical health status are also excluded. The final sample contains 8,428 women and 51,919 woman-year observations.

In each wave of the survey, the BHPS includes a measure of mental health known as the General Health Questionnaire (GHQ) Caseness score. The GHQ score is often used as a screening device for identifying minor psychiatric disorders in the general population. The score is derived from the answers to a series of 12 questions. The answer to each question is a number between 1 and 4 and the numerical sum of the answers yields the score. The minimum score is 12 (best mental health) and the maximum score is 48 (worst mental health).[2]

Figure 1: Distribution of Mental Health



Note: The number of woman-year observations is 51,919. The full set of distribution values is reported in Table 20 in the Appendix.

Figure 1 displays the distribution of our transformed GHQ score over all woman-year observations. The transformation recodes the GHQ score so that it ranges from 1 to 37, where 1 is the lowest level of mental health and 37 is the highest. There is considerable variation in the score. The distribution is skewed to the left with a fat tail on the right. The modal value is 25, the median is 26 and the mean is 25.3.

In each wave of the BHPS, the respondent is also asked about health and welfare services used. In response to the question, "Which (of the listed health and welfare) services have you used?" respondents can choose “psychotherapist” as one of the possible answers. If a respondent reports using the services of a psychotherapist then we consider the individual to be attending psychotherapy during the survey year. On average, 2.3 percent of the sample is attending psychotherapy at any given age.

[2]The score is based on the following questions: Have you recently... 1) been able to concentrate on whatever you’re doing? 2) lost much sleep over worry? 3) felt that you were playing a useful part in things? 4) felt capable of making decisions about things? 5) felt constantly under strain? 6) felt you couldn’t overcome your difficulties? 7) been able to enjoy your normal day-to-day activities? 8) been able to face up to problems? 9) been feeling unhappy or depressed? 10) been losing confidence in yourself? 11) been thinking of yourself as a worthless person? 12) been feeling reasonably happy, all things considered?

In each wave of the survey except 1999, the BHPS contains a questions pertaining to physical health as well. Following Blundell et al. (2023) and Salvati (2020), we use multiple component analysis in order to determine a measure of subjective physical health. The predicted result is then instrumented with a set of objective health measure and the resulting predicted variables are the final measure of health.

The measures used for subjective health are: first, "Please think back over the last 12 months about how your health has been. Compared to people of your own age, would you say that your health has on the whole been ...". The response range is between 1 (excellent) and 5 (very poor). This is then reduced to two categories (Excellent and Good are set to be equal to 1 and Fair, Poor and Very Poor are set to be 0). Second, "Health limits type or amount of work", the possible responses are No (1) or Yes (0). Third, "Does your health in any way limit your daily activities compared to most people of your age?", the possible answers are No (1) and Yes (0). The measures of objective health that are used to instrument the predicted variable from principal component are: First, problems with arms, legs, hands, etc. Second, problem with sight. Third, problem with hearing. Fourth, skin conditions or allergies. Fifth, hearth and blood pressure conditions. Sixth, stomach or digestive problems. Seventh, epilepsy. Eight, migraines. Ninth, other health problems.

Figure 2: Distribution of Average Health

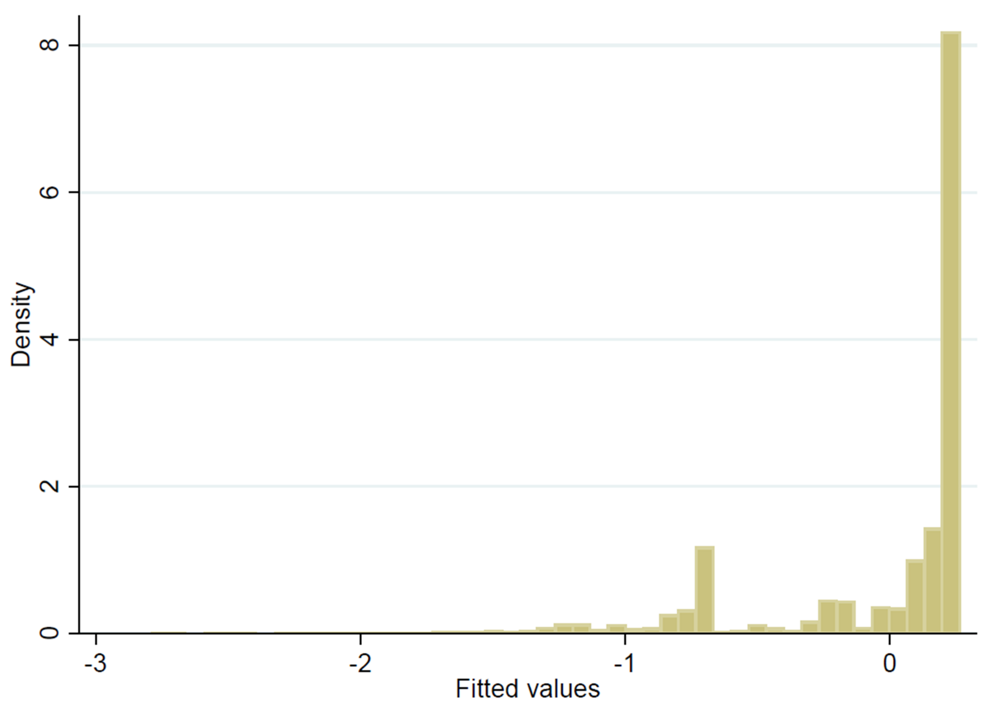
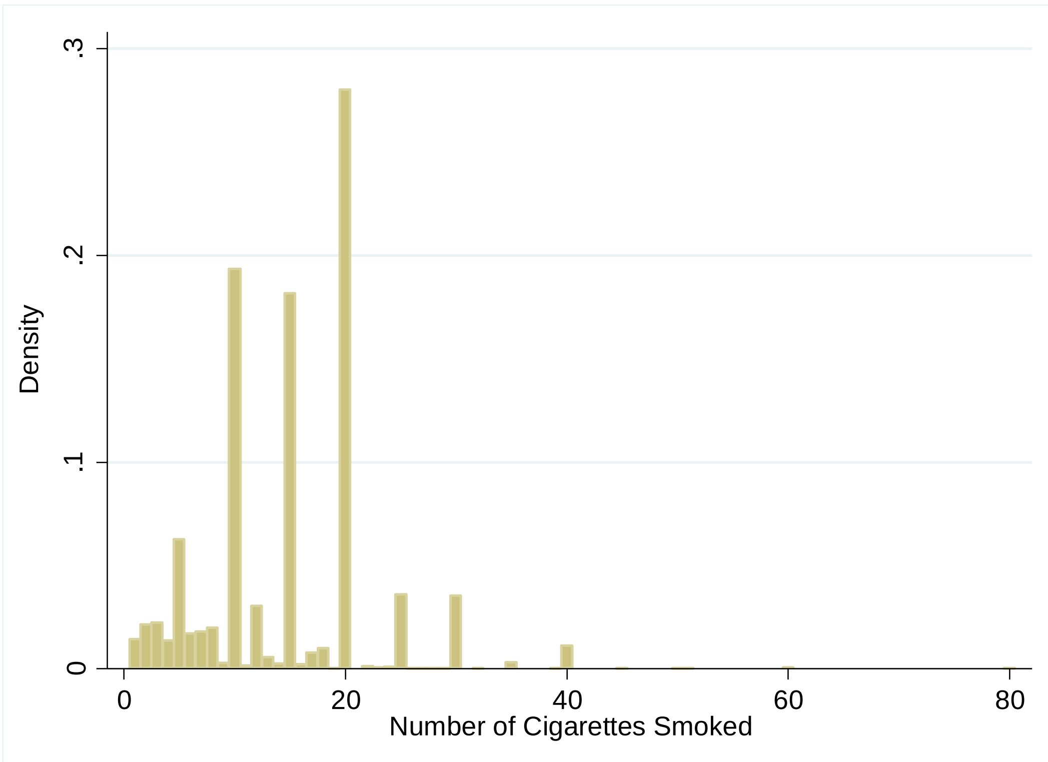


Table 2 shows the sample distribution of physical health. Relatively few individuals report being in poor or very poor health. Most of the variation is between the excellent, good and fair health levels. In fact, preliminary analysis suggests that little information is lost if the distribution is collapsed into only two composite categories: good physical health and poor physical health. As shown in the Table, the good physical health category is composed of those who report excellent or good health and are close to .5 on the scale.

Related to physical health, the survey asks respondents if they smoke cigarettes, and how many cigarettes are smoked per day. The question posed is, "Approximately how many cigarettes a day do you usually smoke, including those you roll yourself?"

Figure 3: Distribution of Number of Cigarettes per Day (>0)



Note: The number of woman-year observations is 15,445. The full set of distribution values is reported in Table 20 in the Appendix.

Figure 3 displays the distribution of the number of cigarettes smoked per day amongst those who smoke at least one cigarette. There are noticeable spikes in the distribution at 5, 10, 15, 20, 25, 30 and 40 cigarettes per day.

Preliminary analysis of the smoking data suggests that the exact number of cigarettes does not have much explanatory power. Rather, almost all of the variation is picked up by classifying individuals into only two categories: being a smoker or a non-smoker. Assigning individuals to only two smoking categories also helps reduce the choice set in the model to computationally practical dimensions. The average proportion of the sample that smokes at any given age is 29.8 percent.

Other important information available in each year of the survey includes an individual's highest completed education level, marital status, number of children, employment hours, annual employment earnings, spousal employment status and spousal annual earnings. Means, standard deviations and sample sizes for these characteristics, as well as the others mentioned above, are presented in Table 2.

Table 1: Sample Characteristics

	Mean	Std. Dev.	N	NT
Education 1	28.24	45.02	7,136	44,857
Education 2	50.31	50.00	7,136	44,857
Education 3	21.45	41.05	7,136	44,857
Single	17.25	37.79	8,428	51,907
Married	72.19	44.81	8,428	51,907
Divorced	10.55	30.72	8,428	51,907
No Children	45.09	49.76	8,428	51,919
One Child	22.50	41.76	8,428	51,919
Two Children	22.85	41.99	8,428	51,919
Three or More Children	9.56	29.40	8,428	51,919
Unemployed	24.88	43.23	8,424	51,715
Part-time	26.03	43.88	8,424	51,715
Full-time	49.09	50.00	8,424	51,715
Annual Earnings Part-time	7,799.64	5,407.53	3,299	12,548
Annual Earnings Full-time	19,199.80	9,671.18	5,422	25,385
Spouse Employed	90.05	29.94	6,207	37,473
Spouse Annual Earnings	29,328.53	20,690.49	5,402	28,328
Mental Health	25.30	5.58	8,428	51,919
Psychotherapy	2.30	15.00	8,426	51,907
Years of Psychotherapy Experience (>0)	1.45	0.72	784	4,058
Physical Health	0.0001	0.437	8,207	48,291
Smoker	.300	.460	8,418	51,762
Number of Cigarettes per Day (>0)	14.72	7.50	3,294	15,445

Note: N is the number of women and NT is the number of woman-year observations. Annual earnings are in 2010 constant pounds sterling.

The four education levels listed in Table 1 are composite categories that indicate the highest educational qualification an individual has obtained over the sample period. The original survey allows for 13 education categories. Table 19 in the Appendix displays the sample proportions of the 13 original education levels and defines the four composite education categories. The reduction to four education levels is also empirically motivated via preliminary analysis.

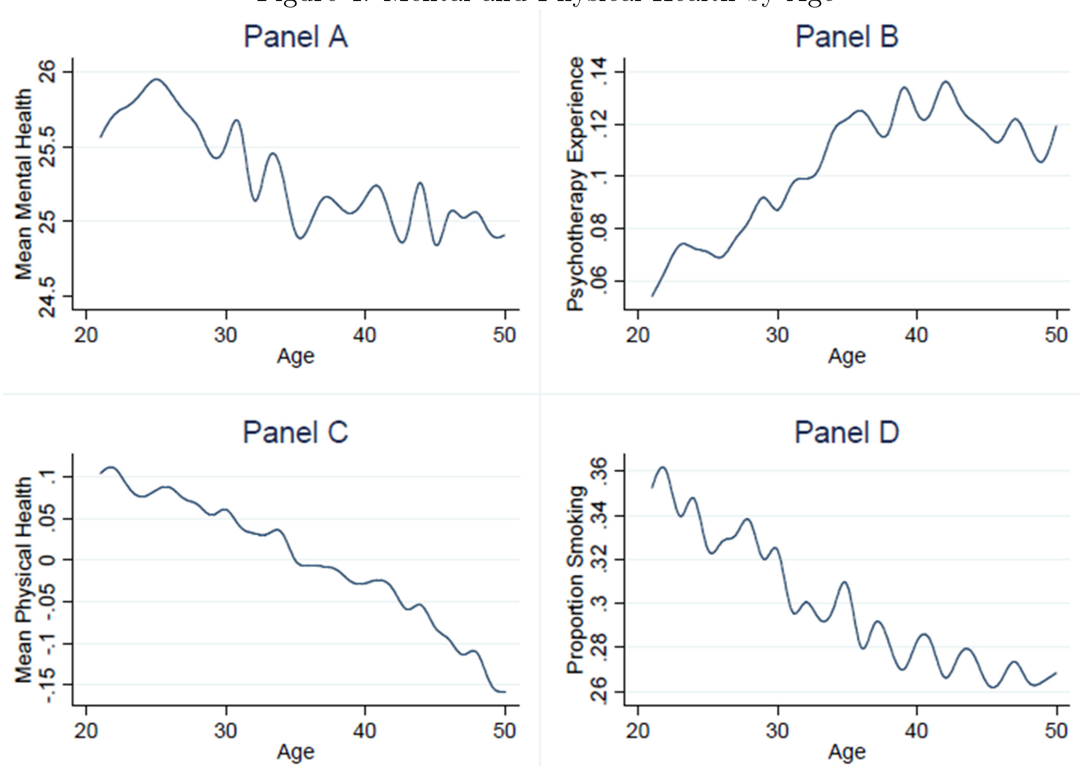
The employment classifications in Table 1 follow BHPS definitions. The survey classifies an individual as unemployed if the respondent is in family care, a full-time student, in government training or "other", which includes waiting to take up a job. The survey defines full-time employment as working at least 30 hours per week, otherwise the individual is classified as working part-time.

2.1 Descriptive Statistics

In this section and the subsequent one, we analyze the relations between the variables at play, which are then used to inform and guide the model. Overall, we are going to focus on the interplay between mental and physical health and employment, wages, marital status, fertility, age, education, psychotherapy, and smoking.

Figure 4 displays the development of mental and physical health, psychotherapy experience and smoking status with age. Panel A shows that mean mental health generally declines from a peak in the early 20s to a low-point in the mid-30s. Between one's mid-30s and 50 years of age, mental health remains at a relatively low level, with the trough occurring at age 45.

Figure 4: Mental and Physical Health by Age



Note: The numerical values and sample sizes for each panel can be found in Table 21 in the Appendix.

Panel B shows that accumulated annual psychotherapy experience rises roughly linearly from a low in the early 20s to a peak in one's late 30s. Subsequently, mean psychotherapy experience fluctuates around its maximum for a couple of years and then starts to fall.

Together, Panels A and B illustrate that as mental health declines with age until the mid-

Table 2: One-Period Transition Matrices

Panel A: Psychotherapy

	Age $a+1$		
Age a	Not Attending	Attending	NT
Not Attending	.984	.016	42,615
Attending	.716	.284	933
NT	42,586	962	43,548

Panel B: Smoking

	Age $a+1$		
Age a	Non-Smoker	Smoker	NT
Non-Smoker	.970	.030	30,441
Smoker	.099	.901	12,821
NT	30,784	12,478	43,262

Note: In each panel, NT is the number of woman-year observations. The fractions are row percentages that sum to one.

30s, accumulated psychotherapy experience generally increases. Further, between the mid-30s and 50 years of age, when mental health bottoms out, accumulated psychotherapy experience stabilizes. The relationship between declining mental health and increasing psychotherapy experience could be bidirectional.

Panel C displays the change in the average physical health with age. Physical health is at a maximum in the early 20s and then starts to gradually decline. The downward trend slows significantly between the ages of 37 and 43. Subsequently, a sharp drop in physical health occurs.

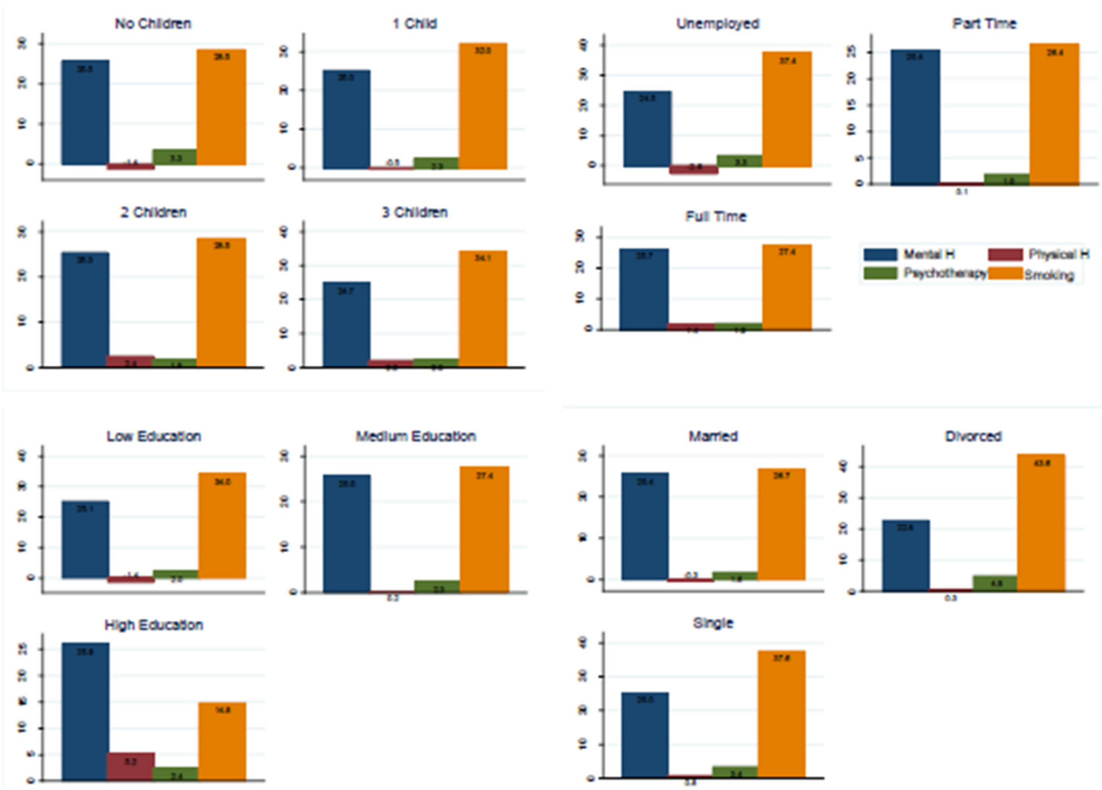
Panel D shows that the proportion of women smoking cigarettes at age 21 is at its maximum at around 36 percent. The smoking proportion drops approximately linearly to 27 percent by age 39. Between the ages of 39 and 50, the proportion falls more slowly reaching a trough at around 26 percent.

Together, Panels C and D illustrate that both the proportion in good physical health and the proportion smoking decline with age with the smoking rate falling relatively more rapidly. The co-movement in the two proportions is still consistent with a positive health effect of quitting smoking. It is possible that quitting smoking slows the decline in physical health.

Table 2 displays the average one-period transitions for the binary outcomes of attending psychotherapy, being in good physical health and smoking. Panel A shows that the proportion of individuals that attend psychotherapy at age $a+1$, given not attending psychotherapy at age a, is 1.6 percent. In contrast to this low uptake rate, the quit rate is much larger. Amongst those attending psychotherapy at age a, 28.4 percent choose not to continue attending at age $a+1$.

Panel B presents transition rates for smoking status. The smoking initiation rate rate is,

Figure 5: Mental and Physical Health by Characteristics



on average, three percent. The quit rate is relatively higher. Amongst those who are smokers at age a, ten percent report being non-smokers at age $a + 1$.

Simple correlations between individual characteristics, other than age, and mental and physical health levels, psychotherapy attendance, and smoking status are presented in Table 5. Correlations with the number of children in the household are displayed in Panel A. Women with no children have clearly higher mental but lower physical health levels than those with three or more children. Of course, the mental health effect could be due to an underlying age effect, which will be addressed in the regression analysis.

Interestingly, the proportion smoking amongst women with three or more children have the highest proportion of smoking, while women with two children have the lowest rate of psychotherapy attendance. Panel B demonstrates that both mental and physical health levels increase with greater labor market participation. The highest levels are observed among full-time workers, while the lowest levels are observed among the unemployed. The unemployed are also much more likely to be smokers and attending psychotherapy. Panel C illustrates that mental and physical health levels consistently rise with education. The proportion smoking falls with education while the proportion attending psychotherapy does not display a clear pattern.

Panel D highlights how divorce is associated with much lower mental health levels and considerably higher rates of psychotherapy attendance and smoking. Comparing single individuals who have never married to married individuals, it appears that singles are in better mental and physical shape, but attend psychotherapy and smoke more often. Married individuals, however, exhibit lower levels of physical health, which may be influenced by age.

2.2 Regression Analysis

The main goal of the regression analysis is to further explore conditional correlations in the data. The conditional correlations inform various specifications in the DCDP model and aid in identifying structural parameters. Both Ordinary Least Squares (OLS) and Fixed Effects (FE) regression results are reported. Estimation of the DCDP model, as formulated in the next section, addresses biases such as simultaneity and selection, enhancing the causal interpretation compared to OLS and FE results.

2.2.1 Mental Health

Table 3 displays the results of Instrumental Variables (IV) and Instrumental Variables with individual Fixed Effects (IV FE) regressions related to mental health. All regressions that contain physical health are either IV or IV FE, because of the way physical health is defined as being subjective health instrumented by objective health following Blundell et al. (2023), (see section 2 for a detailed description of the methodology). First stage estimates are not presented for sake of brevity[3] but F-Tests on the first stage of regression are presented.

The dependent variable in columns (1) and (2) is the mental health score, ranging between 1 and 37. The dependent variable in columns (3) and (4) is a dummy for whether or not the individual is currently attending psychotherapy.

In the first column, IV results indicate positive conditional correlations between mental health and factors such as education level, physical health, and marital status. Having children, having worked part-time or full-time in the previous year and accumulating more years of psychotherapy (1,2, and 3 years) are associated with lower mental health levels. Psychotherapy experience is discretized to align with the narrower range used in the DCDP model, thereby reducing the size of the state space.[4]

[3] They remain available upon request.

[4] The FE results with the discretization are qualitatively similar to the linear specification.

Table 3: Mental Health and Psychotherapy Regressions

	Mental Health		Psychotherapy	
	IV	IV FE	IV	IV FE
	(1)	(2)	(3)	(4)
Age	.008	-.077	.003*	.0006***
	(.043)	(.077)	(.002)	(.002)
Age Squared	-.0003	-.001	-.00004**	-.000060**
	(.0006)	(.001)	(.00001)	(.00002)
Education 2	.383***		.002	
	(.073)		(.002)	
Education 3	.522***		.003	
	(.089)		(.002)	
Married	.208***	-0.306	-.003	-.008**
	(.098)	(.1496)	(.003)	(.006)
Divorced	-.580***	-1.026***	.010*	.009
	(.150)	(.282)	(.004)	(.010)
One child	-.326***	-.086	-.005*	-.0005
	(.089)	(.131)	(.002)	(.003)
Two children	-.323**	-.166	-.007***	-.004
	(.096)	(.034)	(.002)	(.002)
Children $\geq$3	-.780***	-.314	-.004	-.003
	(.135)	(.042)	(.003)	(.005)
Therapy a_{t-1}		-0.032		
		(.316)		
Therapy = 1	-.713***	.831***	.069***	-.113***
	(.162)	(.348)	(.007)	(.017)
Therapy = 2	-1.056***	1.439***	.123***	-.274***
	(.332)	(.479)	(.017)	(.035)
Therapy $\geq$ 3	-1.744***	2.593***	.171***	-.463***
	(.385)	(.720)	(.022)	(.050)
Physical Health	1.938***	1.699***	-.012***	-.012***
	(.095)	(.090)	(.003)	(.005)
part-time a_{t-1}	-.188*	-0.244		
	(.097)	(.127)		
full-time a_{t-1}	-.297***	-.348***		
	(.092)	(.129)		
Mental Health (-1)			-.0019***	-.001***
			(.0002)	(.0003)
Constant	25.260***		.025	
	(.714)		(.019)	
First Stage F-Test	261.56	51.84	253.34	55.37
NT	30,752	31,210	30,829	34,297
Adjusted R^2	.004	.067	.056	.066

Note: Standard errors in parentheses. * $p<.05$, ** $p<.01$, *** $p<.001$. Standard errors are robust in columns 1 and 3 and robust and clustered at individual level in columns 2 and 4. The estimates presented in Column 2 are used for matching.

All the coefficients in column (1) are precisely estimated except for age and age squared. It is noteworthy that the coefficients on psychotherapy's years of experience reverse sign from negative to positive in the IV FE specification in column (2) while remaining precisely estimated. This suggests selection of those with lower mental health levels into psychotherapy and a positive causal effect of psychotherapy. Additionally, a control for previous-year psychotherapy is introduced, but its estimate lacks precision, probably due to its correlation with years of psychotherapy experience. The effect of divorce on mental health remains strongly negative in the FE specification, as well as the positive coefficient of physical health and the negative coefficients for part-time and full-time previous employment. In Column (2) the effect of age is negative but not precisely estimated, which is also true for fertility.

The IV results in column (3) demonstrate that age has a significant effect on the probability of attending psychotherapy. The probability increases with age at a decreasing rate. The probability also increases significantly with accumulated psychotherapy experience. The probability of attending psychotherapy is negatively associated with good physical health and a higher lagged mental health score. Being divorced is positively associated with psychotherapy, while having children (1 and 2) is negatively associated with it. The correlations with education and being married are weak. The IV FE results in column (4) are in line with the IV results, with a decrease in significance for having children and being divorce. Furthermore, the positive effect of accumulated psychotherapy experience reverses sign in Column (4), indicating that individuals with more accumulated psychotherapy experience are less likely to currently seek psychotherapy.

2.2.2 Physical Health

Table 4 displays the results of OLS and FE regressions related to physical health. In columns (1) and (2), the dependent variable is an indicator of physical health, which is the predicted outcome of the principal component analysis of subjective health measures when regressed using objective health measures. Columns (3) through (5) present IV and IV FE regressions with the dependent variable being a smoker indicator.

The OLS results in column (1) show that the probability of being in good physical health increases if one is in the highest educational category and with a higher mental health score. Being a smoker significantly decreases the probability of being in good physical health. Having children is correlated with being in good mental health.

The FE results are in line with the OLS results. Divorce is positively significantly correlated with being in good health in the FE regression. However, the magnitudes of the precisely estimated coefficients in the FE specifications are reduced in comparison to OLS for having 3+ children and employment stati.

Table 4: Physical Health and Smoking Regressions

	Physical Health		Smoking		
	OLS	FE	IV	IV FE	IV FE
	(1)	(2)	(3)	(4)	(5)
Age	-.042***	-.007	-.0100	-.0091*	-.0086**
	(.003)	(.004)	(.006)	(.0039)	(.003)
Age Squared	-.00001	-.0001	.000065	.00004	.00006
	(.00004)	(.0001)	(.00008)	(.000051)	(.00004)
Education 2	-.002		-.070***		
	(.006)		(.016)		
Education 3	.032***		-.192***		
	(.007)		(.017)		
Married	.007	.012	-.075***	-.030*	-.024*
	(.007)	(.011)	(.002)	(.012)	(.009)
Divorced	.005	.046**	.061***	.0095	.008
	(.011)	(.017)	(.025)	(.014)	(.012)
One Child	.032***	.030***	.025	-.019**	-.005
	(.007)	(.010)	(.013)	(.007)	(.005)
Two Children	.057***	.039***	.002	-.018*	-.005
	(.007)	(.012)	(.013)	(.007)	(.005)
Children $\geq$3	.077***	.022	.0210	-.032**	-.012
	(.010)	(.016)	(.021)	(.0113)	(.009)
Mental Health	.009***	.002***	-.002***	-.0005	-.0005
	(.0005)	(.0004)	(.001)	(.0005)	(.0003)
Physical Health (-1)			-.043***	-.004	-.00004
			(.013)	(.008)	(.007)
Smoking	-.043***	-.029*			
	(.006)	(.011)			
Smoking (-1)					.308***
					(.016)
part-time a_{t-1}	0.0214***	-.003			
	(.007)	(.007)			
full-time a_{t-1}	.035***	-.011			
	(.007)	(.008)			
Constant	.106*		.290***		
	(.053)		(.077)		
F-Test Pr$>\chi^2$			.0000	0.204	0.248
First Stage F-Test			99.82	54.78	54.82
NT	32,509	37,305	30,143	33,559	33,495
Adjusted R^2	.042	.022	.041		

Note: Standard errors in parentheses. * $p<.05$, ** $p<.01$, *** $p<.001$. Columns 1 and 3 present robust standard errors. Columns 2,4 and 5 present robust standard errors clustered at individual level.

In column (3), the IV results illustrate that the probability of being a smoker decreases with education. It is also lower if one is married or in good mental health. The probability of smoking is higher when divorced, and there is not a significant correlation with having children. An F-test of mental and physical health show that they are jointly significant.

In comparison to IV, the IV FE specification in column (4) yields an effect of children that changes sign from positive to negative and becomes statistically significant. In addition, the association with marital status and mental health is substantially reduced, with the association with mental health not being statistically significant, which is confirmed by the F-test of joint significance between physical and mental health.

The IV FE specification in column (5) adds smoking status in the previous year. The results are similar to those in column (4) except the effect of children loses significance. The coefficient on lagged smoking status suggests substantial persistence even after adding several controls. The negative effect of the linear component of age is also precisely estimated.

2.2.3 Employment, Marriage and Fertility

Table 5 presents regression results that focus on the effects of mental and physical health on employment, marriage and fertility outcomes. All regressions are IV FE, where physical health is instrumented. All specifications include a constant, a quadratic in age and fixed effects.

The dependent variable in column (1) is whether the woman is employed or not at the time of the survey. An increase of approximately 25 points from the lowest to the average mental health score corresponds to a 3.3 percentage point increase in the probability of employment. The baseline probability is .75. While being in good physical health decreases the probability of employment, it's worth noting the correlation between mental and physical health, as indicated by the F-test. Additional controls in column (1) include spousal income and indicators for marital status and the number of children. As expected, being married and having children are negatively associated with employment.

Column (2) shows that higher mental health scores significantly increases the probability of being married at the time of the survey. An increase of 25 points in the mental health score raises the probability of being married by 5.8 percentage points. The baseline probability is .72. Being in good physical health is again negative and not precisely estimated. A joint significance test for mental and physical health again shows that they are jointly significant.

Table 5: Employment, Marriage and Fertility IV FE Regressions

	Employment (1)	Marriage (2)	Conception (3)	Accepted Wages (4)
Mental	.0013**	.0023***	.001*	.003***
Health	(.0004)	(.0005)	(.0003)	(.001)
Physical	-.004	-.015	-.005	.070***
Health	(.012)	(.011)	(.007)	(.0164)
F-Test Pr>χ^2	0.014	0.000	0.140	0.001
First Stage F-Test	44.37	54.97	35.27	34.77
NT	28801	33627	22931	26150

Note: Standard errors in parentheses. * p<.05, ** p<.01, *** p<.001. All specification have robust standard errors clustered at individual level. All specifications include a quadratic in age and fixed effects. The employment and conception regressions also spousal income and indicators for marital status and the number of children. F-Tests show joint statistical significance for mental and physical health in all specifications, except for the results of column 3.

Column (3) shows that better mental health has a positive and significant effect on conception, with 2.5 percentage point increase in the probability of conceiving for a 25 points increase in mental health. Again, physical health is not precisely estimated, but in this case is not jointly significant with mental health. Additional controls include marital status, the number of children and spousal income. Being married substantially increases the probability of conceiving a child and, as already noted, better mental health raises the probability of being married. Therefore, higher mental health scores are associated with a higher probability of conceiving a child, which is partially mediated by marital status.

Column (4) displays results when the unemployed are excluded and accepted wages are regressed on mental and physical health. Better mental mental health substantially increases female wages. Going from the lowest lowest mental health score to the average raises wages by 6.8 percent. Being in good physical health reduces wages by .5 percent, but the effect is not precisely estimated. The regression also controls for full-time work.

2.2.4 Wages

Table 6 presents parsimonious Mincer style regressions, in which mental and physical health are added as factor of production. The dependent variables are: part-time, full-time, and spousal wages. Columns 1, 3, and 5 presents IV estimates, while columns 2, 4, and 6 presents IV FE estimates. All columns display the F-test for the joint significance of mental and physical health (which is statistically significant in all cases except for the IV FE estimates of part-time wage in column (2)), along with the First Stage F-test results for exclusion restrictions. In all estimates (except for Column (2)) the quadratic expression for age shows positive returns with decreasing rates.

Column (1) shows that more education and physical health are associated with higher part-time wages, while mental health is negative and very small in magnitude. On the other hand Column (2) does not show strong significance in any regressor, and does not indicate a particularly strong first stage. Full-time employment (Columns (3) and (4)) is better explained by the mincer style regression, with significant coefficients implying that a change from the lowest level of mental health to the average increase full-time accepted wages by 10% (IV) and by 7.5% (IV FE), with a one standard deviation change increasing full-time wage by 2.5% (IV) and 1.9% (IV FE). A standard deviation change in physical health would increases full-time accepted wages by 2.2% (IV), while it is negative for the IV FE (Column 4). Again, it should be noted that mental and physical health are correlated and jointly significant.

Table 6: Employment, Marriage and Fertility IV FE Regressions

	PT Accepted Wage		FT Accepted Wage		Spousal Earnings	
	IV	IV FE	IV	IV FE	IV	IV FE
	(1)	(2)	(3)	(4)	(5)	(6)
Age	0.044**	.035	0.080***	.081***	0.074***	.080***
	(.016)	(.025)	(.007)	(.007)	(.008)	(.008)
Age^2	-0.0004*	.0001	-0.001***	-.001***	-0.001***	-.001***
	(.0002)	(.0003)	(.00001)	(.0001)	(.0001)	(.0001)
Education 2	0.209***		0.154***		0.095***	
	(.031)		(.018)		(.020)	
Education 3	0.665***		0.496***		0.248***	
	(.050)		(.020)		(.026)	
Mental Health	-.0000	.001	0.004***	.003***	0.005***	.002
	(.002)	(.002)	(.001)	(.001)	(.001)	(.001)
Physical Health	0.088**	.023	0.05**	-.005	0.074***	.033
	(.031)	(.041)	(.001)	(.018)	(.019)	(.022)
Constant	7.560***		7.924***		8.398***	
	(.300)		(.119)		(.147)	
F-Test Pr$>\chi^2$	0.008	.576	0.000	.000	0.000	.012
First Stage F-Test	18.22	9.48	93.46	21.80	127.88	21.25
NT	7,401	6,762	16,149	15,283	19,910	17,164
Adjusted R^2	.098		.166		.042	

Note: Standard errors in parentheses. * $p<.05$, ** $p<.01$, *** $p<.001$. Accepted wages and spousal income in columns are in natural logs and the unemployed are excluded from Columns 1, 2, 3, and 4, while single and divorced are excluded from Columns 5 and 6. Columns 2, 4 and 6 are used as moments to match.

The spousal accepted wage regression in column (5) excludes unemployed spouses and uses female characteristics as covariates. The woman's characteristics proxy for the productivity characteristics of the male, as in the structural model, helping to reduce the size of the state space. This strategy generally works well in explaining the variation in spousal earnings when there is assortative mating, which is strongly suggested by the data. The impact of improved mental and physical health is more pronounced in spousal earnings than in women's employment, with moving from a low level to an average level of mental health being associated with a 12.5% increase in spousal earnings, and a change from "bad" to "good" physical health being associated with a 7.4% increase in spousal earnings. Column (6) shows results that are smaller in magnitude and less precisely estimated, but it should be noted that mental and physical health are still jointly significant at 5% level.

Overall, the data suggests that there are significant relations between mental and physical health and fertility, marital decisions and employment. The data also indicates that these relations are a two-way stream (as previously demonstrated by Jolivet and Postel-Vinay (2024) in their study on male employment). In the next section we present a dynamic model that takes into account these mechanisms and two-way interactions.

3 The Model

In the model, a woman makes joint and sequential decisions at the beginning of each period about: whether to consult a psychotherapist, whether to smoke cigarettes, what type of employment to engage in (unemployment, part-time, full-time), to be single or married, and whether to conceive a child. The objective of the woman is to choose, in each period, mental and physical health levels together with employment, marital, and fertility states to maximize her discounted present value of lifetime utility. The multivariate and simultaneous decisions are made annually between the ages of 20 and 52.

At age 19, the start of the decision horizon, women differ according to their completed education level, mental and physical health, and unobserved type. Unobserved type is a time-invariant individual effect. While education is not explicitly included in the choice set, it is treated as endogenous, being correlated with unobserved type through the discrete type mixing distribution. The last decision period in the model is at age 51.

It is important to note that the model assumes women are forward-looking when making choices that influence their mental and physical health. That is, they decide on whether or not to consult a psychotherapist and smoke cigarettes in a rational manner. In the context of the model, rationality means one fully takes into account the expected future labour market, marriage and fertility consequences of today's lifestyle choices.

3.1 The Choice Set

A woman's overall health is divided into two separate but related components; mental and physical health. Mental health state at each age a is partially determined by the choice to see a psychotherapist. The psychotherapy choice variable is denoted as p_a. If a psychotherapist is consulted, for any amount of time during the year, $p_a = 1$, otherwise $p_a = 0$.

A woman's physical health state at each age a is partially determined by the choice to be a smoker. The smoking choice variable is denoted as s_a. If any amount of cigarettes is smoked during the year, $s_a = 1$, otherwise $s_a = 0$.

The employment choice set at the beginning of age a contains three mutually exclusive elements: non-employment ($k = 1$), part-time employment ($k = 2$) and full-time employment ($k = 3$). The employment choice variable, d_a^k, $k \in K$, is defined such that $d_a^k = 1$ if a woman chooses employment state k at age a and $d_a^k = 0$ otherwise. Part-time and full-time job offers, at various stochastically generated wage offer levels, are assumed to always be available.

At each age a, a woman may choose to be single or married. Marital choices are partially constrained. When a woman is single, she can marry only if a marriage offer is received. The probability of receiving a marriage offer is denoted by π_a^m. The marital status choice variable is m_a, where $m_a = 1$ if a woman is married (or cohabiting) and $m_a = 0$ if single (or divorced). Since divorce is a separate state variable, the categorical variables m_{1a} and m_{2a} are also defined, such that $m_{1a} = 1$ if the individual is married and zero otherwise, and $m_{2a} = 1$ if the individual is divorced and zero otherwise. The base category is single and never married.

A woman can also choose to conceive a child at each age a. The fertile period is restricted to $a \leq 40$. This restriction is motivated by the data. The fertility choice variable is b_a, where $b_a = 1$ if a child is conceived at age a and $b_a = 0$.

3.2 Utility Flow and Budget Constraint

The utility flow at age a, denoted by U_a, is specified as CRRA in consumption with several additively separable components,

$$U_a = \frac{\mu_k C_a^{1-\lambda}}{1-\lambda} + \psi_a^m + \psi_a^n + \psi_a^{mh} + \psi_a^{ph} + \psi_a^{th} + \psi_a^s + d_a^1 \varepsilon_a^u \tag{1}$$

where C_a is consumption and $1 - \lambda$ is the parameter of constant relative risk aversion. λ determines the curvature of the utility function and μ_k shifts the marginal utility of consumption depending on employment state k. μ_k equals one when $k = 1$ (non-employed) and $0 < \mu_k \leq 1$ for $k = 2, 3$. These restrictions strengthen the interpretation of μ_k as the disutility of work effort (or foregone leisure). Moreover, $\mu_2$and $\mu_3$depend on mental (H^m) and physical (H^m) health stati at age a, representing the increase in disutility of effort deriving from being ill

$$\mu_k = \frac{exp(\beta_{\mu k0} + \beta_{\mu k1} H_a^m + +\beta_{\mu k2} H_a^p}{1 + exp(\beta_{\mu k0} + \beta_{\mu k1} H_a^m + \beta_{\mu k2} H_a^p} \tag{2}$$

The first additively separable component in (1), ψ_a^m, is the utility of being married. ψ_a^n is the utility derived from having children. Ψ_a^{mh}, Ψ_a^{ph}, Ψ_a^{th} and Ψ_a^s are the utilities of mental health, physical health, being in psychotherapy and smoking cigarettes, respectively. ε_a^u is a preference shock in the non-employment state.

The quasi-linear nature of contemporaneous utility allows the consumption of goods, being married, having children, being in good mental and physical health, attending psychotherapy and smoking to be partial substitutes. This implies that marriage, children, psychotherapy and smoking choices are all endogenous to the labour supply decision and earnings. Similar to marital satisfaction and the utility derived from having children, good mental and physical health, attending psychotherapy, and smoking can provide sources of utility. These factors may substitute for greater labor market earnings and consumption of goods. Conversely, good mental and physical health may also encourage labor supply by increasing earning capacity. This tension is incorporated into the model and the relative strengths of these different effects are estimated.

The budget constraint at age a is specified as

$$C_a = \tau^{m_a}\{bd_a^1 + w_a^{pt}d_a^2 + w_a^{ft}d_a^3 + w_a^h m_a - c_a^n(k) - c_a^{mn} - c_a^{th} - c_a^s\} \tag{3}$$

where τ^{m_a} is the household income sharing parameter. $\tau^{m_a} = 1$ if $m_a = 0$ and $0 \leq \tau^{m_a} \leq 1$ if $m_a = 1$. τ^1 must be sufficiently high to induce high wage women to marry low wage men. The lower is τ^1, the higher the spousal wage w_a^h must be to compensate for income sharing. This drives positive assortative mating in the model which is also observed in the data.

The first term in brackets in (3), bd_a^1, represents unobserved consumption when non-employed. w_a^{pt} and w_a^{ft}, are accepted wages in part-time and full-time employment, respectively. The final three terms are, respectively, the monetary equivalents of the costs of children, $c_a^n(k)$, consulting a psychotherapist, c_a^{th}, and smoking cigarettes, c_a^s.

The costs of children $c_a^n(k)$ are dependent on employment state k because childcare costs may be higher when working. Childcare costs that increase with the amount of time devoted to the labor market, together with the disutility of work effort, can induce women who receive relatively low-wage offers to have children and choose non-employment or part-time work as an optimal combination. c_a^{mn} represents the child support for single mothers.

High spousal earnings, w_a^h, can also lead to less time devoted to the labour market if additional consumption from labour market earnings does not outweigh the disutility of work effort and additional childcare costs. This non-labour income effect will be more pronounced the more curvature there is to the CRRA component of the utility flow. Note that because the costs of children, psychotherapy and smoking are shared when married, there is a disincentive to divorce which goes beyond the loss of spousal income.[5]

[5] Asset accumulation is not incorporated into the model. This is common in the dynamic programming literature on female labor supply (see Eckstein and Wolpin (1989), van der Klaauw (1996) , Francesconi (2002) and Keane and Wolpin (2010)).

3.3 Mental and Physical Health

The way in which mental and physical health functions are specified and how they influence employment, marital and fertility choices are key assumptions of the model. The specifications are informed by the descriptive statistics and regression results discussed earlier.

3.3.1 Mental Health

The mental health of a woman at age a, is assumed to be determined as follows,

$$
\begin{aligned}
ln\,(H_a^m) = {} & \beta_{0,mh} + \beta_{1,mh}A + \beta_{2,mh}I(X_a^{th}=1) + \beta_{3,mh}I(X_a^{th}=2) + \beta_{4,mh}I(X_a^{th}\geq 3) \\
& + \beta_{5,mh}I(p_{a-1}=1) + \beta_{6,mh}m_{1a} + \beta_{7,mh}m_{2a} \\
& + \beta_{8,mh}I(n_a=1) + \beta_{9,mh}I(n_a=2) + \beta_{10,mh}I(n_a\geq 3) + \beta_{11,mh}H_a^p \\
& + \beta_{12mh}d_{a-1}^2 + \beta_{13mh}d_{a-1}^3 + \varepsilon_a^{mh}
\end{aligned} \tag{4}
$$

where $A=1$ denotes the individual is "type 1" and $A=0$ signifies the individual is "type 0".

Since an individual's unobserved type A is time-invariant, unobserved type appearing in the mental health function allows for persistence in mental health outcomes. As the probability of being type 1 is dependent on education level, mental health is also indirectly a function of education.

The dependence of unobserved type on education is through the discrete type mixing distribution. The mixing distribution is characterized by the probability of being type 1 and the probability of being type 0. The probability a woman is type 1 is a function of completed education level at age 20, i.e.,

$$
\pi^A = \Pr(A=1) = L(\alpha_{0,A} + \alpha_{1,A}E_1 + \alpha_{2,A}E_2) \tag{5}
$$

where $E_j, j=1,2$ are the categorial variables representing the three education levels described earlier. The probability a woman is type 0 is simply $1-\pi^A$. The logistic functional form, $L(\cdot) = \frac{exp(\cdot)}{1+exp(\cdot)}$, serves to constrain probabilities to between zero and one.

Persistence in mental health outcomes can also arise from accumulated psychotherapy experience, X_a^{th}. In order to limit the size of the state space, the range of psychotherapy experience is constrained to be between zero and three. This limitation is justified by the observed data as the sample proportion with more than three years of experience is very small. The indicator function in (4), $I(\cdot)$, is equal to one if the expression in brackets is true, and zero otherwise.

Accumulated therapy experience obeys the following law of motion,

$$\begin{cases} X_{a+1}^{th} = X_a^{th} + p_a & if\, X_a^{th} < 3 \\ X_{a+1}^{th} = X_a^{th} & if\, X_a^{th} \geq 3 \end{cases} \tag{6}$$

with the initial condition $X_{20}^{th} = 0$.

Once an individual has accumulated three years of psychotherapy experience, choosing to consult a psychotherapist for an additional year does not augment the experience variable. However, the term $I(p_{a-1} = 1)$, whether or not one was in psychotherapy the previous year, provides an incentive for remaining in psychotherapy beyond three years. This latter term also incorporates a benefit to remaining in psychotherapy continuously rather than taking annual breaks.

The terms m_{1a} and m_{2a} in (4) incorporate the role of marital status (single never married, married or divorced) for mental health levels. The number of children in the household, n_a, is also allowed to influence mental health. In order to limit the size of the state space, n_a stops accumulating after three children.

The law of motion for n_a is,

$$\begin{cases} n_{a+1} = n_a + b_a & if\, n_a < 3 \\ n_{a+1} = n_a & if\, n_a \geq 3. \end{cases} \tag{7}$$

This restriction is also consistent with the observed data.

Note that (4) recognizes that physical health status, H_a^p, can influence mental health levels. Physical health is defined such that $H_a^p = 1$ if the woman is in good physical health and $H_a^p = 0$ otherwise. The log transformation for H_a^m is necessary for yielding simulated mental health scores that are always greater than zero. Previous year employment status also affects mental health, and the equation allows for different coefficients between part-time (d_{a-1}^2) and full-time (d_{a-1}^3) employment. Finally, ε_a^{mh} is a transitory mental health shock that is i.i.d. and follows a normal distribution with zero mean and variance σ_{mh}^2.

Utility from good mental health is derived through the term ψ_a^{mh}, appearing in (1), as well as through increased earnings capacity, described in the next subsection. The utility of mental health is assumed to be non-negative and increasing in the individual's mental health level, i.e.,

$$\psi_a^{mh} = e^{\left(\delta_{1,mh} + \delta_{2,mh} H_a^m\right)}. \tag{8}$$

Attending psychotherapy also has direct utility value, separate from the utility of good mental health. ψ_a^{th}, appearing in (1), is specified as a non-negative constant,

$$\psi_a^{th} = e^{\delta_{0,th}}. \tag{9}$$

A separate utility value for attending psychotherapy helps explain why people with already high levels of mental health may nonetheless choose to attend psychotherapy.

While psychotherapy experience brings benefits through direct utility and the channel of better mental health, it comes with a cost, c_a^{th}, as shown in (3). The monetary equivalent of the annual cost of psychotherapy, which includes the monetary equivalent of any stigma costs, is the non-negative constant,

$$c_a^{th} = e^{\delta_{1,th}}. \tag{10}$$

3.3.2 Physical Health

The physical health of a woman at age a is specified as,

$$\begin{aligned} H_a^p = {} & \beta_{0,ph} + \beta_{1,ph}A + \beta_{2,ph}s_a + \beta_{3,ph}m_{1a} + \beta_{4,ph}m_{2a} + \beta_{5,ph}H_a^m \\ & \beta_{6,ph}I(n_a = 1) + \beta_{7ph}I(n_a = 2) + \beta_{8,ph}I(n_a \geq 3) \\ & + \beta_{9ph}a + \beta_{10ph}d_{a-1}^2 + \beta_{11ph}d_{a-1}^3 + \varepsilon_a^{ph} \end{aligned} \tag{11}$$

where $s_a = 1$ if the woman chooses to be a smoker at age a and $s_a = 0$ otherwise. Physical health is also a function of age, unobserved type, marital status, number of children and mental health. Unobserved type captures persistence in physical health conditions over time and, indirectly, the effect of education. ε_a^{ph} is a transitory mental health shock which is i.i.d. and follows a normal distribution with zero mean and variance σ_{ph}^2.

Note that in (11) physical health affects mental health and in (11) mental health influences physical health. Thus, the simultaneity of the relationship between the two components of health is taken into account. Note also that psychotherapy experience affects only mental health while smoking status influences only physical health. These are "natural" exclusion restrictions. Age appears in the physical health function but is absent from the mental health function. This latter exclusion restriction is empirically motivated.

As with mental health, a woman derives benefit from good physical health through direct utility as well as through increased earnings capacity and decreased disutility of effort. The utility value of physical health, ψ_a^{ph}, appearing in (1), is the non-negative constant,

$$\psi_a^{ph} = e^{\delta_{1,ph}}. \tag{12}$$

The direct utility value of smoking, ψ_a^s, is similarly specified as,

$$\psi_a^s = e^{\delta_{0,s}} + e^{\delta_{1,s}} A + e^{\delta_{2,s}} I(n_a > 0) + e^{\delta_{3,s}} D_a. \tag{13}$$

A contemporaneous utility value of smoking is indispensable for explaining why people choose to smoke, when smoking has current monetary costs as well as future opportunity costs through a lower probability of being in good physical health.

The monetary equivalent of the annual cost of smoking, c_a^s, appearing in (3), is

$$c_a^s = e^{\delta_{1,s}} \tag{14}$$

3.4 Employment

The monetary benefits of good mental and physical health levels work through the wage offer functions. Mental and physical health levels are assumed to be observable to employers, and key factors that affect productivity on the job, in contrast to psychotherapy experience and smoking. Wage offers are also modeled as a function of unobserved type. Therefore, mental health, physical health and wage offer functions have correlated error terms. The presence of unobserved type in the wage offer functions contributes to additional earnings persistence, beyond that accounted for by time-varying accumulated work experience and mental and physical health levels. It subsumes an indirect effect of education as well.

More formally, wage offers in part-time and full-time work are specified as Mincer-style functions of unobserved type, accumulated work experience, physical and mental health levels, and time-varying productivity shocks,

$$\begin{aligned} ln(w_a^{pt}) &= \beta_{0,p} + \beta_{1,p} A + \beta_{2,p} X_a^w - \beta_{3,p} \left(X_a^w\right)^2 \\ &\quad + \beta_{4,p} H_a^m + \beta_{5,p} H_a^p + \varepsilon_a^{pt} \end{aligned} \tag{15}$$

$$\begin{aligned} ln(w_a^{ft}) &= \beta_{0,f} + \beta_{1,f} A + \beta_{2,f} X_a^w - \beta_{3,f} \left(X_a^w\right)^2 \\ &\quad + \beta_{4,f} H_a^m + \beta_{5,f} H_a^p + \varepsilon_a^{ft} \end{aligned} \tag{16}$$

where X_a^w is accumulated work experience and ε_a^{pt} and ε_a^{ft} are time-varying productivity shocks in part-time and full-time employment, respectively.

The non-employment preference shock in (1) and the employment productivity shocks, ε_a^{pt} and ε_a^{ft} in (15) and (16) are allowed to be correlated. The joint distribution of the non-employment and employment shocks is $(\varepsilon_a^u, \varepsilon_a^p, \varepsilon_a^f) \sim N(0, \Sigma)$, where $\Sigma = C'C$. C is the Cholesky factor and is restricted for identification reasons to be,

$$C = \begin{bmatrix} a_{uu} & 0 & 0 \\ a_{pu} & a_{pp} & 0 \\ 0 & a_{fp} & a_{ff} \end{bmatrix}. \tag{17}$$

Through the wage offer functions, good mental and physical health levels provide an additional source of utility beyond the direct utility components in (1). Therefore, high levels of mental and physical health can encourage labour supply rather than only discourage it through a substitution effect. Depending on the relative strengths of the direct utility components and the labor market returns to mental and physical health, consumption of goods and mental and physical health can be net complements. Consumption of goods and mental and physical health can also be net complements through the cost channel. To afford the costs of psychotherapy and benefit from its utility, individuals may need to increase their labor supply and earnings. This is analogous to the labor-supply inducing effect of childcare costs for women with higher earnings potential.

The accumulated work experience term appearing in (15) and (16), X_a^w, obeys the following law of motion:

$$X_{a+1}^w = X_a^w + d_a^2 + 2d_a^3 \tag{18}$$

where a woman does not accumulate work experience when she is non-employed, accumulates one extra unit of work experience when she works part-time and 2 extra units when she works full-time. The initial condition at age 20 is $X_{20}^w = 0$.

3.5 Marriage

The marital status decision in the model is also affected by mental and physical health levels as well as a process of learning about the match. If a woman is single at age a, a marriage offer is not assumed to arrive with certainty. Rather, a marriage offer is received with probability π_a^m. The marriage offer probability is specified as dependent on mental and physical health, i.e.,

$$\pi_a^m = \frac{exp(\alpha_{0,m} + \alpha_{1,m} H_a^m + \alpha_{2,m} H_a^p)}{1 + exp(\alpha_{0,m} + \alpha_{1,m} H_a^m + \alpha_{2,m} H_a^p)} \tag{19}$$

If a woman receives a marriage offer, she is not assumed to know the quality of the match with certainty either. During marriage the true match quality will be discovered over time, influencing the duration of marriage as well as all other decisions in the model.

The match quality learning process is as follows. Let Q^m denote the true unknown match quality. The quality of the match is either good ($Q^m = 1$) or bad ($Q^m = 0$). Q^m is randomly assigned upon receipt of a marriage offer and remains constant for the duration of the marriage. The probability of drawing a good match, ϕ_q, is

$$\phi_q = Pr(Q^m = 1) = L(\alpha_{0,q}). \tag{20}$$

ϕ_q is interpretable as the steady-state proportion of good matches in the population and is the initial belief that the drawn match is a good one.

During the first period of marriage, a noisy signal of the true match quality is received, denoted as ν_a^m. The quality signal is either good ($\nu_a^m = 1$) or bad ($\nu_a^m = 0$), consistent with the binary nature of the true match quality. The precision of the signal, denoted as φ, is the probability of receiving a good signal $\nu_a^m = 1$ given the true match is good $Q^m = 1$,

$$\varphi = Pr(\nu_a^m = 1|Q^m = 1) = L(\alpha_{0,p}). \tag{21}$$

The precision of the signal is assumed to have the same value when the true match is a bad one, i.e., $Pr(\nu_a^m = 1|Q^m = 1)$ is equal to $Pr(\nu_a^m = 0|Q^m = 0)$. The signal is also assumed to be overall informative so that it is constrained to the range $0.5 < \varphi < 1$. The closer precision is to one, the faster is learning about the true match quality, and the more likely the duration of marriage will be shorter for bad matches.[6]

After the first period of marriage, belief about the quality of the match is updated according to the noisy signal ν_a^m that has been received. The updated belief, denoted as ϕ_a, is determined by Bayes' rule.

If $v_a^m = 1$,

$$\begin{aligned}\phi_a &= Pr(Q^m = 1|\nu_a^m = 1)\\ &= \frac{Pr(Q^m = 1 \; and \; \nu_a^m = 1)}{Pr(\nu_a^m = 1)} = \frac{\phi_q \varphi}{\phi_q \varphi + (1-\phi_q)(1-\varphi)}\end{aligned} \tag{22}$$

and if $v_a^m = 0$ then

[6]If the marriage is terminated, the woman must remain single for one period before it is possible to receive new marriage offers.

$$\phi_a = Pr(Q^m = 1 | \nu_a^m = 0)$$
$$= \frac{Pr(Q_m = 1 \, and \, \nu_a^m = 0)}{Pr(\nu_a^m = 0)} = \frac{\phi_q(1-\varphi)}{\phi_q(1-\varphi) + (1-\phi_q)\varphi}. \quad (23)$$

If the marriage continues, the updating proceeds in the same way in subsequent periods with ϕ_{a-1} replacing ϕ_q in (22) and (23). Since the signal is assumed to be informative, belief about the quality of match, ϕ_a, will tend towards either zero (bad match) or one (good match) over the duration of the marriage.

The utility of marriage Ψ_a^m, appearing in (1), is specified as a linear function of the current belief in the quality of the match and mental and physical health levels,

$$\Psi_a^m = \beta_{0,m} + \beta_{1,m}\phi_a + \beta_{2,m}H_a^m + \beta_{3,m}H_a^p + \varepsilon_a^m. \quad (24)$$

Because the utility of marriage and the probability of remaining married in the future changes with the current belief, other dimensions of choice during marriage such as labor supply and fertility decisions are affected. In particular, labor supply can become more attractive and fertility delayed as negative signals about the quality of the match are received and the probability of remaining married in the future is adjusted downwards (see also Anderberg et al. (2023)).

Allowing the value of the current belief to affect marriage utility resembles adding a random component to the utility of marriage. However, the random component here is more systematic and persistent than a time-varying idiosyncratic marriage utility shock. In essence, the learning mechanism introduces a theoretically-motivated form of serial correlation into the utility of marriage.

In addition to the current belief, the utility of marriage changes with mental and physical health. Having H_a^m affect marriage utility is consistent with findings in the psychology literature that suggest better mental health improves marital satisfaction (Whisman et al. (2004)). Better physical health, H_a^p, is also likely to improve marital satisfaction through various channels. Since the choice to seek psychotherapy and to be a smoker influence mental and physical health, these latter decisions have indirect effects on the utility and duration of marriage.

Marriage also offers monetary benefits, such as sharing childcare, psychotherapy, and smoking costs, as well as spousal earnings. In order to economize on the state space, the spousal earnings function is not directly affected by male characteristics. Rather, spousal earnings is specified as a Mincer-style function of the woman's characteristics,

$$ln(w_a^h) = \beta_{0,h} + \beta_{1,h}A + \beta_{2,h}a + \beta_{3,h}a^2 + \beta_{4,h}H_a^m + \beta_{5,h}H_a^p + \varepsilon_a^h. \quad (25)$$

The woman's unobserved type, age, mental and physical health status proxy for the productivity characteristics of the male. This generally works well in explaining the variation in spousal earnings when there is assortative mating, as suggested by the data. ε_a^h is a transitory income shock to the husband's earnings which is assumed to be i.i.d. and distributed normal with variance σ_h^2.[7]

3.6 Fertility

The decision to conceive a child or not at each age a is based on the utility benefits of children as well as their monetary costs. The utility of having children, Ψ_a^n, appearing in (1), is specified as,

$$\begin{aligned}\Psi_a^n &= \beta_{1,n} I(n_a = 1) + \beta_{2,n} I(n_a = 2) + \beta_{3,n} I(n_a \geq 3) \\ &+ b_a \varepsilon_a^n.\end{aligned} \tag{26}$$

The utility of children is a function of the number of children and mental and physical health. There is also a transitory shock to utility while pregnant, ε_a^n, which is i.i.d. and distributed normal with variance σ_n^2. The fertile period is restricted to $a \leq 40$, which is consistent with the data.

The utility of children is a function of mental and physical health in order to capture, in a reduced form way, the possibility that women with poor mental and physical health may choose to have less (or no) children. Poor health can lead to difficulties in properly caring for children and induce a fear of producing "lower quality" offspring. It may also capture a more complicated and undesirable gestation period.[8]

Note that the mental and physical health functions (4) and (11) have the number of children as a determinant, and the utility of children is affected by mental and physical health. Thus, the model takes into account both possible directions of causality between mental and physical health and the number of children.

The cost of children, $c_a^n(k)$ is specified as a function of the number of children and the woman's employment status, i.e.,

$$c_a^n(k) = \rho^k(\beta_{1,c} I(n_a = 1) + 2 * \beta_{2,c} I(n_a = 2) + 3 * \beta_{3,c} I(n_a \geq 3) \tag{27}$$

[7] Female characteristics only in the spousal earnings function has been the standard strategy in the structural discrete choice dynamic programming literature. See, e.g., van der Klaauw (1996), Francesconi (2002), Keane and Wolpin (2010) and Sauer (2015).

[8] A dependence between physical health and live birth outcomes has been confirmed in several health studies (see, e.g., Pasquali et al. (2003)).

Employment state affects the costs of children through the term ρ^k. ρ^3 is normalized to one and ρ^k, $k = 1, 2$, is constrained to be between zero and one. Thus, when a women works full-time, $c_a^n(3) = \beta_{1,c}I(n_a = 1) + 2 * \beta_{2,c}I(n_a = 2) + 3 * \beta_{3,c}I(n_a \geq 3)$, and "full" childcare costs are incurred. When a woman is non-employed or works part-time, childcare costs are a fraction, ρ^1 or ρ^2, respectively, of full-time costs. The lower costs in non-employment and part-time work can derive from both less hired childcare and more public assistance. Single and divorced mothers receive child support that depends on the number of children:

$$c_a^{ma} = \beta_{1,cm}I(n_a = 1) + 2 * \beta_{2,cm}I(n_a = 2) + 3 * \beta_{3,cm}I(n_a \geq 3) \tag{28}$$

3.7 Solution Method

The objective of the individual is to choose an employment, marital, conception and psychotherapy state to maximize the expected present discounted value of remaining lifetime utility at each age a. Remaining lifetime utility, at the optimal choice combination, is

$$V_a(\Omega_a) = \max E\left[\sum_{\tau=a}^{\overline{a}} \delta^{\tau-a} U_\tau | \Omega_a\right] \tag{29}$$

where $V_a(\Omega_a)$ is the value function, Ω_a is the state space, δ is the subjective discount factor and $\overline{a}$ is the terminal age. The expectation is taken over the distribution of future preference and productivity shocks and marriage opportunities.

The maximization problem in (29) can be recast as a dynamic program by writing $V_a(\Omega_a)$ as the maximum over alternative-specific value functions $V_a^j(\Omega_a)$, where $j \in J$ is a feasible choice combination $(p_a, s_a, \{d_a^k\}_{k\in K}, m_a, b_a)$, and $V_a^j(\Omega_a)$ obeys the Bellman equation. That is,

$$\begin{aligned} V_a(\Omega_a) &= \max_{j\in J}\left[V_a^j(\Omega_a)\right] \\ V_a^j(\Omega_a) &= \begin{cases} U_a^j + \delta E\left(V_{a+1}(\Omega_{a+1}) | j \in J, \Omega_a\right) & for\, a < \bar{a} \\ U_{\bar{a}}^j & for\, a = \bar{a} \end{cases} \end{aligned} \tag{30}$$

and a woman chooses the option j at each age a that corresponds to the maximum $V_a^j(\Omega_a)$. The solution is generally not analytic, but can be solved numerically. A full numerical solution is performed and requires calculating $E\left(V_{a+1}(\Omega_{a+1}) | j \in J, \Omega_a\right)$ in (30) by backward recursion for all j and elements of Ω_a.

Our model contains 48 alternative-specific value functions, $V_a^j(\Omega_a)$, since there are two psychotherapy choices, two smoking choices, three employment choices, two marital states, and two conception choices. The deterministic part of the state space, Ω_a, contains unobserved type (two values), accumulated psychotherapy experience (four values), whether one was attending psychotherapy in the previous period (two values), accumulated work experience (25 values), marital status (three values), belief about the quality of the match (20 values), and the number of children (four values).

Show and explain simultaneous equation solution for mental and physical health here.

4 Estimation

The model is estimated by the method of simulated moments (MSM) (see McFadden (1989) and Pakes and Pollard (1989)). Estimation also includes elements of Indirect Inference. This approach entails solving the model by backward recursion, for each trial vector of parameters, then forward simulating the model to obtain simulated panel data.We use a full numerical solution method, solving the Emax function at every t = 1, . . ., T (Keane and Wolpin, 1994). The Emax function, for each time t , represents the expected value of the maximum over alternative value functions at time $t+1$ for any given point in the state space, which corresponds to each possible alternative in the choice set at time t, and includes, for each each alternative value function, a set of draws for the *i.i.d.* shocks. The deterministic part of state space at time t is a set containing $\{t, A, n_{t-1}, m_{t-1}, X_t^p, s_{t-1}, d_{t-1}^k, p_{t-1}, X_t^w, \phi_t\}$. After solving the Emax, the model is then forward simulated. This results in a simulated panel data with life-cycle decisions and about 1e+52 possible paths for a large number of individuals. The simulated panel data is used to calculate moments and regression parameters. These values are then utilized in the MSM minimum distance objective function, which minimizes the discrepancy between the observed moments and those generated from the simulated data set.

The objective function to be minimized with respect to the structural parameter vector θ is:

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}}(m_d - m_s(\theta))' W (m_d - m_s(\theta)) \tag{31}$$

where m_d is a vector of empirical moments calculated from the sample data and $m_s(\theta)$ is the corresponding vector of moments simulated by the model. W is the weighting matrix, which in our case is the Identity Matrix.

The model is solved starting from the age of 20 until the age of 52. However, moments are calculated, both from the actual data and from the simulated model, between the ages of 21 and 50. Simulating from age 20 until 52 while matching moments from age 21 to 50 helps address the initial conditions problem and avoids distortions due to end of horizon effects.

In order to establish a good initial trial vector of parameters, and ensure identification, only the nested employment model, with the mental and physical health functions, was estimated first. That is, parameters were fixed so that no individual would ever choose to be married or have children. The moments needed to fit the employment model were established and a subset of the model parameters was estimated.

Having estimated the employment-only model, the main parameters associated with marriage were then unconstrained, fixing parameters associated with fertility so that nobody would choose to have children. Additional moments needed to identify the marriage parameters were established and the employment and marriage parameters were estimated jointly. Finally, the fertility parameters were introduced, additional moments established, and the full model parameter vector was re-estimated.

Standard errors are obtained by taking the square root of the diagonal elements of the variance-covariance matrix $Q_s(W)$,

$$Q_S(W) = (1 + \frac{1}{S}) \left[\frac{\partial m_s(\theta)'}{\partial \theta} W^* \frac{\partial m_s(\theta)'}{\partial \theta} \right]^{-1} \tag{32}$$

where $\frac{\partial m_s(\theta)}{\partial \theta}$ is the first derivative of the vector of moments $m_s(\theta)$ with respect to the parameter vector θ. S is the number of simulated woman-year observations (15,000*30). Since there is a very large number of observations, $\frac{1}{S} \approx 0$. Use of the identity matrix for W does not affect consistency but rather reduces efficiency. $\frac{\partial m_s(\theta)}{\partial \theta}$ is numerically approximated using parameter bump sizes that vary between .01% and 1% depending on the sensitivity of the moments.

Table 22 in the Appendix displays the sets of 142 moments that are nested within the model, while Table 23 in the Appendix shows the various parameters estimated for each component of the model.

4.1 Parameter Estimates and Model Fit

In this section we, present the results of the model's estimates. First, the estimated parameters are presented and discussed (Table 7 and Table 8). Second, the moments are presented from Table 9 through Table 16). In our research, we estimate a total of 93 parameters. These parameters align with observed moments derived from basic descriptive statistics and indirect inference and often contain dynamic elements.

Table 7 presents the key parameter estimates for health, psychotherapy, and smoking. The estimates of the mental health function H_a^m show that much of the variation of mental health is explained by physical health $\beta_{11,mh}$, which is not surprising given the complementarity between the two, and would explain an variation of 2.85 points on average in mental health. Other key determinants include having one, two and three years of psychotherapy experience (respectively$\beta_{2,mh}$, $\beta_{3,mh}$, and$\beta_{4,mh}$). One year experience increasing mental health by an average 2.38 points, two years by 2.25 points and 3 years by 2.65 points. In terms of reducing mental health, divorce seems to have a persistent effect ($\beta_{7,mh}$ implying a decrease of 1.38

points) as well as, in smaller levels, being married, having children, and having been employed in the previous year. In particular having been in full-time employment in the previous year takes a bigger toll of mental health then part-time employment, with an average reduction of .6 points.

The Physical health function H_a^p is mostly negatively impacted by marital changes, with a significant lasting impact derived from divorce ($\beta_{4,ph}$). Other important components are having children, which are associated with an increase in physical health ($\beta_{6,ph}, \beta_{7,ph}$ and $\beta_{8,ph}$). Smoking decreases physical health by 6.4% in each year ($\beta_{2,ph}$). In contrast to mental health, part-time employment seems to have a stronger effect on physical health than full-time employment. This indicates the possibility that available part-time work ($\beta_{10,ph}$) is less stressful but more psychically demanding than full-time employment ($\beta_{11,ph}$).

The rest of Table 7 presents the type probabilities linking education level to the probability of having high or low unobserved abilities, which increase with the level of education, as expected.

Moreover, Table 7 reports the unobserved utility derived from the two types of health, as well as the utility and cost of smoking and psychotherapy. The utility of smoking depends on various components, showing that smoking does not occur with the same probability for all people and in every period. In particular, a big (negative) predictor of smoking is fertility, reflecting the fact that many women stop smoking when trying to conceive or being pregnant, while a positive predictor is divorce, which is a trigger event for smoking women. The cost of smoking is estimated at £2,210 per year. Given an average cost of £4 per 20 cigarettes in the year 2000 (ONS Statistics, 2024[9]), which is the modal point in the distribution (See Table 20 in the Appendix). This implies a higher cost than the actual average cigarette costs that would result (£1,460), associated to opportunity costs that include the time spent smoking or buying cigarettes compared to undertaking productive activities. The same is true for the yearly cost of psychotherapy, which is, however, more difficult to pin point, given the lack of official data and the variation is psychotherapy costs (from counseling to clinical psychologists).

[9]https://www.ons.gov.uk/economy/inflationandpriceindices/timeseries/czmp, accessed on 30/04/2024

Table 7: Parameter Estimates - Mental and Physical Health

Parameter	Estimate	SE	Parameter	Estimate	SE
Mental Health Function H_a^m			Physical Health Function H_a^p		
$\beta_{0,mh}$	3.112	.001	$\beta_{0,ph}$	.955	.025
$\beta_{1,mh}$	.031	.003	$\beta_{1,ph}$	.305	.033
$\beta_{2,mh}$	.095	.002	$\beta_{2,ph}$	-.064	.047
$\beta_{3,mh}$	.090	.014	$\beta_{3,ph}$	.090	.029
$\beta_{4,mh}$	.106	.004	$\beta_{4,ph}$	-1.000	.062
$\beta_{5,mh}$	.006	.002	$\beta_{5,ph}$	-.021	.002
$\beta_{6,mh}$	-.052	.001	$\beta_{6,ph}$	.121	.012
$\beta_{7,mh}$	-.055	.010	$\beta_{7,ph}$	.076	.010
$\beta_{8,mh}$	-.004	.010	$\beta_{8,ph}$	.064	.022
$\beta_{9,mh}$	-.012	.001	$\beta_{9,ph}$	-.030	.001
$\beta_{10,mh}$	-.003	.001	$\beta_{10,ph}$	-.026	.011
$\beta_{11,mh}$	.114	.001	$\beta_{11,ph}$	-.023	.009
$\beta_{12,mh}$	-.006	.001	$\delta_{0,ph}$	.340	.020
$\beta_{13,mh}$	-.024	.006	Utility of Physical Health ψ_a^{ph}		
$\delta_{0,mh}$	.105	.002	$\delta_{1,ph}$	3.403	5.467
Utility of Mental Health ψ_a^{mh}			Cost of Smoking c_a^s		
$\delta_{1,mh}$	.0417	.144	$\delta_{1,s}$	2210	299
$\delta_{2,mh}$	.134	.007	Utility of Smoking ψ_a^s		
Type Probability π^A			$e^{\delta_{0,s}}$	22.423	2.948
$\alpha_{0,A}$	1.000	.087	$e^{\delta_{1,s}}$	-2.480	3.462
$\alpha_{1,A}$	2.000	.077	$e^{\delta_{2,s}}$	-11.091	3.998
$\alpha_{2,A}$	3.000	.126	$e^{\delta_{3,s}}$	2.396	6.100
Utility of Psychotherapy ψ_a^{th}			Cost of Psychotherapy c_a^{th}		
$\delta_{0,th}$	2.111	3.289	$\delta_{1,th}$	5969	512

Note: The functional forms for H_a^m and H_a^p are given in (4) and (11), respectively. $\sigma_{mh} = exp(\delta_{0,mh})$, $\psi_a^{mh} = exp(\delta_{1,mh} + \delta_{2,mh} H_a^m)$, $\psi_a^{th} = exp(\delta_{0,th})$, $c_a^{th} = exp(\delta_{1,th})$, $\sigma_{ph} = exp(\delta_{0,ph})$, $\psi_a^{ph} = exp(\delta_{1,ph})$, $\psi_a^s = exp(\delta_{0,s})$, $c_a^s = exp(\delta_{1,s})$ and $\pi^A = L(\alpha_{0,A} + \alpha_{1,A}E_1 + \alpha_{2,A}E_2 + \alpha_{3,A}E_3)$ where $L(\cdot)$ is the logistic function and E_k, $k = 1, 3$ are education dummies.

Table 8 shows the rest of the parameters estimated from the model presented in Section 3, including part-time, full-time, and spousal offered wages parameters, unobserved consumption, marital and fertility decisions and evolution parameters, and the Cholesky elements.

Part-time and full-time wage offers depend discretely on unobserved abilities, quadratically on work experience with decreasing returns, and linearly on health status. In particular, an improvement in physical health ($\beta_{5,p}$ and $\beta_{5,f}$), increases part-time offer wages by 4.5% per standard deviation (on average £275 per year), while increasing full-time offers by 3.0% (£356) per standard deviation. Similarly, the coefficients of mental health ($\beta_{4,p}$ and $\beta_{4,f}$) have a stronger impact on part-time employment, with a standard deviation change in mental health increasing part-time wage offers by 8.9% (£545) and full-time wage offers by 6.7% (£790). Moving from poor to good physical health and from low to average mental health would bring even bigger increase in offered wages.

Results for mental and physical health are weaker for spousal earnings, showing a very small and negative coefficient for mental health ($\beta_{4,h}$) and a positive and bigger coefficient for physical health ($\beta_{5,h}$), implying an average increase in spousal earnings by £697 for a one standard deviation change in physical health. The negative coefficient for mental health is due partially to the complementarity with physical health. Moreover, it is sensible to assume that the model's estimates predict a less clear separate identification between mental and physical health, as well as a less clear connection for spousal income compared to one's income, even taking into account assortative mating.

We also estimate the disutility of work effort for both part-time and full-time work, and include health status as a predictor of the disutility of working. Results in Table 8 shows that, as predictable, part-time employment requires overall less effort than full-time ($\beta_{\mu 20}$ and $\beta_{\mu 30}$ respectively). It also shows that being in better mental and physical health can make work effort more sustainable, with slightly higher effects for part-time, which is reasonable given that the baseline is higher.

Moreover, the estimation process incorporates parameters that cannot be directly observed in the data but are derived from the model's underlying mechanisms. This includes estimating the components of the lower triangular matrix of the Cholesky decomposition, which captures intricate relationships within the model in terms of wage offer shocks.

Next, Table 8 presents the utility of marriage, showing that the main predictor of the utility is the woman's belief about the compatibility of the couple $\beta_{2,m}$. Our research explores the utility of marriage, underscoring its significance in life decisions and emphasizing its importance. We focus on the impact that the belief that one is in a "good" marriage, indicating a Bayesianly updated belief in a positive match. The model reveals that without a positive match between partners, there is actually a cost to being married. While this cost can be offset by income sharing, it is often not substantial enough and may result in divorce. Moreover, mental and physical health are important determinants of marriage utility ($\beta_{3,m}$ and $\beta_{4,m}$), respectively. Additionally, we estimate the probability of receiving a marital offer when single or divorced, which also depends on mental and physical health.

The final component of the parameter set regards fertility: we estimate the utility of having 1,2, and 3 children, as well the cost associated with each, and the reduction in cost associated with childcare, which is enjoyed by non-employed ($\alpha_{\rho^1,0}$) and part-time working mothers ($\alpha_{\rho^2,0}$). Costs of childcare are reduced, but are far from being completely offset, for single mothers.

Table 8: Parameter Estimates - Employment, Marriage and Fertility

Parameter	Estimate	SE	Parameter	Estimate	SE
Part-time Wage Offers $ln\left(w_a^{pt}\right)$			Full-time Wage Offers $ln\left(w_a^{ft}\right)$		
$\beta_{0,p}$	7.994	.043	$\beta_{0,f}$	8.427	0.019
$\beta_{1,p}$	0.361	0.052	$\beta_{1,f}$	0.371	0.031
$\beta_{2,p}$	0.018	0.003	$\beta_{2,f}$	0.024	0.001
$\beta_{3,p}$	-0.0001	0.0000	$\beta_{3,f}$	-0.00004	0.00000
$\beta_{4,p}$	0.016	0.003	$\beta_{4,f}$	0.012	0.001
$\beta_{5,p}$	0.103	0.037	$\beta_{5,f}$	0.069	0.030
Spousal Earnings $ln\left(w_a^h\right)$			Cholesky Factor C		
$\beta_{0,h}$	10.262	0.036	a_{uu}	0.384	0.047
$\beta_{1,h}$	0.295	0.047	a_{pu}	0.135	0.053
$\beta_{2,h}$	0.039	0.002	a_{pp}	-0.015	0.013
$\beta_{3,h}$	-0.002	0.000	a_{fu}	0.068	0.036
$\beta_{4,h}$	-0.001	.000	a_{ff}	0.024	0.017
$\beta_{5,h}$	0.064	0.038	Disutility of Work Effort μ_k		
$\delta_{0,h}$	0.336	0.084	$\beta_{\mu 20}$	1.888	0.176
Utility of Marriage ψ_a^m			$\beta_{\mu 21}$	0.033	0.004
$\beta_{1,m}$	-35.851	4.575	$\beta_{\mu 22}$	0.137	0.053
$\beta_{2,m}$	1421.46	97.630	$\beta_{\mu 30}$	0.967	0.071
$\beta_{3,m}$	0.625	0.245	$\beta_{\mu 31}$	0.030	0.004
$\beta_{4,m}$	19.328	6.891	$\beta_{\mu 32}$	0.110	0.004
ε_a^m	6.459	5.705	Unobserved Consumption b		
Marriage Offer Probability π_a^m			$\delta_{0,b}$	8.484	0.060
$\alpha_{0,m}$	-2.033	0.064	CRRA Parameter		
$\alpha_{1,m}$	0.008	0.066	λ	.500	
$\alpha_{2,m}$	0.001	0.002	Discount Factor		
			δ	.95	
Good Match Probability ϕ_q			Income Sharing Parameter τ^1		
$\alpha_{0,q}$	0.846	0.071	$\alpha_{0,\tau}$	.50	
Good Signal Probability φ			Utility of Children ψ_a^n		
$\alpha_{0,p}$	0.692	0.016	$\delta_{1,n}$	22.893	2.145
Cost of Children $c_a^n(k)$			$\delta_{2,n}$	20.043	1.994
$\alpha_{\rho^1,0}$	0.484	0.027	$\delta_{3,n}$	4.214	0.883
$\alpha_{\rho^2,0}$	0.427	0.034	$\delta_{0,n}$	76.206	8.882
$\delta_{1,c}$	5452.830	537.032	Child Care Support		
$\delta_{2,c}$	4943.170	287.873	$\beta_{1,cm}$	758.017	152.471
$\delta_{3,c}$	2491.260	174.416	$\beta_{2,cm}$	540.408	33.829
			$\beta_{3,cm}$	226.924	143.053

Note: The functional forms for $ln\left(w_a^{pt}\right)$, $ln\left(w_a^{ft}\right)$ and $ln\left(w_a^h\right)$ are given in (15), (16) and (25), respectively. $\sigma_h = exp(\delta_{0,h})$, $\sigma_n = exp(\delta_{0,n})$ and $b = exp(\delta_{0,b})$. ψ_a^m in (24) has the parameter constraints $\beta_{k,m} = exp(\delta_{k.m})$, $k = 1,3$. ψ_a^n in (26) has the parameter constraints $\beta_{k,n} = exp(\delta_{k,n})$, $k = 1,5$. $c_a^n(k)$ in (27) has the parameter constraints $\beta_{k,c} = exp(\delta_{k,c})$, $k = 1,3$. $\rho^k = L\left(\alpha_{\rho,0}\right)$, $k = 1,2$, $\mu_k = L\left(\alpha_{0,\mu_k}\right)$, $k = 2,3$ and $\tau^1 = L\left(\alpha_{0,\tau}\right)$ where $L(\cdot)$ is the logistic function. CRRA Parameter, the discount factor and the income sharing parameter are fixed and not estimated.

Tables 9,10, 11,12 13, 14, 15 and 16 present the moments matched from the model. Overall, the fit is rather precise, with some minor imprecision, which is justifiable given the large number of moments matched over the life-cycle.

Table 9: Model Fit - Employment and Marriage Choice Distribution by Age Range

Panel A: Employment and Marriage Choice Distribution by Age Range

	Unemployed		Part-time		Full-time		Married	
Age	Actual	Model	Actual	Model	Actual	Model	Actual	Model
21-25	0.351	0.296	0.096	0.141	0.553	0.563	0.453	0.362
26-30	0.282	0.342	0.175	0.234	0.543	0.424	0.705	0.603
31-35	0.293	0.284	0.275	0.266	0.432	0.451	0.773	0.679
36-40	0.256	0.240	0.313	0.279	0.431	0.481	0.784	0.760
41-45	0.212	0.180	0.302	0.285	0.486	0.535	0.784	0.832
46-50	0.212	0.160	0.270	0.288	0.518	0.552	0.801	0.880
Total	0.267	0.248	0.242	0.249	0.490	0.503	0.741	0.686
Marital Duration at Divorce							3.558	3.912

Note: the fractions at each age are row percentages that sum to one separately for Actual and for Model.

Table 10: Model Fit -Employment and Marriage Transition Matrices

	Age $a+1$				
Age a	Unemployed	Part-time	Full-time	Single	Married
Unemployed	.788	.144	.073		
	(.718)	(.236)	(.045)		
Part-time	.092	.752	.157		
	(.220)	(.667)	(.112)		
Full-time	.039	.062	.899		
	(.031)	(.047)	(.921)		
Single				.879	.121
				(.878)	(.122)
Married				.034	.966
				(.022)	(.978)

Note: In Panel B, the fractions are row percentages that sum to one. The row percentages generated by the estimated model are in parentheses. The mean duration of marriage in the actual data is 3.558 years and the predicted mean in the model is 3.912 years.

Table 9 shows the choices in terms of employment and marital status over time. Overall, the does a rather good job in reflecting the actual choices and states for employment, with some larger divergence in the first periods due to adjustments over-time. As time evolves the model predicts more accurately choices, except for an over-shooting in the marital status.[10].

[10]This could be partially due to the lack of widowhood modeled in the data, as well as the mechanisms for

The model also estimates the duration of marriage at divorce, which is rather dependent on the Bayesian updating of the compatibility.

Table 9 shows the transition matrices for employment and marital status. These are mostly well matched, with a slightly lower persistence of part-time employment than in the actual data.

Table 11: Model Fit - Actual and Simulated Means

	Accepted Wages		Health		Spousal
	Part-time	Full-time	Mental	Physical	Earnings
Education Level 1	8.810	9.580	25.090	-0.014	
	(8.672)	(9.498)	(24.545)	(-0.049)	
Education Level 2	8.778	9.712	25.480	-0.002	
	(8.899)	(9.673)	(25.117)	(.052)	
Education Level 3	9.233	10.039	25.900	0.024	
	(9.061)	(9.807)	(25.808)	(0.163)	
Total	8.719	9.375	25.296	0.000	10.124
	(8.891)	(9.659)	(25.099)	(.046)	(10.056)
Standard Dev	0.523	0.745	5.579	0.437	0.576
	(0.346)	(0.409)	(3.337)	(0.534)	(0.588)
Median			26.000	0.264	
			(25.000)	(0.101)	

The row percentages generated by the estimated model are in parentheses

Table 12: Model Fit - Auxiliary Earnings Regressions

Panel B: Auxiliary Log Earnings Regressions

	PT Accepted Wage		FT Accepted Wage		Spousal Earnings	
	Actual	Model	Actual	Model	Actual	Model
	(1)	(2)	(3)	(4)	(5)	(6)
Age	0.044	0.037	0.080	0.052	0.074	0.0744
Age^2	-0.0004	0.000	-0.001	0.000	-0.001	-0.0009
Education 2	0.209	0.186	0.154	0.136	0.095	0.0953
Education 3	0.665	0.311	0.496	0.235	0.248	0.248
Mental Health	-.0000	0.014	0.004	0.010	0.005	0.0048
Physical Health	0.088	0.218	0.05	0.119	0.074	0.0743
Constant	7.560	7.555	7.924	7.650	8.398	8.399

Column 1,3,5 are presented with standard errors respectively in Columns 1,3,5 of Table 6.

Table 11 instead focuses on observed wages and health stati. The observed wages for part-time and full-time work, as well as mental and physical health are matched by education level

middle-age divorce, including the impact of becoming empty-nesters and the effect of menopause. These issues are the scope of future research.

too, while the spousal earning are only matched overall. Wages, health and mental health all follow the correct path in increasing with levels of education.

One of the trickiest components to estimate is the difference between the mean and median health distribution, given the skewness, while maintaining a relatively low standard deviation. The model performs well in this task, especially considering the magnitude of the moments.

Table 12 presents OLS estimates of wages for women (divided into part-time and full-time employment) and their partners. Although it is not trivial to match auxiliary regressions by indirect inference, the model is quite close. The only substantial divergence is the positive sign of the matched coefficient for mental health in part-time employment, which was however not well identified in the regression (see Table 6). The relations between coefficients are for the rest well maintained.

Table 13 shows the most complicated aspect to match, which is provided by the auxiliary FE health regressions. The number of parameters to match in this case, while necessary, substantially increases the complexity of the problem at hand. Overall, the relationships between the various regressors are maintained for both regressions. In the mental health equation, there is an overshooting for the impact of one year of psychotherapy and an undershooting for two years of psychotherapy, but the overall trend between 0 and 3 years of psychotherapy is maintained. The negative impact of part-time and full-time work is also observed.

The physical health regression overall works well, an overshooting on the positive effect on health of being married.

Table 13: Model Fit - Auxiliary Health Regressions

	FE Mental Health		Physical Health	
	Actual	Model	Actual	Model
	(1)	(2)	(3)	(4)
Age	-0.077	-0.216	-0.007	-0.064
Age Squared	0.001	0.002	0.0001	0.000
Therapy = 1	0.831	1.540		
Therapy = 2	1.439	0.604		
Therapy $\geq$ 3	2.593	2.641		
Therapy Last Year	-0.032	-0.362		
Smoking			-0.029	-0.115
Married	-0.306	-0.221	0.013	0.410
Divorced	-1.026	-0.491	0.048	0.125
One Child	-0.086	-0.167	0.031	0.038
Two Children	-0.132	-0.396	0.040	0.079
Children $\geq$3	-0.218	-0.076	0.023	0.031
Physical Health	1.699	2.169		
Mental Health			0.004	0.037
part-time	-0.244	-0.131	-0.002	-0.032
full-time	-0.348	-0.471	-0.008	-0.051

Column 1 is presented with standard errors in Column 2 of Table 4. Column 3 is presented in Column 2 in Table 4.

Table 14 focuses on the overall birth rate and by age, as well as the stock of children at the end of the sample period. There is a slight increase in fertility early on and a decrease in fertility above the age of 40, but overall, the numbers are very small. The number and distribution of children are matched well. Finally, the curve showing the probability of having at least one child for each employment status overshoots for unemployment and part-time work, but maintains the correct pattern among employment statuses, indicating that women in full-time employment are 50% less likely to have children compared to their part-time working counterparts.

Table 14: Model Fit - Fertility

	Birth by age			Children	
	Actual (1)	Model (2)		Actual (3)	Model (4)
Overall birth rate	0.030	0.048	Average N of Children	1.697	1.641
Birth rate 21-25	0.035	0.121	Women 0 children	0.179	0.185
Birth rate 26-30	0.058	0.085	Women 1 children	0.187	0.210
Birth rate 31-35	0.051	0.043	Women 2 children	0.394	0.384
Birth rate 36-40	0.023	0.040	Women 3 children+	0.241	0.221
Birth rate 41-45	0.006	0.000			
Birth rate 46-50	0.002	0.000	% UN with children	0.794	0.921
			% PT with children	0.860	0.980
			% FTwith children	0.433	0.492

Table 15 presents the psychotherapy yearly attendance and cumulative experience, as well as the transitions. Overall, the numbers are comparable, although women in the model tend to consult psychotherapists earlier compared to women in the sample. The direction of the curve of cumulative experience is correct, and the transition follows the data (presented in Table 3) well.

Table 15: Model Fit - Therapy

	PST by age		Cumulative Experience		
	Actual (1)	Model (2)		Actual (3)	Model (4)
Overall on PST	0.023	0.020	Av 1 year PST	0.254	0.193
PST 21-25	0.023	0.089	Av 2 year PST	0.062	0.162
PST 26-30	0.021	0.026	Av 3+ year PST	0.051	0.001
PST 31-35	0.024	0.004			
PST 36-40	0.025	0.000			
PST 41-45	0.021	0.000			
PTS 46-50	0.020	0.000			
Transtion in the model (DATA in Table 3)	Not Attending age a	Attending age a+1			
Not attending	.985	0.015			
Attending	.731	.269			

Note: Cumulative Experience in the data is multiplied here by the ratio of years in the simulation and divided by the average years in the sample.

Table 16: Model Fit - Smoking

	Smoke by age	
	Actual	Model
	(1)	(2)
Overall on Smoke	0.298	0.286
Smoke 21-25	0.345	0.308
Smoke 26-30	0.328	0.335
Smoke 31-35	0.299	0.292
Smoke 36-40	0.281	0.271
Smoke 41-45	0.274	0.247
Smoke 46-50	0.267	0.263
Transtion in the model	Not smoking age a	Smoking age a+1
Not smoking	.917	.083
Smoking	.202	.798

Note: Actual statistics for the smoking transition are presented in Table 2, Panel B.

Finally, 16 shows the number of smokers by age and the transition matrix. Both follow rather well what found in the actual BHPS dataset.

Figure 6: Matching by Age

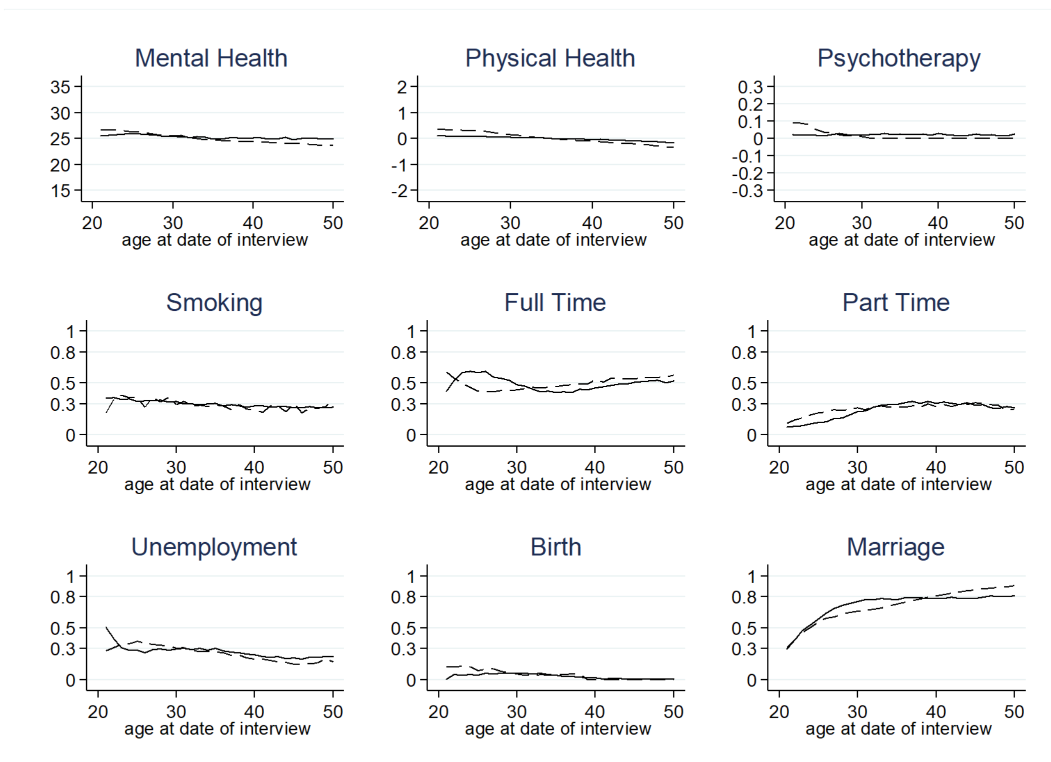


Figure 6 presents averages for the main components of the model by age. Overall, while there are some discrepancies, especially early on due to adjustment, the overall trajectories are followed rather closely for all choices and stati, which speaks to external validity checks given that we do not match varialbes for each age point.

4.2 Identification and Sensitivity Analysis

In this section we discuss the main parameters identification and the relation to the model, following the method proposed by Andrews et al. (2017), as used also in Anderberg et al. (2023). The sensitivity measure is defined as:

$$\Lambda = (S'WS)^{-1}S'W \tag{33}$$

Where $W$is the (152x152) weight matrix, defined as the Identity Matrix as for the standard errors calculation (see equation 31), S is the Jacobian matrix of partial derivative of $m_s(\theta)$ evaluated at θ_0, which should be interpreted as a local approximation of the effect of parameters on moments. We estimate Λ and report the the results of the elasticity components $\hat{\varepsilon}_{ks} = \hat{\lambda}_{ks}(\hat{m}_s/\hat{\theta}_k)$. The element $\hat{\lambda}_{ks}$ is the element referring to parameter k and moment s of the empirical sensitivity measure $\hat{\Lambda}$, $\hat{m}_s$ the estimated moment and $\hat{\theta}_k$the estimated parameters.

As discussed in Section 4 we have a total of $K = 93$ parameters and $M = 152$ moments. As a result we have over 14,000 estimated elements of sensitivity and we use inverse of the standard deviation as weights for each sensitivity. Due to space limitations we present sensitivity results for 16 estimated parameters on all moments. The parameters chosen are related to mental and physical health and their interaction with other states in the model. Results are presented in Figures 7 and 8.[11]

In both figures moments are divided in four categories: category I represents moments related to mental health, category II moments related to physical health, III fertility moments, IV marriage and spousal earning moments and V income and employment related moments.

Figure 7 shows the impact of parameters that focus on the effect of mental and physical health on income and effort. Panels A and B represent the impacts of parameters $\beta_{5f}$and β_{4f} (the coefficients of mental and physical health on full-time wage offers) respectively. Panels

[11] For readability, we only show sensitivity elements between -6 and 6, thus excluding 1,945 observations of 14,136 in total. Full elements of the sensitivity analysis are available upon request.

C and D do the same for part-time wage offers ($\beta_{5p}$and β_{4p}). Overall, we do not observe a general over-sensitivity to these parameters, but it seems that the moments in the model respond more strongly to the mental health component, with an interesting indirect effect on fertility and physical health.

Panels E and F represent the impact of mental health on disutility of part-time and full-time effort $\beta_{\mu 21}$ and $\beta_{\mu 31}$ respectively, while panels G and H do the same for physical health ($\beta_{\mu 22}$ and $\beta_{\mu 32}$). In this case we observe a bigger dispersion for physical health, with a strong impact on employment moments and fertility.

Figure 7: Sensitivity Analysis 1

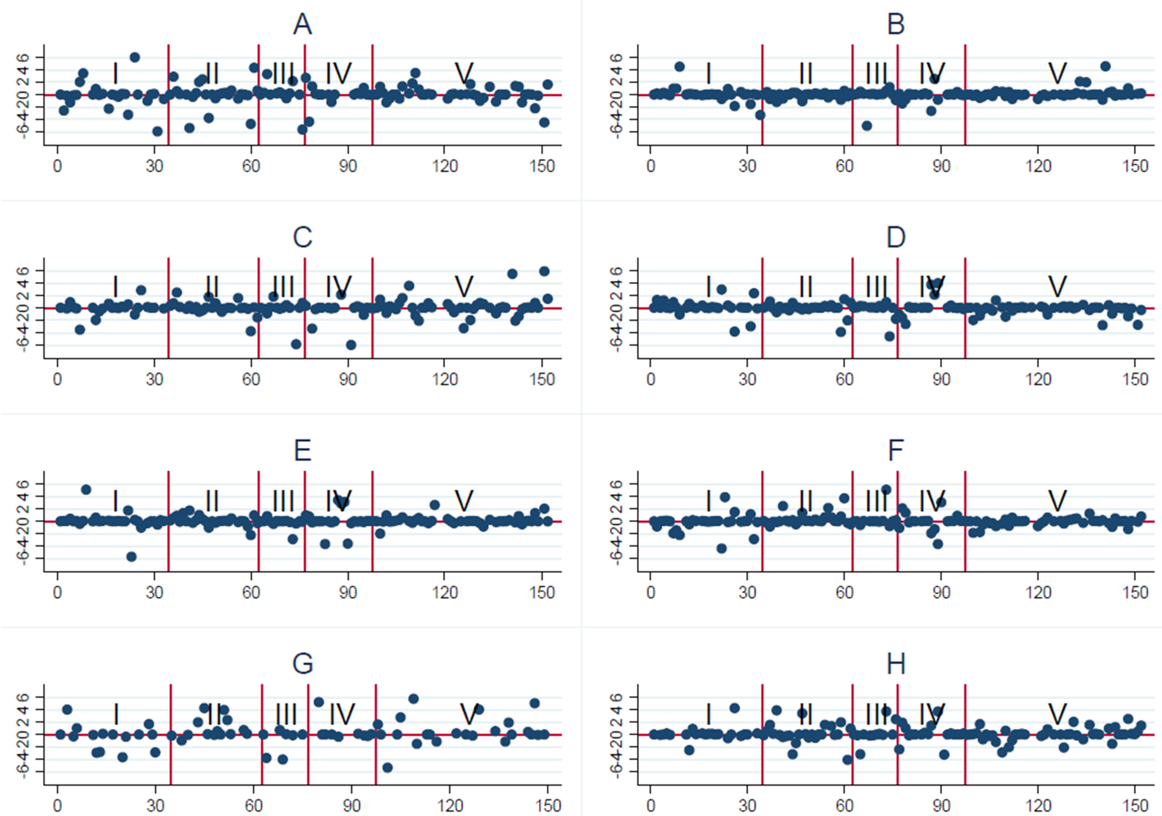


Figure 8 show parameters that have a direct impact on health and marital status. Panels A and B represent the cost of psychotherapy and the cost of cigarettes respectively ($\delta_{1,th}$ and $\delta_{1,s}$). There is a reasonable sensitivity to these parameters.

Panels C and D show instead the impact of part-time and full-time employment on mental heath ($\beta_{12,mh}$ and $\beta_{13,mh}$), with an overall lack of over-sensitivity, and an interesting indirect effect on physical health and spousal income.

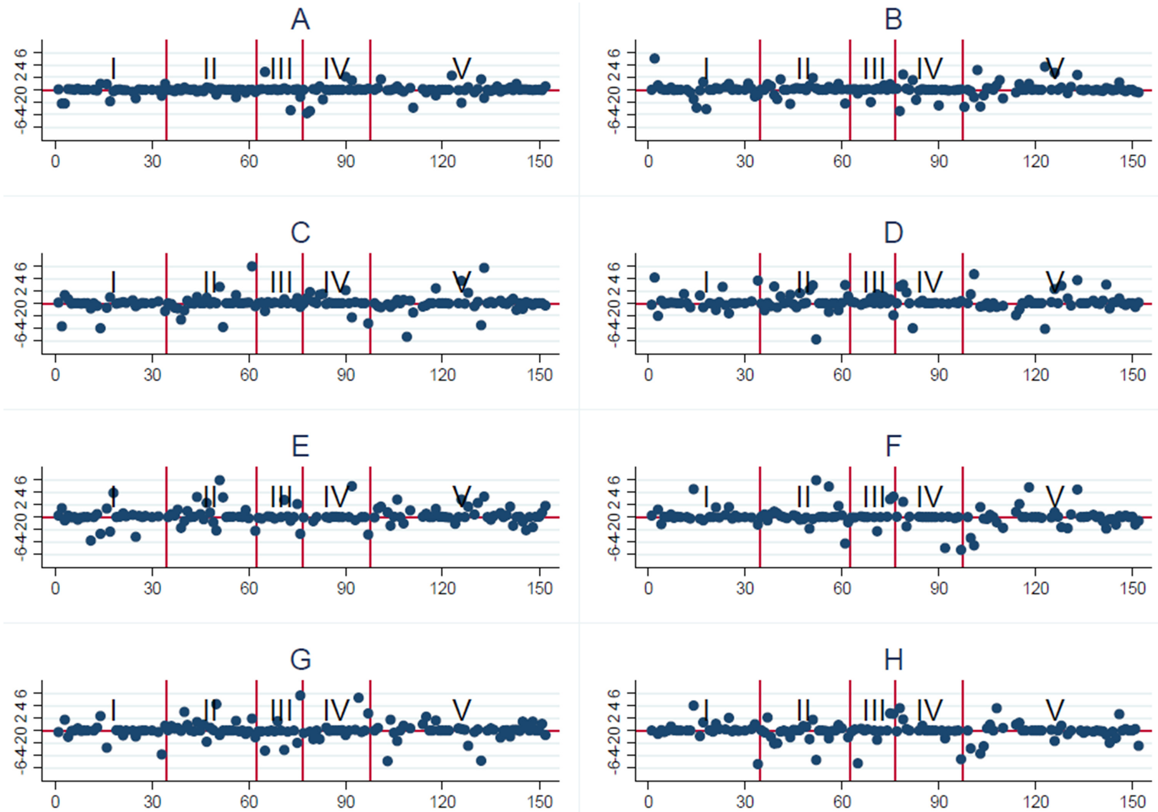
Panels E and F repeat the same for physical health parameters ($\beta_{10ph}$and β_{11ph}) which show a similar if slightly higher variance compared to Panels C and D.

Finally, panels G and H represent the impact of mental and physical health on the utility of marriage ($\beta_{2m}$and β_{3m}). There is a similar impact for both. with an effect both on fertility and marital stati and on employment and income.

The overall sensitivity analysis shows that parameters tends to be mostly identified within their specific area, but also that there is a substantial level of interconnectedness.

With regards to parameters other than health related ones: parameters related to employment and wages are identified mostly by the employment moments and health moments; the transition and distribution of employment are particularly sensitive. Spousal parameters are identified by spousal moments, in particular moments are sensitive to the Bayesian updating parameters and functional form. Fertility parameters are identified both via fertility moments and via the transition matrix of employment status given the strong connection between employment and fertility choices in women.

Figure 8: Sensitivity Analysis 2



5 Counterfactual Experiments

A significant advantage of the DSE approach is its capacity to perform counterfactual scenarios, including policy experiments. By comparing the new results from the simulated model to the baseline estimation, we can observe the effects of changes in various parameters on the final partial equilibrium and explore the underlying mechanisms.

In this section, we present counterfactual experiments of both permanent and temporary nature. Permanent shocks demonstrate the impact of mental and physical health over the life-cycle, as well as policy shocks affecting health accumulation (such as the cost of cigarettes and psychotherapy) and childcare costs for employed women.

Temporary shocks affect mental, physical health, and productivity only at age 20, with simulated moments matched from age 21.

5.1 Permanent Health Shocks and Policy Changes

Table 17 and figures 9 and 10 present the effects of counterfactual experiments based on permanent changes on health and policy throughout the life-cycle.

These experiments focus on comparing the baseline results with cases in which a permanent change is introduced. The first two experiments affect mental and physical health stati, with a reduction 30% in both cases[12]. Results from these experiments show that a 30% permanent negative average mental health shock has more substantial impact than an equivalent physical health shock on fertility and full-time employment.

Column (1) in Table 17 and the blue lines in Figure 9 shows the result of a negative mental health shock. The main result is that it shifts women away from full-time employment by -14.4% with an increase in part-time employment and unemployment of 24.9% and 4% respectively. Because the estimations point to the fact that full-time employment affects more strongly mental health and part-time employment physical health, women move towards part-time employment and unemployment to avoid further impacting their mental health. Due to the change in employment composition we also observe a 15.2% decrease in average wages, which is consistently diverging more as women age. Moreover, a reduction in mental health leads to a 4% reduction in fertility, given the need to have a stronger mental health in order to cope with parenting. We also observe an increase in smoking due to the higher distress and an increase in psychotherapy winch is due to an attempt to reduce the toll on mental health. Of all the simulations, this is the one that shows the highest impact on life-time utility, with a 13.2% reduction.

[12]Reductions of lower or higher levels lead to qualitatively similar results with different magnitudes.

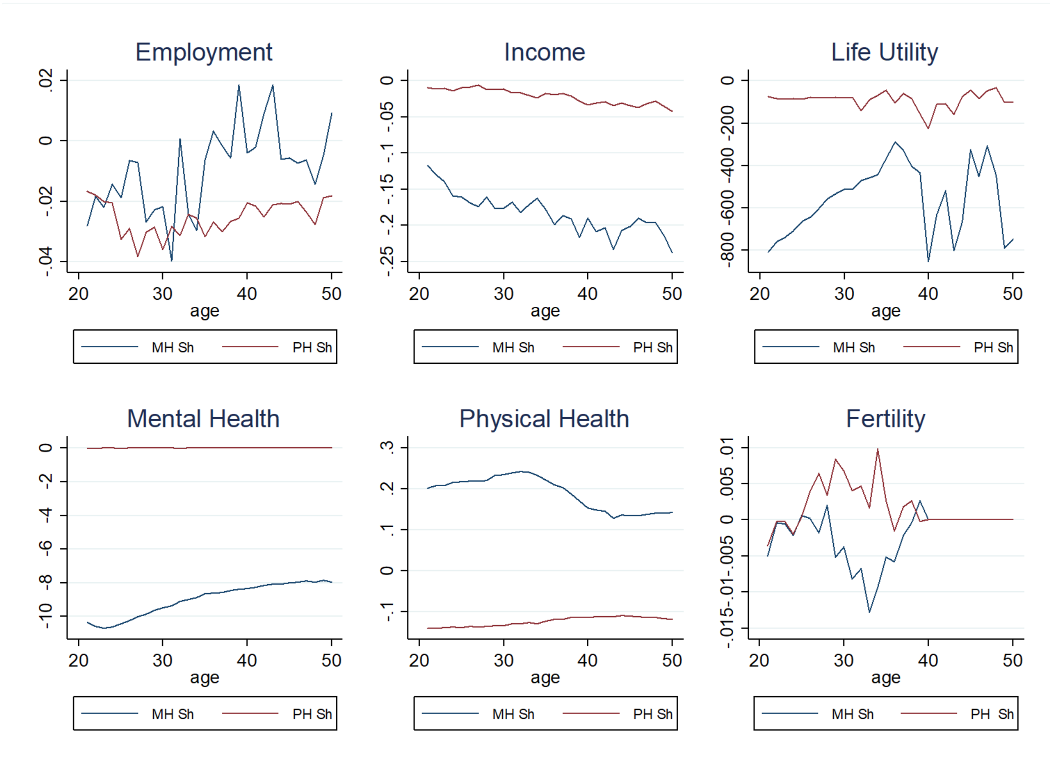
Table 17: Counterfactual - Permanent Shocks and Policy Change

	-30% Ment Health	-30% Phis Health	No PT Cost	50% Cig Cost	Child Care Cost
	(1)	(2)	(3)	(4)	(5)
Pr Married	0.872	-0.145	0.000	0.291	-0.581
Phis Health	406.466	-265.948	-10.129	76.724	82.112
Ment Health	-35.814	0.044	1.128	0.394	0.108
Av PST	45.000	0.000	247.000	-5.000	5.000
Av Smoke	21.678	-3.147	-1.748	-100.000	-51.399
Nr of Child	-3.839	2.620	0.914	17.063	37.904
Pr Unempl	4.000	10.400	2.800	11.600	-54.000
Pr Work PT	24.900	0.000	2.410	18.876	14.458
Pr Work FT	-14.371	-4.990	-2.595	-15.170	11.776
Av Wage	-15.196	-1.624	-0.546	-4.406	0.158
Life Utility	-13.239	-2.151	0.804	-1.939	4.113

Percentage differences from the baseline estimation, calculated as the difference between the simulations and the baseline divided by the baseline value.

Column (2) presents the results of a 30% reduction in physical health. The reduction brings about a 5% decrease in part-time work, with little impact on full-time work and a 10.4% increase in unemployment. Again, because part-time is more associated with an impact on physical health, women switch away from the most harmful forms of employment. Smoking decreases in order to counterbalance the decrease in physical health by 3.1%, and there is a slight increase in fertility (2.6%), which derives from the strong and negative relation between smoking and having children. The opportunity cost of giving up smoking to have children is smaller in this case as individuals are trying to improve their physical health. It is interesting to see how mental health shock and physical health shock have opposite effects on fertility (see Figure 9).

Figure 9: Trajectories Following Permanent Mental and Physical Health



The lines represent the difference in each age between the average for the baseline and for the simulated scenarios from age 21.

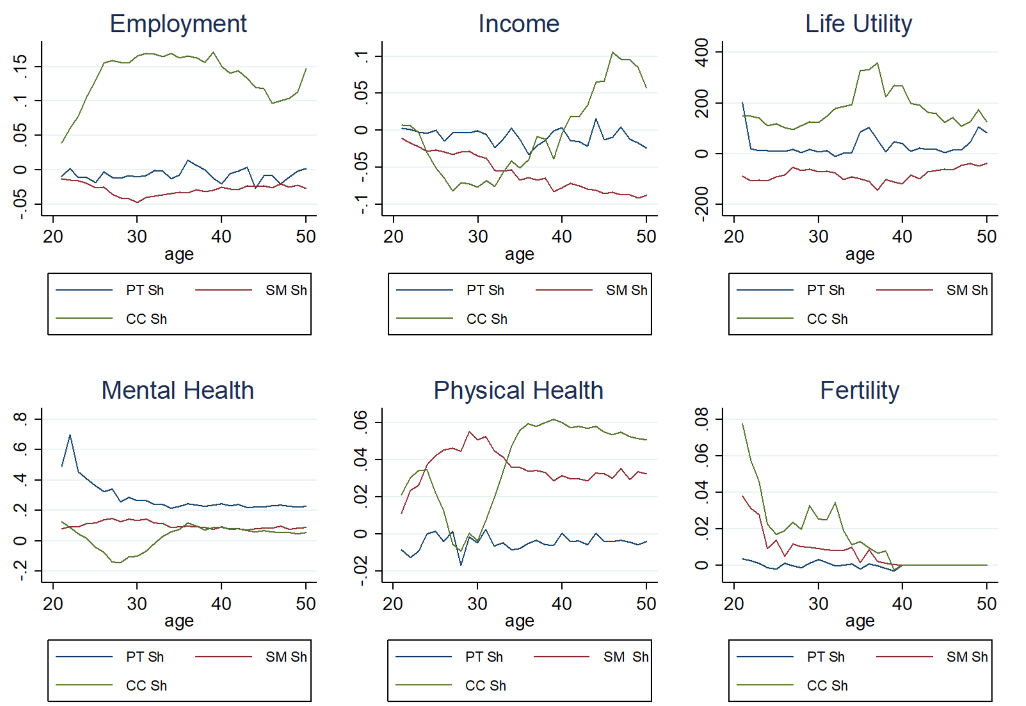
Column (3) remove costs associated with psychotherapy. The biggest impact is on the significant uptake in therapy, which, however, does not really translate into an big improvement in mental health (1.1% change). There is a small reduction in smoking (-1.7%) and increase in the number of children (.9%), while we observe a reduction in full-time work (-2.5%) and an increase in part-time work and unemployment (2.4% and 2.8%, respectively). This is due to an income effect: because psychotherapy is costly, a reduction in the cost means more available income and a lower need to work full-time for individuals who require psychotherapy. This result should not be read in isolation, but in conjunction with the results in Column (1), indicating that a blanket policy of free psychotherapy is not helpful, but that an increase in the availability of psychotherapy would be beneficial for people experiencing a mental health crisis.

The next experiment, presented in Column (4), involves a 50% increase in the cost of cigarettes and yields unsurprising results of a significant reduction in smokers and consequently a substantial increase in physical health. There is also a very modest improvement in mental health, due to the complementarity with physical health and a consequent reduction in the need for psychotherapy (-5%). The reduction in smoking has a big positive impact on fertility (17.1%), due to the negative association between the two and the income effect deriving from the reduction in smoking and psychotherapy. The increase in fertility, however, has the unintended effect of decreasing full-time employment by 15%, while part-time employment and non-employment increase by 18.9% and 11.6% respectively.

Finally, Column (5) presents the results of a 30% reduction in childcare costs for women who are employed part-time and full-time. This is an extremely relevant and timely policy experiment, given the recent changes in the UK childcare policy for employed parents, that are being phased in starting from April 2024[13]. The experiment demonstrates a big increase in fertility, with a 37.9% increase in the number of children, along with a substantial decrease in smoking (-51.4%) and an increase in mental and physical health. The expectation in this case (see Anderberg et al. 2023) is that the increase in fertility would shift women away from employment by changing their path trajectory. Instead, because the model includes impacts on mental and physical health, we observe an increase in both part-time and full-time employment on average (14.5% and 11.8%, respectively) and a very big decrease in non-employment (-54%). The mechanism at work here shows that more support for working mothers puts them on a path in which they can both work and have children, without experiencing an increase in stress in the long term. This is unexpected given that estimates predict that an increase in children and employment could have a negative impact on health. However, the mechanism works through both a substitution and an income effect in the long run, which depend also on the shift of health capital investments. Women significantly reduce their smoking due to the increase in fertility, which occurs at an earlier age compared the baseline model. This, following an initial dip in mental and physical health due to the increased stress of having children while being employed, leads over time to a better physical health and thus better mental health as the two are complementary. Moreover, because mothers have lower child care expenditures, they can afford to pay for psychotherapy and further improve their mental

[13] See https://educationhub.blog.gov.uk/2023/03/16/budget-2023-everything-you-need-to-know-about-childcare-support/ for more information

Figure 10: Trajectories Following Psychotherapy, Smoking and Child Care Policy



The lines represent the difference in each age between the average for the baseline and for the simulated scenarios from age 21.

health. An increase in mental and physical health increase productivity and wage offers. This, coupled with the lower cost of childcare for working mothers, improves employment rates significantly.

5.2 Temporary Health and Employment Shocks: a Long Term Impact

Table 18 and Figure 10 show the results of a big one time shock to health and employment and their subsequent effect throughout the life-cycle. The experiments show the effect of a 90% decrease at age 20 in mental health, physical health and offered wage. Because the analysis starts at age 21, the year of shock is excluded from the calculation of Table 18 and the graphical representation of Figure 10 as we focus on the long term impact.

In all three cases, the impact of the shock is not short-lived. While Jolivet and Postel-Vinay (2024) find that employment shocks can have a persistent effect for up to 6 years before returning to the baseline results, due to the more complicated nature of mental and physical health for women, owing to the intersection with the role of fertility, as well as the health investments present in this model, we are able to observe persistent differences.

Column (1) in Table 18 and the blue line in Figure 10 show the results of a strong shock on mental health at age 20, observed from age 21. Mental health is very low until the mid-twenties, after which, surprisingly, we observe a slight increase, due to the increase in investment in mental health (15% increase in psychotherapy). There is a decrease in full-time employment (4.2% overall), which reduces wages more and more over time due to the reduction in the accumulation of experience. Part-time employment and unemployment increase by 2% and 6.4% respectively. On the other hand, because of the reduction full-time employment due to the lower mental health, women increase their fertility, with a 1.65% increase in the number of children, which in turns reinforces the decrease in full-time employment and income.

Column (2) in Table 18 and the red line in Figure 10 present the effects of a physical health reduction at age 10. Results are mostly consistently in line with the mental health shock, but are less strong. The main difference is the slight decrease in fertility in this case (-.06%). Again, as in the case of mental health, the initial decrease in physical health is offset by an increase in investment in physical health, resulting in an overall higher level of physical health.

Table 18: Counterfactual - Temporary Shocks

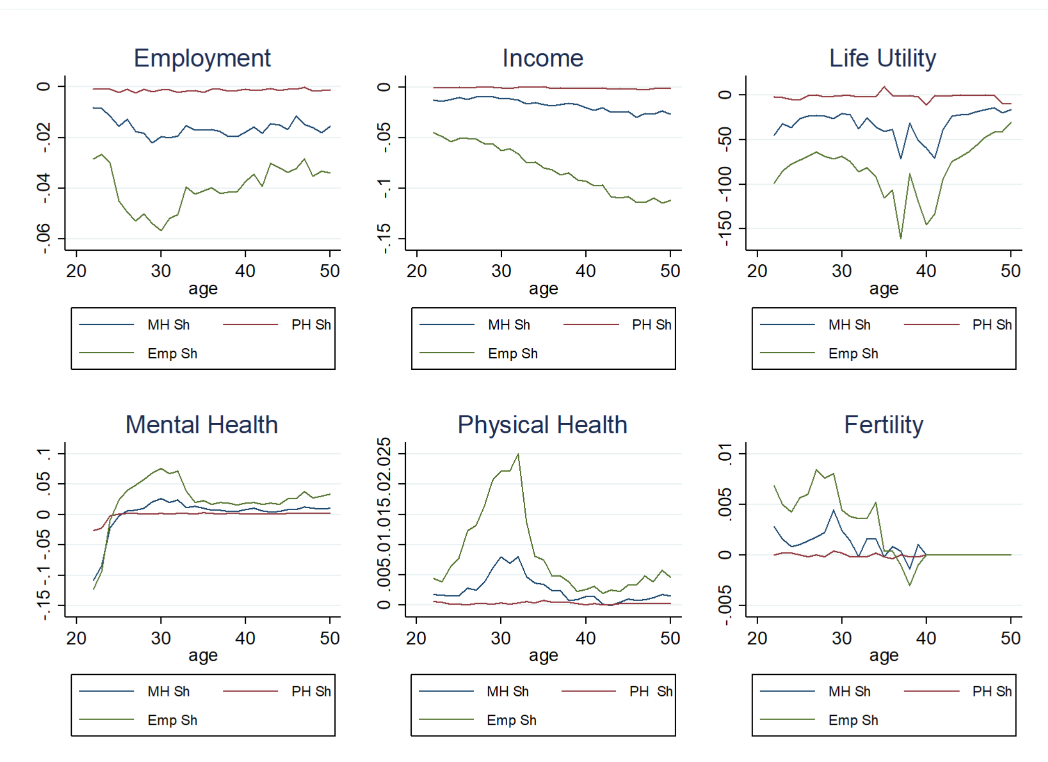
	Temp MHS	Temp PHS	Temp Empl Shock
	(1)	(2)	(3)
Pr Married	0.000	0.000	1.599
Phisycal Health	5.603	0.647	17.888
Mental Health	0.004	0.004	0.124
Av PST	15.000	5.000	11.500
Av Smoke	-4.545	-0.350	-13.636
Nr of Children	1.645	-0.061	4.692
Pr Unemployed	6.400	0.800	15.600
Pr Work PT	2.008	0.000	11.647
Pr Work FT	-4.192	-0.200	-13.772
Av Wage	-1.359	-0.058	-7.691
Lifetime Utility	-0.254	-0.023	-0.571

Percentage differences from the baseline estimation, calculated as the difference between the simulations and the baseline divided by the baseline value. The shock is at age 20 and averages are calculated from age 21, thus after the shock has occurred.

Finally, Column (3) in Table 18 and the blue line in Figure 10 show the results of a one off decrease in offered wages at age 20. This appears to have the most significant impact in terms of magnitude. The lack of employment prospects shifts young women towards earlier and higher levels of fertility (4.7%). This, in turns, decreases their employment levels through their life time (-13.8%) full-time employment. Part-time employment eventually increases and overshoots compared to the baseline stati (11.6%) and the proportion of unemployed increases by 15.6%. Following the increase in fertility, however, we observe a decrease in smokers, partly due to the decrease in income. This leads to an increase in physical health. Moreover, the initial shock on employment and shift towards fertility affect mental health strongly until the mid-twenties, when the uptake in psychotherapy improves overall mental health to higher levels compared to the baseline.

It should be noted that in all cases, there is a persistent reduction in life-time utility which does not converge back to the baseline.

Figure 11: Trajectories Following Temporary Shocks



The lines represent the difference in each age between the average for the baseline and for the simulated scenarios from age 22. The age at the temporary shocks (20) is not shown for readability.

6 Conclusion

In summary, our research aims to examine the intricate interplay between mental and physical health dynamics and their impact on key life cycle decisions, including employment, marital status, fertility choices, as well as health investment decisions such as smoking and consulting a psychotherapist.

The main finding of our work is the significant role played by mental health, particularly in relation to employment and fertility, in shaping individuals' life trajectories. Mental health is strongly influenced by employment, fertility, and divorce. A notable highlight is the pronounced influence of negative mental health shocks, which have a more substantial impact than physical health shocks. These repercussions manifest as increased unemployment, reduced fertility, and substantial declines in wages, all of which significantly affect overall lifetime utility.

Our policy experiments provide several critical insights and highlight the positive impacts that more availability and affordability of psychotherapy could have in mitigating mental health problems. Secondly, we demonstrate the positive effect on fertility that an increase in cigarette cost can have and the subsequent impact on both mental and physical health. Thirdly, we emphasize the positive life-cycle outcome that an improvement in the affordability of childcare can have on overall health, employment, and fertility.

Contrary to existing literature, we also find that temporary shocks on health and employment at the beginning of the working life have a permanent, rather than temporary, impact on life-cycle outcomes. Our results differ from the recent literature (Jolivet and Postel-Vinay (2024)) for two main reasons. First, this is the first dynamic study of mental health and employment for women, which highlights the important role of timing and levels of fertility in determining future employment levels and trajectory changes. Secondly, we introduce health investment in the form of psychotherapy and smoking, and demonstrate their interaction with employment and fertility.

In the broader context of existing literature, our study adds a unique dimension by presenting a novel framework for analyzing and comparing the influences of mental and physical health on women's life cycle decisions. By shedding light on the dynamic relationship between these health factors and life outcomes, our research contributes to a deeper understanding of the complexities surrounding individual choices and their relative implications for welfare and society.

In conclusion, our study highlights the profound impact of mental and physical health on critical life decisions and underscores the need for comprehensive policies and interventions that account for these complex dynamics. Additionally, our framework offers promising avenues for further investigation, including the interplay of menopause with mental and physical health and the long-term impact of life events, along with the mechanisms governing such interactions.

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8 Appendix

Table 19: Education Categories

Highest Educational Qualification (QF)	Composite Education Category	%
Higher Degree	Education 3	.025
First Degree	Education 3	.134
Teaching QF	Education 2	.024
Other Higher QF	Education 2	.225
Nursing QF	Education 2	.023
GCE A Levels	Education 2	.130
GCE O Levels or Equivalent	Education 1	.229
Commercial QF, No O Levels	Education 1	.034
CSE Grade 2-5, Scot Grade 4-5	Education 1	.045
Apprenticeship	Education 1	.002
Other QF	Education 1	.006
No QF	Education 1	.123
Still at School no QF	Education 1	.001

Note: The number of woman-year observations is 51,561. The final column contains sample proportions that sum to one.

Table 20: Distribution of Mental Health and Number of Cigarettes Smoked

Mental Health Score	%	Number of Cigarettes	%
1	.001	1	.014
2	.001	2	.022
3	.001	3	.023
4	.002	4	.014
5	.002	5	.063
6	.002	6	.017
7	.002	7	.018
8	.002	8	.020
9	.003	9	.003
10	.004	10	.194
11	.005	11	.002
12	.006	12	.030
13	.011	13	.006
14	.012	14	.003
15	.013	15	.182
16	.014	16	.002
17	.016	17	.008
18	.020	18	.010
19	.022	19	.001
20	.025	20	.280
21	.030	22	.001
22	.036	23	.001
23	.044	24	.001
24	.054	25	.001
25	.110	26	.0360
26	.091	27	.0001
27	.088	28	.0005
28	.085	29	.0004
29	.083	30	.0001
30	.075	32	.0354
31	.067	35	.0001
32	.030	39	.0001
33	.017	40	.0130
34	.012	45	.0001
35	.006	50	.0003
36	.004	51	.0001
37	.004	60	.0006
		80	.0001
NT	51,919		15,445

Note: NT is the number of woman-year observations. The "%" columns contain sample proportions that sum to one.

Table 21: Mean Mental and Physical Health, Psychotherapy Experience and Smoking by Age

Age	Mental Health	%	Psychotherapy Experience	%	Physical Health	%	Smoke	%
21	25.56	.023	.060	.030	.756	.029	.352	.030
22	25.71	.029	.072	.029	.751	.029	.360	.029
23	25.77	.030	.078	.030	.773	.030	.340	.030
24	25.86	.030	.082	.030	.774	.030	.348	.030
25	25.95	.031	.077	.031	.771	.031	.325	.031
26	25.87	.031	.078	.031	.078	.031	.328	.031
27	25.74	.032	.084	.032	.763	.032	.331	.032
28	25.63	.033	.094	.033	.772	.033	.338	.033
29	25.44	.034	.104	.034	.769	.034	.320	.034
30	25.51	.035	.099	.035	.759	.035	.324	.035
31	25.65	.035	.109	.035	.767	.035	.297	.035
32	25.15	.036	.111	.036	.766	.036	.300	.036
33	25.40	.037	.113	.037	.763	.037	.293	.037
34	25.33	.037	.127	.037	.769	.036	.297	.037
35	24.92	.038	.132	.038	.754	.038	.309	.038
36	24.97	.038	.137	.038	.760	.038	.280	.038
37	25.16	.038	.128	.038	.742	.038	.291	.038
38	25.11	.036	.128	.036	.766	.036	.282	.036
39	25.05	.036	.144	.036	.743	.036	.270	.036
40	25.15	.035	.132	.035	.756	.036	.283	.035
41	25.23	.035	.134	.035	.766	.035	.283	.035
42	24.98	.034	.143	.034	.761	.034	.266	.034
43	24.91	.033	.137	.033	.751	.033	.276	.033
44	25.26	.034	.128	.034	.762	.034	.278	.034
45	24.85	.032	.121	.032	.744	.032	.264	.032
46	24.05	.032	.118	.032	.739	.032	.265	.032
47	25.03	.031	.129	.031	.717	.032	.274	.031
48	25.06	.030	.117	.030	.723	.029	.264	.030
49	24.92	.029	.112	.029	.734	.030	.264	.029
50	24.91	.029	.128	.029	.740	.028	.269	.029
NT	51,919		51,919		48,291		51,762	

Note: NT is the number of woman-year observations. The "%" columns contain sample proportions that sum to one.

Table 22: Moments Used in Estimation

Moments m_d and $m_s(\theta)$	Number of Moments
Employment	
Average wage and standard Error fpr PT and FT	4
Average Wage by Employment Type and Education	6
Employment Choice Distribution by Age Range (Mean Proportions)	21
21-25, 26-30, 31-35, 36-40, 41-45, 46-50 and 21-50	
One-Period Employment Transition Matrix	9
OLS Accepted Wage Regression Parameters	
ln(PT Wage) on Age, Education Level, Mental and Physical Health	7
ln(FT Wage) on Age, Education Level, Mental and Physical Health	7
Sum	54
Health	
Average, Median and Stdev of Mental and Physical Health	6
FE Mental Health Regression Parameters	14
FE Physical Health Regression Parameters	11
MH and PH by Education level	6
Sum	35
Marriage	
Marriage Choice Distribution by Age Range (Mean Proportions)	7
One-Period Marital Status Transition Matrix	4
Mean Duration of Marriage at Divorce	1
Mean spousal wage and standard erros	2
OLS Spousal Earnings Regression Parameters	7
Sum	21
Fertility	
Birth rate by age (Mean Proportions)	7
Proportion of Women with Children by Employment State	3
Proportion of Women with Different Number of Children and average number of children	5
Sum	15
Psychotherapy and Smoking	
Average number of women in therapy	1
Proportion of Women in therapy by age	6
Proportion of therapy experience 1,2,3 or more	3
Transition in and out of therapy	4
Average number of Smokers	1
Proportion of Smokers	6
Transition in and out of smoking	4
Sum	25

The above 142 moments help identify the nested employment model. The 93 parameters in this nested model include the constants and coefficients for the returns to experience and unobserved type in the part-time and full-time wage offer functions, unobserved consumption and the Cholesky elements.

Table 23: Parameters

	Number of Parameters
Employment	
Wage Offers (FT and PT)	11
Cholesky	5
Unemployment Support	1
Disutility of Work	6
Abilities Mapping to Education	3
Sum	26
Health	
Physical Health Parameters	13
Mental Health Parameters	15
Mental and Physical Health Utility	3
Sum	31
Marriage	
Utility of Marriage (Notice we set sharing parameters to .5)	5
Learning Parameters	2
Probability of Marriage Offer	3
Husband Wage	7
Sum	17
Fertility	
Utility of Having Children	4
Cost of Having Children	5
Child Support	3
Sum	12
Psychotherapy and Smoking	
Cost and Utility of Therapy	2
Cost and Utility of Smoking	5
Sum	7