

RELATIVE INCOME AND MENTAL HEALTH IN COUPLES*

Demid Getik

The share of couples where the wife outearns the husband is increasing globally. In this paper, I examine how this dynamic affects mental health. Using data on the 2001 marital cohort in Sweden, I show that while mental health is positively associated with own and spousal income, it is negatively linked to the wife's relative income. In the most conservative specification, the wife starting to earn more increases the likelihood of a mental health diagnosis by 8%–11%. This represents a significant indirect cost of changes in family dynamics.

The share of married couples where the wife is the primary earner is rising globally. Thus, in both the United States and Sweden, it has increased by approximately 25% since the start of the millennium (see Figure 1).¹ The implications of this trend for traditional gender identity and the male breadwinner norm have received significant coverage in economic literature (e.g., Bertrand *et al.*, 2015; Wieber and Holst, 2015; Binder and Lam, 2020). However, less is known about implicit costs of departing from these norms, such as potential mental health implications of doing so. Mental health issues are increasingly prevalent in modern populations, including married Swedes, and can carry substantial economic costs (Currie *et al.*, 2010; Lundborg *et al.*, 2014). With women attaining increasing parity in the labour market, it is therefore important to account for them in this ongoing discussion.

In this paper, I bridge this research gap with the aid of Swedish administrative data linking annual income to clinical mental health diagnoses. Using this panel, I examine how mental health is related to the income make-up within the same couples across time. I discover that while mental health is positively associated with both own and spousal absolute income, the relationship to the wife's relative income is actually negative. To estimate the causal relationship, I then employ a regression discontinuity design where I focus on individuals just above or below the equal earnings threshold. I observe all Swedish couples that got married in 2001 and follow them for ten years or until divorce. This allows me to see what happens to the same individuals' mental health, depending on their position relative to the threshold over time.

I find that crossing the threshold where the wife starts earning more significantly increases the probability of receiving a mental health diagnosis. In the most restrictive specification, the likelihood increases by approximately 8% for the whole sample and by 11% for men. The

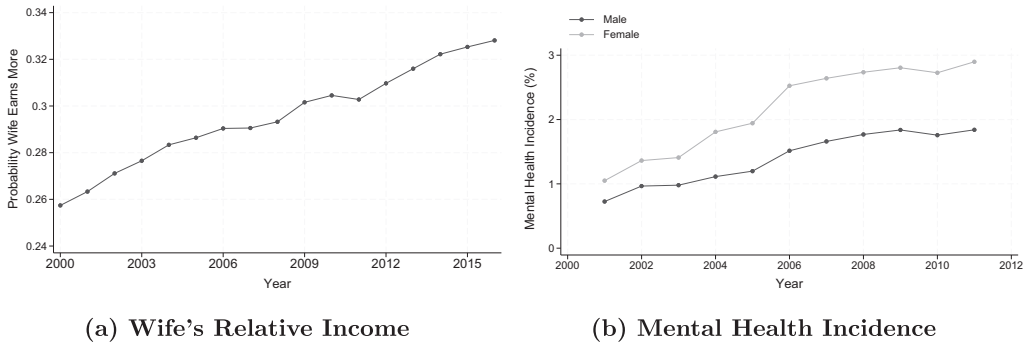
* Corresponding author: Demid Getik, Department of Economics at Durham University and Center for Economic Demography at Lund University, Mill Hill Lane, Durham DH1 3LB, UK. Email: demid.getik@durham.ac.uk

This paper was received on 11 August 2022 and accepted on 18 July 2024. The Editor was Steffen Huck.

The authors were granted an exemption to publish their data because access to the data is restricted. However, the authors provided the Journal with temporary access to the data, which allowed the Journal to run their codes. The codes are available on the Journal repository. The data and codes were checked for their ability to reproduce the results presented in the paper. The replication package for this paper is available at the following address: <https://doi.org/10.5281/zenodo.12743695>.

I thank Armando Meier, Beatrix Eugster, Matthew Collins, Therese Nilsson, Petra Thiemann, Petter Lundborg, Arizo Karimi, Marta Golin, numerous scholars at Lund University and the University of St Gallen, as well as conference participants at the Copenhagen Education Workshop and the RGS Conference, for their comments and input. The data used in this article come from the Swedish Interdisciplinary Panel (SIP), administered at the Center for Economic Demography at Lund University.

¹ For US data, see, e.g., the [figures](#) from the Pew Research Center.



(a) Wife's Relative Income

(b) Mental Health Incidence

Fig. 1. Trends in the Female Earnings Share and Mental Health Diagnoses.

Note: The figure shows the share of married couples where the wife earns more than the husband (a) and mental health incidence (b) over time in Sweden. Both panels are plotted over the years when the relevant data are available.

observed result is largely driven by the middle-age and middle-income male population. While the effect on women is not statistically significant in itself, it is also not significantly different from the effect on men. It is also more pronounced for more urban and educated women. The increase appears mainly driven by substance-related diagnoses for males, and by neurotic and stress-related disorders for females. I also do not find strong evidence for the effect being driven by divorce or one's workplace environment.

To address potential validity concerns, I conduct a series of additional tests and checks. Firstly, the distribution of relative earnings is smooth around the cutoff for the sub-sample used in the analysis. Secondly, the sample is balanced on a range of background variables, including prior mental and somatic health. The estimates are also not sensitive to varying the bandwidth and the regression polynomial. One remaining concern then is that mental health might in itself affect relative spousal income. However, several findings indicate against this effect direction. Firstly, I detect an effect on non-concurrent diagnoses (year $t + 1$), which are less likely to be affecting relative income retroactively. The result is also clustered around the equal earnings threshold and specific diagnostic categories, which is less consistent with a broader impact of mental health on income. Furthermore, the effect is actually more pronounced among those who do not receive health benefits, indicating that it is likely not driven by more severe cases.

This paper contributes to several strands of empirical literature. The first strand studies the connection between relative earnings and household dynamics more broadly. Thus, an increase in either the wife's earnings or relative labour market potential has been linked to a drop in marital satisfaction (Bertrand *et al.*, 2015) as well as a rise in the female bargaining potential in the relationship (Antman, 2014; Majlesi, 2016) and divorce likelihood (Liu and Vikat, 2007; Killewald, 2016; Schwartz and Gonalons-Pons, 2016; Avdic and Karimi, 2018). Conversely, there is evidence of wives increasing their labour supply and income in anticipation of divorce (Poortman, 2005; Teachman, 2010).

Another relevant strand focuses more specifically on the association between family earning dynamics and health outcomes. Thus, earlier interdisciplinary literature shows a relationship between an increase in the wife's income and the husband's physical health (Winkler *et al.*, 2005; Springer, 2010; Springer *et al.*, 2019) and mortality (McDonough *et al.*, 1999). It also

documents a similar trend for male psychological distress (Syrda, 2020), prescription of anti-anxiety medication among women (Pierce *et al.*, 2013) and stress-related issues in men (Springer *et al.*, 2019; Ericsson, 2020). The literature also provides some evidence of a mental health effect of spousal unemployment (Marcus, 2013). I add to these two strands by holistically characterising the relationship between family income distribution and clinical mental health, establishing a causal relationship between the two. To the best of my knowledge, this is the first study to demonstrate these implications on the within-individual level.

Finally, I contribute to the literature studying relative income in the context of gender identity. Persistence of the breadwinner norm has been widely discussed in economic literature (Bertrand *et al.*, 2015; Wieber and Holst, 2015; Killewald, 2016). More recent studies, however, challenge the idea that couples intentionally comply with the norm (Binder and Lam, 2020; Slotwinski and Roth, 2020; Zinovyeva and Tverdostup, 2021; Hederos and Stenberg, 2022). Similarly to Hederos and Stenberg (2022), I do not find evidence of intentional adherence to the norm in Sweden, in spite of the associated mental health costs. At the same time, it is worth noting that due to lack of data I am not able to directly test for intentional changes in the wives' labour supply, even if income data do not suggest such changes.

In the following sections of the paper, I summarise the relevant information on the Swedish mental health care system, data and construction of the main variables. I then present my empirical strategy and ways in which I address potential validity concerns. Afterwards, I show my main results and estimates. Finally, in Section 4, I evaluate some of the mechanisms and provide a discussion of the findings.

1. Institutional Background and Data

1.1. Swedish Mental Health Care

My analysis is based on register data covering mental health diagnoses of all Swedes from 2001 to 2012, issued in specialist care. In most cases, individuals with potential issues initially contact first-line psychiatric care (första linjens psykiatrivård), and can then be referred to a specialist. In most regions, local primary care units (vårdcentral) are responsible for first-line care and treatment of more common mental issues, such as mood disorders.² In more severe cases, one can also contact acute care. The data available in the registers cover diagnoses issued in inpatient and specialised outpatient care by both public and private caregivers. They do not include cases treated by primary care physicians, reflecting more acute cases where the individual is directed to specialised care.

1.2. Data and Descriptive Statistics

1.2.1. Family data and the sample

Data on married couples come from the Population Register (Registret över totalbefolkningen). I use administrative data on heterosexual couples who got married in 2001, when the available health data start. I then follow those couples until 2011, when the data run out, or the year when the couples divorce (Statistics Sweden, 2017). Around 80% of the couples in my sample stay married throughout the observation period. I face a trade-off between how many individuals I can observe and the duration of the observation horizon. I prioritise the latter as my preferred

² See the [report](#) from the National Board of Health and Welfare (Socialstyrelsen) for further detail.

specification compares individuals over time. I follow individuals who are at most sixty-three in 2011 to focus on those who did not reach retirement during the observation period.

1.2.2. *Earnings*

I use data from the Income and Taxation register (Registret över inkomster och taxeringar) to link individuals' earnings. The primary income variable I use to construct my main variable, the relative income share, is work income (inkomst av tjänst). The variable includes annual earnings outside of capital and business income.

1.2.3. *Workplace data*

For a part of my analysis, I use data that come from the Workplace (RAMS) Register. These data give me a workplace indicator for approximately 90% of my sample. I can then estimate the gender composition as well as wage spread in one's place of work. This information is aggregated at the firm level.

1.2.4. *Mental health diagnostic indicators*

I use the National Patient Register to construct the main dependent variable: a binary indicator for whether the individual was diagnosed with a mental health issue in the current or the following year with respect to when earnings are measured. This metric is used since processing patients is a lengthy process in the Swedish healthcare system.³ I identify mental health diagnoses using ICD-10 codes for each patient. I create an indicator variable that takes a value of 100 if the patient has received any of the diagnoses belonging to the psychiatric diagnosis categories (ICD-10 codes between F00 and F99, as constructed by the World Health Organization), and 0 otherwise.⁴ These diagnostic categories also correspond to the definition of mental health issues provided by the National Board on Health and Welfare (Socialstyrelsen).

1.2.5. *Data summary*

Table 1 summarises the main background and diagnostic variables in my sample. The average age in the sample is approximately thirty-nine for men and thirty-seven for women.⁵ Just under a quarter of the individuals have a university degree, with the share being higher in females. The average male annual earnings in the sample are around 300,000 SEK per year, while for females the figure is closer to 200,000 SEK.⁶ Approximately 2.3% of males and 3.4% of females in my sample receive a mental health diagnosis in a given two-year period. The most prominent diagnoses appear to be neurotic and stress-related disorders as well as depression and mood-related disorders.

³ Currently, the average waiting time to see a psychiatrist in most clinics is *estimated* to be between 9–13 weeks, while only *just over half* of patients get access to a psychologist within three months of a referral.

⁴ The 0 and 100 binary designations allow us to interpret the estimates as a percentage change. The ICD-10 codes indicating mental health issues contain ten classifications: organic disorders (F00–F09); mental and behavioural disorders due to psychoactive use (F10–F19); schizophrenia, schizotypal and delusional disorders (F20–F29); mood disorders (F30–F39); neurotic, stress-related and somatoform disorders (F40–F49); behavioural syndromes associated with physiological disturbances and physical factors (F50–F59); disorders of adult personality and behaviour (F60–F69); mental retardation (F70–F79); disorders of psychological development (F80–F89); behavioural and emotional disorders with onset in adolescence (F90–F98).

⁵ The order of marriage is not available in my data. I therefore include all couples who married in 2001, regardless of the order. The average age in the sample is thus higher than the average age of first marriage.

⁶ This gender difference in gross earnings is not atypical for Swedes of that age. In a different project using administrative income data, we discover that the earnings gap peaks at around the age of thirty-five, after which it declines considerably.

Table 1. *Summary Statistics.*

Variable:	Men			Women		
	<i>N</i>	Mean	SD	<i>N</i>	Mean	SD
<i>Background variables</i>						
Age	410,299	38.88	8.69	425,059	36.97	8.70
Immigrant	410,299	0.23	0.42	425,059	0.25	0.43
College degree	410,299	0.19	0.39	425,059	0.28	0.45
STEM degree	410,299	0.07	0.26	425,059	0.03	0.17
Annual earnings (1000 SEK)	410,279	306	306	425,040	193	141
Unemployed	410,299	0.07	0.26	425,059	0.11	0.32
Had child	410,299	0.04	0.19	425,059	0.04	0.19
Sick leave	410,299	0.18	0.39	425,059	0.09	0.28
Share wife's earnings	397,707	0.42	0.23	412,912	0.42	0.23
<i>Diagnostic variables (%)</i>						
Mental health disorder	410,299	2.27	14.89	425,059	3.42	18.18
Hyperactivity and conduct disorder	410,299	0.13	3.64	425,059	0.13	3.62
Substance-related disorder	410,299	0.49	7.00	425,059	0.32	5.68
Depression and mood disorder	410,299	0.75	8.62	425,059	1.45	11.97
Eating and sleeping disorder	410,299	0.07	2.62	425,059	0.17	4.12
Neurotic and stress disorder	410,299	1.01	10.00	425,059	1.75	13.12
Learning and socialisation disorder	410,299	0.02	1.23	425,059	0.02	1.41
Schizotypal disorder	410,299	0.09	3.05	425,059	0.11	3.34
Adult personality disorder	410,299	0.08	2.77	425,059	0.14	3.79
Organic disorder	410,299	0.05	2.12	425,059	0.04	2.10
Mental retardation	410,299	0.01	0.84	425,059	0.01	0.98

Note: This table presents summary statistics for background variables and diagnoses for the years when the couples are observed. The number of observations is somewhat lower for the share of the wife's earnings since it is reported as missing if annual earnings for both spouses are 0. The numbers of males and females are different since spouses are not counted in the main sample. This discrepancy occurs due to the age restriction applied to the sample. Since women, on average, marry younger, there is more of them in the final sample. Thus, the females in the sample are not necessarily always the spouses of the males, and vice versa. Correspondence between diagnosis names and formal ICD definitions is the same as in Table 3 below.

2. Empirical Strategy

2.1. Specification and Identifying Assumptions

While one may observe a relationship between mental health and relative earnings, a direct comparison would not be informative about causality. Couples with different compositions of relative earnings likely also differ on a number of unobserved variables, which can confound causal estimates. Most notably, couples in the middle of the distribution will differ less with respect to skill and productivity compared to those closer to the extremes. To address this issue, I use a regression discontinuity design, comparing couples around the threshold of 1/2, i.e., where one of the spouses just outearns the other.

A potential concern for this empirical strategy is that couples on either side of the threshold might not be directly comparable with respect to unobserved characteristics. This would impede a causal interpretation of the between-couple variation. To address that issue, I rely on individual fixed effects in my preferred specification. Effectively, I consider a within-individual variation with respect to the 1/2 threshold. Just under a half of the individuals in my sample move around the threshold throughout the observation period. This means that in nearly half of the couples, each of the spouses is the main earner for at least one year. This allows for substantial variation to identify the effect. In approximately 64% of cases, both spouses face an increase in income at the point where the wife starts earning more, implying that the growth experienced by the wife

was larger over that given year. In approximately a third of the cases, however, the husband's income declined when the switch occurred.

For my estimates, I use local linear specifications with a bandwidth of 0.15, which encompasses more than 1/2 of my original sample.⁷ The specification is shown in the equation

$$Y_{iy} = \beta_1 \times I[\text{WifeShare}_{iy} > 0.5] + \beta_2 \times \text{WifeShare}_{iy} + X'_{iy}\gamma + \alpha_i + \epsilon_{iy}. \quad (1)$$

In (1), Y_{iy} is a binary indicator of having being diagnosed with a mental health issue in a given or the following year, y ; WifeShare_{iy} is the wife's share of a family's total earnings in that given year, $\text{EarningsWife}_{iy}/(\text{EarningsWife}_{iy} + \text{EarningsHusband}_{iy})$; $I[\text{WifeShare}_{iy} > 0.5]$ is a binary indicator for whether the wife's share exceeds 1/2, with β_1 being the parameter of interest; α_i represents individual fixed effects and trends; $X_{iy}\gamma'$ is a vector of individual-level controls measured in a given year. Variables included in that vector are age, metrics of highest attained education level, migration status, income as well as metrics of prior mental and somatic health. To address potential endogeneity due to fertility decisions (e.g., Adda *et al.*, 2017; Kleven *et al.*, 2019), I also include a variable indicating fertility in a given year.⁸ All time-variant variables are measured concurrently. In the specification with individual fixed effects, this vector is restricted to time-variant controls. I cluster SEs, ϵ_{iy} , at the individual level.

2.2. Validity Checks

2.2.1. Manipulation of the running variable

In this context, manipulation could occur if couples were able to influence their declared earnings. Labour income data utilised in this study come directly from the Swedish Tax Agency (Skatteverket). This leaves relatively little room for intentional manipulation, which has been found to be an issue in some earlier studies (e.g., Slotwinski and Roth, 2020; Kuehnle *et al.*, 2021). Nonetheless, Hederos and Stenberg (2022) do show a drop in the density around the threshold in Swedish data. However, they showed that the drop is largely driven by couples with identical incomes. Those appear to primarily consist of self-employed couples, who can split their shared revenue equally for tax reporting purposes and often choose to do so. The magnitude of the drop diminishes by up to 89% and is no longer statistically significant when excluding those couples.

I replicate their findings in my sub-sample: When including couples with identical earnings (the outlier bin in [Online Appendix Figure A.1](#)), the McCrary test indicates a statistically significant drop at the threshold ($p < .01$). However, when excluding those couples, the drop is no longer significant ($p > .6$). This corroborates the pattern found by Hederos and Stenberg (2022). This suggests to me that my main findings allow for a causal interpretation of the relative income effect for spouses with non-identical earnings. For the purposes of my main analysis I restrict the sample to those couples.⁹ The results also remain highly comparable in a doughnut regression (Hansen, 2015), excluding individuals in the bandwidth between 0.001 and 0.015 on either (or just the left-hand) side of the threshold from the estimation ([Online Appendix Figures A.3 and A.4](#)).

⁷ I discuss sensitivity analysis of the results with respect to the order of the polynomial and the bandwidth in the following section of the paper. The results are robust to varying both of those parameters.

⁸ The results are also essentially identical when restricting the sample to those who did not have a child in a given year. See [Online Appendix Table C.3](#) for more detail.

⁹ When including them, the estimates are virtually identical (see [Online Appendix Table B.1](#)).

2.2.2. Background characteristics

One remaining identification concern is that couples select into marriage based on variables linked to both relative income and mental health. To address that, I conduct balancing checks for all background variables that enter my vector of controls. I measure all of those in 2001 to address the issue of selection into marriage. I also include mental health diagnoses received in the year of marriage as a proxy for prior mental health status. The RD estimates for those variables are presented in [Online Appendix Table A.1](#). Out of all of these variables, only the dummy for having a university degree shows a statistically significant relationship with relative income. At the same time, it is no longer significant ($\beta = -0.007$, $SE = 0.012$) when employing the optimal bandwidth algorithm by Calonico *et al.* (2014). This is in contrast to the main results, which become more pronounced when using the algorithm.¹⁰ The results are also highly comparable when running the balancing tests concurrently rather than in the year of marriage.¹¹

3. Results

3.1. Descriptive Results and Main Estimates

Figure 2 illustrates the relationship between own and spousal income, and incidences of mental health issues in a given or a subsequent year. After an initial increase, there is a precipitous decline in the incidence with increasing income for both genders. The relationship between spousal income and own mental health is also positive, albeit less pronounced. The relationship with spousal income could be partially mechanical: higher spousal earnings often imply higher own earnings, thus largely reflecting the same relationship as with own income. Importantly, I do not observe a negative link between absolute spousal income and own mental health.

The relationship between relative income and mental health, however, looks markedly different. In Figure 3(a), I show a plot of mental health incidence as a function of the wife's relative earnings, with a discontinuity at the threshold of 1/2. There is a shift of approximately 30% (0.7 percentage points) in the likelihood of a mental health diagnosis when crossing the threshold. In panel (b), I then link these data to absolute income. While the function is fairly monotonic for men, women's absolute income peaks at around 65% of the joint share. I observe no particular irregularities around the threshold, suggesting that the effect is linked to relatively small changes in absolute values of income. The shift that is driving the effect appears to stem from women who earn above the female average of around 200,000 SEK per year, while the converse holds for males.

I show numerical estimates of the effect in Table 2. All coefficients are associated with the dummy variable of being above the equal earnings threshold. The main dependent variable, the likelihood of a mental health diagnosis, is coded to be either 0 or 100. This allows interpreting the baselines and the coefficients as percentage shares. The first row of the table demonstrates the effect for the entire sample, while the next two rows show separate estimations for males and females. The specification in column (1) is a simple local linear specification. In column (2),

¹⁰ See Section 3.2 below for further detail.

¹¹ See [Online Appendix Figure A.2](#) for the corresponding graphs. The only additional statistically significant coefficient compared to the original balancing table is that for having a STEM degree. At the same time, neither of the coefficients are statistically significant when employing the optimal bandwidth algorithm ($\beta_{college} = 0.003$, $SE = 0.004$; $\beta_{stem} = 0.003$, $SE = 0.002$).

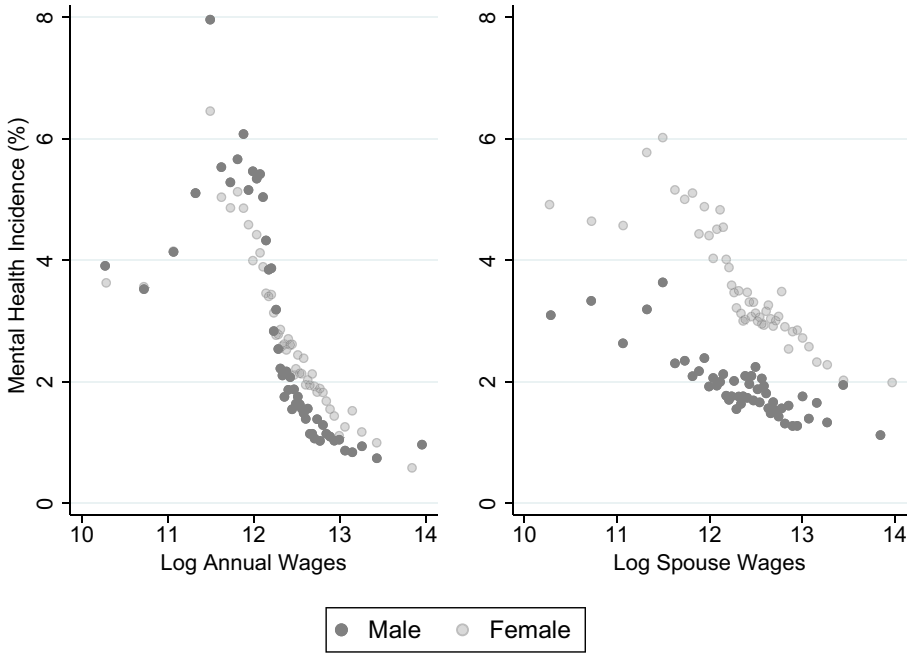


Fig. 2. *Own versus Spousal Earnings and Mental Health.*

Note: The figure shows the relationships between the incidence of mental health diagnoses and own (left) as well as spousal (right) absolute income. The y axis shows mental health incidence in percentage points, and the x axis shows logarithmised annual income for values above 10. The dots show the binned averages across fifty quantiles for each gender in each panel.

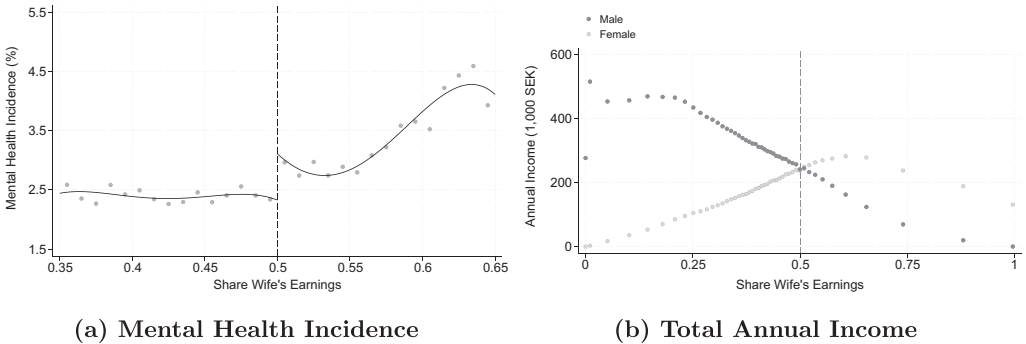


Fig. 3. *Female Earnings Share, Total Income and Mental Health.*

Note: Panel (a) shows the relationship between the incidence of mental health diagnoses and the share of female earnings in a given family, with a discontinuity at the threshold of > 0.5 . Panel (b) shows the relationship for between total and relative income for each spouse in a given couple.

I add a vector of individual controls discussed previously. In columns (3)–(5), I incrementally include individual and year fixed effects, as well as individual time trends, leaving in time-variant controls.

Table 2. *Relative Spousal Income and Mental Health.*

	(1)	(2)	(3)	(4)	(5)
	Mental health diagnosis [0, 100]				
All (2.85%)	0.39*** (0.14)	0.41*** (0.13)	0.18** (0.09)	0.17* (0.09)	0.21** (0.09)
Males (2.26%)	0.51*** (0.16)	0.54*** (0.15)	0.21** (0.10)	0.20** (0.10)	0.24** (0.11)
Females (3.42%)	0.28 (0.18)	0.27 (0.17)	0.15 (0.14)	0.14 (0.14)	0.17 (0.13)
Controls		X	X	X	X
Individual FEs			X	X	X
Year FEs				X	X
Individual trends					X
Observations	433,572	433,572	433,572	433,572	433,572
R ²	0.00	0.01	0.53	0.53	0.71

Note: The table shows the estimated relationship between the share of the wife's earnings in a given household in a given year and the incidence of mental health diagnoses in that or the following year. The coefficients demonstrate the effect of crossing the threshold of > 0.5 (i.e., where the wife outearns the husband). The effect is measured using a local linear estimator with a bandwidth of 0.15 for couples that are not self employed or have identical incomes. The first row shows the results for the sample with both genders. The next two rows show estimates from separate regressions for males and females. Coefficients in parentheses indicate general prevalence in a given sub-sample. Both the baseline and the estimates are shown in percentage points. The number of observations and the corresponding R^2 come from the sample including both genders. The vector of controls includes age, measures of highest educational attainment, income, migration status, fertility in a given year and a dummy for receiving health benefits. All time-variant variables are measured concurrently. SEs (in parentheses) are clustered at the individual level. * $p < .10$, ** $p < .05$, *** $p < .01$.

In the preferred specification shown in column (5), crossing the threshold increases the likelihood of a mental health diagnosis by around 0.21 percentage points, or approximately 8%. The effect is primarily driven by males, for whom the increase corresponds to approximately 11% (0.24 percentage points). This increase is economically significant as it reflects a relatively minor change in both absolute and relative income.¹² The effect also appears symmetric: crossing the threshold in the opposite direction reduces the diagnostic likelihood in males by 0.22 percentage points, or 10%.¹³ This further indicates crossing the threshold as the driver of the result. While I do not find a statistically significant effect on females, the respective estimates are only approximately 30% smaller and are not statistically significantly different from those for males.¹⁴ This is indicative of both genders being affected by the shift. Including individual fixed effects decreases the size of the estimates by approximately a third. This appears consistent with switching from a between- to a within-couple comparison, since couples on either side of the threshold can differ with respect to unobserved characteristics. This change in the size of the estimates, however, is primarily driven by men, with a limited effect on women. However, it remains statistically and economically significant even when comparing the same individuals.

¹² To give an additional perspective on the magnitude, having a parent with a mental health diagnosis is associated with an approximately 85% increase in one's own diagnostic likelihood, as shown by Getik and Meier (2022). Thus, my results constitute approximately 14% of the magnitude of that effect.

¹³ The effect is estimated by running the regression in the same specification using as the independent variable an indicator that becomes 1 when the husband outearns the wife in the current year, while the opposite holds in the previous year.

¹⁴ The p -values of the tests for the difference in the sizes of the estimates between the genders are 0.189, 0.138, 0.747, 0.745 and 0.662 for each specification reported in Table 2, respectively.

3.2. Robustness

3.2.1. Bandwidth

To check that my results are not driven by idiosyncratic bandwidth selection, I follow Hansen (2015) in comparing effect sizes given a range of different bandwidths. The results are shown in [Online Appendix Figure B.1](#). I include bandwidth sizes in the range between 0.05 and 0.2, in increments of 0.005, thus conducting thirty separate regressions. The size of the estimates remains fairly constant throughout, even at significantly narrower bandwidths than that used in the main regressions. This suggests that the results are not driven by bandwidth selection. To additionally check that, I also employ the optimal bandwidth selection algorithm, following Calonico *et al.* (2014). If anything, the obtained estimates for males are somewhat higher than the corresponding ones in [Table 2](#).¹⁵

3.2.2. Polynomial degree

For all of my estimates, I follow the literature in relying on a local linear specification (Hansen, 2015; Avdic and Karimi, 2018). This follows the results of Gelman and Imbens (2019), who suggested against using those polynomials in regression discontinuity designs. To ensure that the results are not specific to local linear estimation, I conduct a check where I include polynomials of the running variable up to degree 5. I present these results in [Online Appendix Table B.2](#). The estimates are robust to polynomial choice.

4. Mechanisms and Discussion

4.1. Effect Heterogeneity

4.1.1. Specific diagnoses

[Table 3](#) shows which of the seven diagnostic types drive the main result.¹⁶ For males, it appears primarily driven by mental health disorders related to substance use. These comprise any mental health issue stemming from use of alcohol and other psychoactive substances. I observe a 25% increase in the relative likelihood of a diagnosis. This result broadly aligns with an earlier estimate of an increase in female potential earnings on this diagnostic category (Ericsson, 2020). For behavioral disorders, which mainly comprise issues related to conduct and attention, being outearned by the wife more than doubles the likelihood.¹⁷

Consistently with the findings in [Table 2](#), I do not find statistically significant results for females. At the same time, I observe an effect on neurotic and stress-related disorders that is of a comparable relative magnitude to the effect on substance-related disorders in men. This category encompasses issues such as phobias, anxieties, compulsive behaviours, severe reactions to stress

¹⁵ The pre-programmed algorithm does not allow for including high-level fixed effects. However, using the optimal bandwidth suggested by the algorithm (0.068) in the preferred specification provides comparable and statistically significant estimates in the preferred specification with individual FEs (e.g., $\beta = 0.27$, $SE = 0.12$ for males).

¹⁶ The WHO ICD classification includes ten main diagnostic categories for mental health. In this table, I include seven of them as the remaining three pertain to diagnoses with biological origins or early onset. Thus, I do not expect those to be affected by relative income. I confirm that in a robustness check where I estimate the effect on those diagnostic categories in [Online Appendix Table A.2](#).

¹⁷ It is worth noting, however, that this diagnostic category has a relatively low prevalence in the adult population. Thus, affliction rate in my sample is approximately 0.04%. These issues typically have an onset earlier in life, but are not exclusive to children and adolescents. It is therefore possible that the increase is driven more by a higher likelihood of being diagnosed rather than a higher prevalence. For a more in-depth discussion on prevalence versus discovery in this diagnostic category, see Getik and Meier (2022).

Table 3. *Relative Spousal Income and Diagnosis Type.*

	(1) All	(2) Male	(3) Female
<i>Diagnosis</i>			
Substance-related disorder	0.08** (0.03)	0.14*** (0.05)	0.02 (0.03)
Depression and mood disorder	-0.04 (0.06)	0.03 (0.07)	-0.10 (0.09)
Eating and sleeping disorder	-0.01 (0.02)	-0.00 (0.02)	-0.02 (0.04)
Neurotic and stress disorder	0.11 (0.08)	0.03 (0.10)	0.18 (0.11)
Schizotypal disorders	0.00 (0.01)	0.02 (0.01)	-0.01 (0.01)
Behavioural disorder	0.02 (0.02)	0.06* (0.03)	-0.01 (0.03)
Adult personality disorder	0.00 (0.02)	0.00 (0.03)	0.00 (0.02)
Controls	X	X	X
Individual FEs	X	X	X
Year FEs	X	X	X
Individual trends	X	X	X

Note: The table shows the estimated relationship between the share of the wife's earnings in a given household in a given year and the incidence of a diagnosis from a given specific category in that or the following year. The coefficients demonstrate the effect of crossing the threshold of 0.5 (i.e., where the wife outearns the husband). Column (1) shows the results for the sample with both genders (*All*). The next two columns show coefficients estimated separately for each gender. The dependent variable in each row refers to a specific diagnostic category of ICD-10 codes F00–F99. The names of some of the categories in the table have been adjusted for easier reference of non-psychological/psychiatric readership. Behavioural disorders corresponds to the WHO category behavioural and emotional disorders with onset usually occurring in childhood and adolescence (F90–F98); substance-related disorders to mental and behavioural disorders due to psychoactive substance use (F10–F19); eating and sleeping disorders to behavioural syndromes associated with physiological disturbances and physical factors (F50–F59). The vector of controls includes age, measures of highest educational attainment, income, migration status, fertility in a given year and a dummy for receiving health benefits. All time-variant variables are measured concurrently. * $p < .10$, ** $p < .05$, *** $p < .01$.

and dissociative disorders. The finding aligns with the effect on anxiety-related medication shown by Pierce *et al.* (2013), albeit at a higher magnitude.¹⁸ At the same time, this differs from the results of Springer *et al.* (2019) and Ericsson (2020) in that they find a corresponding effect on males rather than females. However, this disposition of the effect between the genders in this paper is in line with the general pattern of affliction in my sample. Thus, men are 53% more likely to be afflicted by a substance-related disorder, whereas women are 74% more likely to face a neurotic or stress-related issue.

4.1.2. *Absolute income and age*

In [Online Appendix Table C.1](#), I present the effect of relative earnings by income quintiles. The estimates suggest that the observed result is mainly driven by the middle and upper-middle parts of the income distribution (quintiles 3 and 4). There, crossing the threshold increases mental health incidence for men by approximately 17%. In [Online Appendix Table C.2](#), I further split the individuals into four age groups that roughly correspond to age decades.¹⁹ Here, the effect

¹⁸ The relative effect is approximately 18% in this study, while it is around 5% in theirs. However, it is important to keep in mind that I consider diagnoses, while they examined prescriptions.

¹⁹ I include those aged 18–19 in the first group, and those aged 60–64 in the last, for brevity and greater comparability of sample sizes.

is most pronounced for men in their forties, with an approximately 21% increase in the relative likelihood of a diagnosis.

4.1.3. *Education and residence*

I also consider whether the effect is heterogeneous by education level and municipality size since more educated individuals in urban areas are perceived to place less emphasis on norm adherence. For education, I introduce a binary indicator for having a university degree; for residence, I introduce an indicator for whether one's municipality is above median size. The results are shown in [Online Appendix Table C.3](#). The effect size almost doubles for men in smaller municipalities and approaches zero for those in larger ones. Yet, at the same time, I actually observe a significantly higher effect on the more educated women. It is also somewhat larger for women in more urban areas. The magnitude there exceeds that of the general effect on males. This finding indicates a smaller role of norm adherence in the observed effect.

4.2. *Channels*

4.2.1. *Divorce*

Previous literature shows a connection between higher female earnings and divorce likelihood (e.g., Liu and Vikat, 2007; Schwartz and Gonalons-Pons, 2016). Conversely, interdisciplinary literature also links divorce to negative mental health outcomes (e.g., Richards *et al.*, 1997; Tosi and van den Broek, 2020). I therefore consider it as a potential mechanism for my results. To make it comparable across couples and cohorts, I examine whether divorce occurs in the same or the following year, similarly to the main results. I present the findings in [Online Appendix Table D.1](#). I do not find a substantial effect of the wife earning more on the probability of divorce in those years. This suggests that divorce in itself does not explain the observed increase in mental health diagnoses. It is worth noting, however, that my results do not imply any consequences for marital stability in the long run.

4.2.2. *Workplace effect*

Another potential channel for the observed effect is one's workplace. It is possible that workplace environment and culture shape one's attitude towards earnings and relative income. While it is difficult to proxy these metrics in administrative data, I evaluate two potential candidates: the share of men and the wage spread in one's firm. With the former, I aim to gauge whether the effect could be transmitted through a more male-dominated environment, i.e., to what extent it could be enforcing a perceived norm. The intuition behind the latter is that environments with a higher wage spread could induce a more competitive perception of earnings.

I show the outcomes of this exercise in [Online Appendix Table D.2](#). The first row shows a replication of my main results for individuals for whom workplace data are available (roughly 90% of the sample). In the next two rows, I interact them with the share of men and the wage spread in one's workplace, respectively. There appears to be no substantial effect of these interactions. This indicates that more male-dominated and less equal environments are not driving the observed result. This finding is particularly interesting in conjunction with the effect being larger among more educated and urban women.

4.3. Direction of the Effect

While I observe a link between relative income and mental health within individuals, one potential concern is that mental health could, in turn, be driving changes in relative income. In this subsection, I present a list of additional checks and arguments that make me conclude that it is not the primary driver of my results.

4.3.1. Non-concurrent diagnoses

While concurrent diagnoses could also reflect reverse causality, mental health issues recorded in the year $t + 1$ are less likely to be affecting relative income retroactively. I show the estimates where I restrict the diagnostic horizon to only include the subsequent year in [Online Appendix Table D.4](#). The estimates are comparable, with an approximately 7% increase in the relative likelihood of diagnosis. Additionally, mental health in year $t - 1$ does not appear related to current income. This indicates that my estimates are unlikely to be driven by only prior or concurrent mental health.

4.3.2. Sick leave and diagnostic categories

In this study, I detect a mental health effect of relatively small changes in income, suggesting that it is also present outside of cases where one's working capacity is strongly affected. In fact, excluding the individuals who received any sick leave compensation in a given year makes the estimates somewhat more pronounced (see [Online Appendix Table D.3](#)).²⁰ This indicates that the effect is at least comparable for those whose mental health does not prompt them to reduce their labour supply.

As shown in [Table 3](#), the effect is also mainly driven by a few of the diagnostic categories. Furthermore, I find no significant effect on mental health issues that have biological origins often determined at birth: organic disorders and mental retardation (Wittchen, 2001; Costeff *et al.*, 2008). If the causality were reversed, one could also expect a more even distribution across the categories.²¹ One could also expect a non-zero result for the more biologically driven disorders as they would likely affect labour supply.

4.3.3. Placebo thresholds

Finally, I replicate the results of my preferred specification whilst moving the discontinuity point within the chosen bandwidth in increments of 0.01. I present the results for those thirty arbitrary cutoffs in [Online Appendix Figure A.5](#). The effect is most pronounced at the 1/2 threshold, indicating the importance of the wife earning more for the observed result. If the effect were caused by mental health affecting income, one would expect a more uniform distribution across placebo thresholds.

5. Conclusion

In this paper, I examine the link between spousal income and mental health. I find that the wife outearning the husband results in higher incidence of mental health issues for both spouses. The effect is more pronounced for males, with an approximately 11% increase in the probability of

²⁰ While I do not directly know the grounds for claiming the benefits, I observe that individuals with a mental health diagnosis are approximately 30% more likely to do so.

²¹ For instance, one could expect an effect on depression and mood disorders that has been previously linked to income (e.g., Blattman *et al.*, 2017).

a diagnosis. This occurs despite mental health being positively associated with both own and spousal earnings for both genders. The results are highly robust to manipulations of the chosen specification.

For men, the result is mostly driven by mental health diagnoses related to substance use. While I do not observe a statistically significant result for females, it is not statistically significant from the effect on men. The findings are not directly explained by divorce or observable workplace-related factors.

Mental health is a crucial outcome linked to a host of important economic and life outcomes. In this study, I find tangible evidence of relative income in couples playing an important role in mental health outcomes, even in an ostensibly more egalitarian society like Sweden. This indicates non-negligible costs that should be accounted for in the discussion on changes in family dynamics. In order to draw more precise conclusions about the underlying mechanisms of the effect, further research would highly benefit from utilising data on labour supply, which were unavailable in this study.

Durham University Business School, UK

Additional Supplementary material may be found in the online version of this article:

Online Appendix Replication Package

References

- Adda, J., Dustmann, C. and Stevens, K. (2017). 'The career costs of children', *Journal of Political Economy*, vol. 125(2), pp. 293–337.
- Antman, F.M. (2014). 'Spousal employment and intra-household bargaining power', *Applied Economics Letters*, vol. 21(8), pp. 560–3.
- Avdic, D. and Karimi, A. (2018). 'Modern family? Paternity leave and marital stability', *American Economic Journal: Applied Economics*, vol. 10(4), pp. 283–307.
- Bertrand, M., Kamenica, E. and Pan, J. (2015). 'Gender identity and relative income within households', *The Quarterly Journal of Economics*, vol. 130(2), pp. 571–614.
- Binder, A.J. and Lam, D. (2020). 'Is there a male breadwinner norm? The hazards of inferring preferences from marriage market outcomes', *Journal of Human Resources*, doi: 10.3368/jhr.58.2.0320-10803R1.
- Blattman, C., Jamison, J.C. and Sheridan, M. (2017). 'Reducing crime and violence: Experimental evidence from cognitive behavioral therapy in Liberia', *American Economic Review*, vol. 107(4), pp. 1165–206.
- Calonico, S., Cattaneo, M.D. and Titiunik, R. (2014). 'Robust data-driven inference in the regression-discontinuity design', *Stata Journal*, vol. 14(4), pp. 909–46.
- Costeff, H., Cohen, B.E. and Weller, L.E. (2008). 'Biological factors in mild mental retardation', *Developmental Medicine & Child Neurology*, vol. 25(5), pp. 580–7.
- Currie, J., Stabile, M., Manivong, P. and Roos, L.L. (2010). 'Child health and young adult outcomes', *Journal of Human Resources*, vol. 45(3), pp. 517–48.
- Ericsson, S. (2020). 'Backlash: Female economic empowerment and domestic violence', Working Paper 2019:12, Lund University.
- Gelman, A. and Imbens, G. (2019). 'Why high-order polynomials should not be used in regression', *Journal of Business and Economic Statistics*, vol. 37(3), pp. 447–56.
- Getik, D. and Meier, A.N. (2022). 'Peer gender and mental health', *Journal of Economic Behavior & Organization*, vol. 197, pp. 643–59.
- Hansen, B. (2015). 'Punishment and deterrence: Evidence from drunk driving', *American Economic Review*, vol. 105(4), pp. 1581–617.
- Hederos, K. and Stenberg, A. (2022). 'Gender identity and relative income within households: Evidence from Sweden', *Scandinavian Journal of Economics*, vol. 124, pp. 744–72.
- Killewald, A. (2016). 'Money, work, and marital stability: Assessing change in the gendered determinants of divorce', *American Sociological Review*, vol. 81(4), pp. 696–719.

- Kleven, H., Landais, C. and Sogaard, J.E. (2019). 'Children and gender inequality: Evidence from Denmark', *American Economic Journal: Applied Economics*, vol. 11(4), pp. 181–209.
- Kuehne, D., Oberfichtner, M. and Ostermann, K. (2021). 'Revisiting gender identity and relative income within households: A cautionary tale on the potential pitfalls of density estimators', *Journal of Applied Econometrics*, vol. 36, pp. 1065–73.
- Liu, G. and Vikat, A. (2007). 'Does divorce risk in Sweden depend on Spouses' Relative income? A study of marriages from 1981 to 1998', *Canadian Studies in Population*, vol. 34(2), pp. 217–50.
- Lundborg, P., Nilsson, A. and Rooth, D.O. (2014). 'Adolescent health and adult labor market outcomes', *Journal of Health Economics*, vol. 37(1), pp. 25–40.
- Majlesi, K. (2016). 'Labor market opportunities and women's decision making power within households', *Journal of Development Economics*, vol. 119, pp. 34–47.
- Marcus, J. (2013). 'The effect of unemployment on the mental health of spouses—Evidence from plant closures in Germany', *Journal of Health Economics*, vol. 32(3), pp. 546–58.
- McDonough, P., Williams, D.R., House, J.S. and Duncan, G.J. (1999). 'Gender and the socioeconomic gradient in mortality', *Journal of Health and Social Behavior*, vol. 40(1), pp. 17–31.
- Pierce, L., Dahl, M.S. and Nielsen, J. (2013). 'In sickness and in wealth: Psychological and sexual costs of income comparison in marriage', *Personality and Social Psychology Bulletin*, vol. 39(3), pp. 359–74.
- Poortman, A.R. (2005). 'Women's work and divorce: A matter of anticipation? A research note', *European Sociological Review*, vol. 21(3), pp. 301–9.
- Richards, M., Hardy, R. and Wadsworth, M. (1997). 'The effects of divorce and separation on mental health in a national UK birth cohort', *Psychological Medicine*, vol. 27(5), pp. 1121–8.
- Schwartz, C.R. and Gonalons-Pons, P. (2016). 'Trends in relative earnings and marital dissolution: Are wives who outearn their husbands still more likely to divorce?', *RSF*, vol. 2(4), pp. 218–36.
- Slotwinski, M. and Roth, A. (2020). 'Gender norms and income misreporting within households', Discussion Paper 20–001, Centre for European Economic Research.
- Springer, K.W. (2010). 'Economic dependence in marriage and husbands' midlife health: Testing three possible mechanisms', *Gender and Society*, vol. 24(3), pp. 378–401.
- Springer, K.W., Lee, C. and Carr, D. (2019). 'Spousal breadwinning across 30 years of marriage and husbands' health: A gendered life course stress approach', *Journal of Aging and Health*, vol. 31(1), pp. 37–66.
- Statistics Sweden. (2017). 'Microdata online access', Retrieved via the Center for Economic Demography at Lund University. <https://www.scb.se/en/services/ordering-data-and-statistics/ordering-microdata/mona--statistics-swedens-platform-for-access-to-microdata/> (last accessed: 5 July 2024).
- Syrda, J. (2020). 'Spousal relative income and male psychological distress', *Personality and Social Psychology Bulletin*, vol. 46(6), pp. 976–92.
- Teachman, J. (2010). 'Wives' economic resources and risk of divorce', *Journal of Family Issues*, vol. 31(10), pp. 1305–23.
- Tosi, M. and van den Broek, T. (2020). 'Gray divorce and mental health in the United Kingdom', *Social Science and Medicine*, vol. 256, 113030.
- Wieber, A. and Holst, E. (2015). 'Gender identity and women's supply of labor and non-market work: Panel data evidence for Germany', Discussion Paper 9471, DIW Berlin.
- Winkler, A.E., McBride, T.D. and Andrews, C. (2005). 'Wives who outearn their husbands: A transitory or persistent phenomenon for couples', *Demography*, vol. 42(3), pp. 523–35.
- Wittchen, H.-U. (2001). 'Mental and behavioral disorders, diagnosis and classification of', in (N.J. Smelser and P.B. Baltes, eds.), *International Encyclopedia of the Social & Behavioral Sciences*, pp. 9628–39, Oxford: Pergamon.
- Zinovyeva, N. and Tverdostup, M. (2021). 'Gender identity, coworking spouses, and relative income within households', *American Economic Journal: Applied Economics*, vol. 13(4), pp. 258–84.