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Abstract

The share of couples where the wife out-earns the husband is increasing in many countries. In this paper, I investigate how this income dynamic affects mental health. Using data on all Swedish couples who married in 2001, I show that mental health is positively associated with own and spousal income. However, it is negatively linked to the wife's relative income. Crossing the threshold where the wife starts earning more increases the likelihood of a mental health diagnosis by 8-12 per cent. This effect does not appear driven by divorce or spouses being on different income trajectories.

JEL Classifications: I12, I19, I21, I31, J16, J24

Keywords: gender, mental health, income, relative income

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1 Introduction

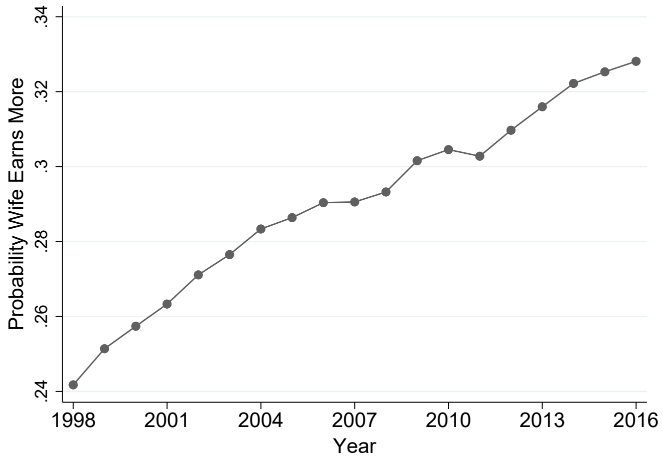
The share of married couples in which the wife out-earns the husband has been on the rise over the last decades. In the United States, the proportion of such couples has increased from 9% in 1970 to 27% in 2010.[1] The magnitude of change is comparable in Sweden, as can be seen in Figure 1. One consequence of this dynamic is a more frequent violation of the male breadwinner norm, whereby the husband is expected to earn more than the wife (Farré and Vella, 2013; Fortin, 2005). To test for the presence of this norm, researchers have mainly studied the distribution of relative earnings in couples. Bertrand, Kamenica and Pan (2015) presented original evidence for the norm by showing a dip in the distribution of households where the wife just out-earns the husband. However, several subsequent papers show that the results are likely driven by couples who intentionally equalize their earnings, such as couples that co-own a business (Binder and Lam, 2020; Zinovyeva and Tverdostup, 2018; Hederos and Stenberg, 2019). These more recent findings suggest that it is difficult to empirically test for the norm by only focusing on the distribution of spousal earnings.

An alternative approach is to instead study the link between relative earnings and other important outcomes. While couples may not intentionally comply with the norm, deviating from it could still be costly. Previous literature documents the effects of relative spousal income on marriage longevity and satisfaction (Bertrand, Kamenica and Pan, 2015). This link seems to translate to broader mental health. Male psychological distress appears the lowest when the wife earns about 40% of total income, after which it starts to increase (Syrda, 2020). In the Swedish context, Ericsson (2020) shows a link between wives' earning potential and mental health issues for their husbands. There is also suggestive evidence of the effects of crossing the equal earnings threshold. Thus, Pierce, Dahl and Nielsen (2013) show an increased uptake in anti-anxiety medication in wives that out-earn their husbands. In a similar vein, Springer, Lee and Carr (2019) show an association of higher wife's earnings with increased stress-related diseases.

These findings suggest that deviating from the breadwinner norm can be consequential for couples' well-being. In this paper, I therefore examine the causal effect of transferring the role of the main earner from the husband to the wife on their respective mental health. I do this by examining whether there is a discontinuous jump in the likelihood of a diagnosis when crossing the equal earnings threshold. I build on previous results by looking at direct within-

[1] See Bertrand, Kamenica and Pan (2015) for more detail.

Figure 1: Probability of Wife Out-Earning Husband by Year in Sweden



Note: The figure above shows the share of married couples in which the wife earned more than the husband in a given year. The y-axis denotes the the probability that the wife earns more. It is plotted over the years for which both family and income data are available.

individual effects on clinically diagnosed mental health. If such jump is present, it would suggest that the equal earnings threshold is important, even if couples do not deliberately adjust their relative earnings. While a crucial outcome in itself, it is also linked to a host of economic (e.g. Lundborg, Nilsson and Rooth (2014); De Quidt and Haushofer (2019); Meier (2019))[2] and other outcomes, including broader life satisfaction.[3] It is therefore important to understand the mental health implications of the changing earnings dynamics.

To estimate the impact, I follow previous literature and employ a regression discontinuity design, where I focus on individuals just above or below the 0.5 relative earnings threshold. I observe all couples that are recorded to have married in Sweden in 2001 and follow them for ten years, or until the year when they are no longer registered as married.[4] This allows me to include individual fixed effects, which restricts the variation to only within-subject. Effectively, this allows me to see what happens to the same individuals' mental health, depending on their position relative to the threshold.

I find that crossing the threshold significantly increases the likelihood of receiving a mental health diagnosis. This appears to hold both in the cross-section and over time. In

[2]For further literature discussing the effects of mental health on productivity, see, e.g., Prinz et al. (2018); Bütikofer, Cronin and Skira (2020); Ridley et al. (2020); Blattman, Jamison and Sheridan (2017).

[3]See, for instance, Headey, Kelley and Wearing (1993); Guney, Kalafat and Boysan (2010)

[4]In the registers, I observe the first year during which the couple are recorded as married. Therefore, the actual date of marriage might fall in the previous year. Similarly, for divorce I record the first year when the couple is no longer registered to be married.

the most restrictive specification, the likelihood increases by approximately 8%. The results are primarily driven by men, who experience a 12% increase in the likelihood. While I do not find significant overall results for women, I observe effects on neurotic and stress-related disorders that are of a higher magnitude than the observed effects on males. The effects are more pronounced for middle-age and middle-income individuals and are likely not driven by divorce or workplace environment.

I conduct additional balancing checks to address possible remaining selection into marriage. Firstly, there appears to be no significant manipulation of the running variable, i.e. the density of relative earnings does not change significantly around the cut-off.[5] Secondly, the sample appears balanced on background variables in the year of marriage, including prior mental and somatic health. My main estimates also do not appear sensitive to varying the bandwidth, the chosen order of the polynomial, conducting a "donut" regression, and relying on relative labor income only. One remaining concern after these checks is that mental health might, in turn, affect relative spousal income. While this concern is valid in my setting, the timing and magnitude of the effects, their pattern with respect to diagnostic categories and relative income thresholds suggest that it is not the main driver for the results. I present a more in-depth discussion of these factors in Section 5.5.

This paper contributes to two main strands of empirical literature. The first focuses on relative spousal income and the breadwinner norm. Bertrand, Kamenica and Pan (2015) originally showed a significant drop in the share of married couples just to the right of the threshold where the wife out-earns the husband. While Wieber and Holst (2015) find similar results in Germany, this finding is not corroborated by several more recent papers. Roth and Slotwinski (2020) suggest that in Switzerland the observed drop is largely explained by income misreporting around the threshold. In the US context, Binder and Lam (2020) show that the discontinuity is largely driven by individuals with identical incomes. Hederos and Stenberg (2019) and Zinovyeva and Tverdostup (2018) find similar results in Swedish and Finnish data, respectively. Finally, Kuehnle, Oberfichtner and Ostermann (2021) suggest that the observed drop is unstable across different estimation methods. I contribute to this literature by examining potential implications of the norm rather than directly studying spousal income distributions.

[5]This appears to hold even when including individuals with exactly the same income (see Hederos and Stenberg (2019)). I discuss the details of this exercise and how it fits into previous literature in Section 3.2.

The second strand more broadly describes the relationship between relative earnings, household dynamics, and marriage satisfaction. Bertrand, Kamenica and Pan (2015) find that self-reported marital satisfaction was lower when the wife just out-earned the husband. Additionally, Avdic and Karimi (2018) find that greater paternal participation at home increased the likelihood of divorce. Majlesi (2016) shows that an increased relative income also increases bargaining and decision-making power within households, which could be an explanation for higher divorce incidence.[6] When it comes to mental health more specifically, Ericsson (2020) finds that a higher female earnings potential increases diagnostic incidence in men. Finally, in a related paper, Pierce, Dahl and Nielsen (2013) consider the effect of relative income on the uptake of certain prescription medications. They find that the wife earning more is linked to a higher uptake of anti-anxiety medication for women and erectile dysfunction medication for men. I contribute to this strand of literature by examining within-individual clinical mental health effects and potential mechanisms that underlie them.

This paper is structured as follows. In the next section, I present some information on the Swedish mental health care system, relevant data, and construction of the main variables. In Section 3, I present my empirical strategy and ways in which I address potential validity concerns. In the subsequent section, I present the main results and estimates. In section 5, I evaluate mechanisms that could be driving the effects. Finally, in Section 6, I provide a brief discussion and interpretation of the findings.

2 Institutional Background and Data

2.1 Swedish Mental Health Care

My analysis relies on nationwide register data covering mental health diagnoses of all Swedes from 2001 to 2012 issued in specialist care. In most cases, individuals with potential issues first 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 (Heurgren, 2019). In more severe cases, one can also contact acute care and be admitted directly. The data available in the registers covers diagnoses issues in inpatient and specialized outpatient care by both public and private caregivers. It does not include cases treated by primary

[6] Please see Syrda (2020) for a more in-depth discussion on this link.

care physicians. Diagnoses observed in my data, therefore, reflect more acute cases where individuals were directed to specialized care and received a respective diagnosis.[7]

2.2 Data and Descriptive Statistics

Family Data and the Sample. The data on married couples comes from the Population Register (Registret över totalbefölkningen). I use administrative data on couples who are recorded to have married in 2001, when the health data available to me starts. I then follow those couples until 2011, or the year when the couple divorce.[8] The year 2011 was chosen since diagnostic data was originally available to me until 2012 and I measure diagnoses received concurrently or in the subsequent year. In this instance, one faces a trade-off between how many individuals one can observe and the duration for which they can be observed. I prioritized the duration of the observation horizon as my preferred specification deals with individual fixed effects, whereby the analysis benefits the most from increasing the time dimension. The sample covers heterosexual couples since same-sex marriage was not recognized in Sweden until 2009. I follow individuals who are at most 63 in 2011 to focus on those who did not reach retirement during the observation period. I further drop individuals for whom income data is missing (around 0.2%).

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, could be translated as "work income" (inkomst av tjänst). This is a variable that includes any obtained annual earnings outside of capital and business income. (SCB, 2021). I use a broader variable to account for income sources outside of wage that could be responsible for the ratio.[9]

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

[7] Due to standardized admission to care through outpatient referrals, the outpatient data covers over 90% of all mental health diagnoses (Getik and Meier, 2022).

[8] Around 80% of the couples in my sample do not divorce during the observation period.

[9] As a robustness check, I also re-define the independent variable using only labor income. The results of this estimation are qualitatively similar. Please see Section 4 for more detail.

are measured. This metric is used, among other reasons, since processing patients is a lengthy process within the Swedish mental health care. 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 diagnoses category (ICD-10 codes between F00 and F99, as constructed by the World Health Organization), and 0 otherwise.[10] These diagnostic categories also correspond to the definition of mental health issues provided by the National Board on Health and Welfare.

Occupational Data. For a part of my mechanisms analysis, I use data that comes from the Workplace Register (Yrkesregister). This data gives 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 on the firm level. I discuss the relevance and application of this data in Section 5.3.

Data Summary. Table A.1 summarizes the main background variables and diagnoses for the sample used in this study in the year of marriage. The average age in the sample is 33, with males in a couple being approximately 2 years older that their wives.[11] Just under a quarter of the individuals have a university degree, with the share being higher in females. Around 5% of the individuals hold a degree in a STEM field. As could be expected from Figure 1, male annual earnings are higher on average, by approximately 70,000 SEK, or 50%. Around 8% of males and 14% of females collected unemployment benefits in 2001. These statistics are generally close to the corresponding values in the general population.[12]

[10] The 0 and 100 binary designation allows us to interpret the estimates as a percentage change. The ICD-10 codes indicating mental health issues contain 10 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 behavior (F60 - F69); mental retardation (F70 - F79); disorders of psychological development (F80 - F89); behavioural and emotional disorders with onset in adolescence (F90 - F98).

[11] It is worth noting that in the data available to me, I cannot trace one's order of marriage since spousal indicators are only available since 1998. It is thus possible that an individual was married to someone prior to that year without that being reflected in the data. Therefore, the statistic I present here does not reflect average age at first marriage.

[12] In the general population, the proportion of university-educated individuals is around 22%, with 4% holding a degree in a STEM field. There is a moderate over-representation of the immigrant population in my sample, as in the general population of that age it is around 17%, and 20% among married couples (please see 4.2 for the addressing of this issue). The average annual earnings in that period is around 190,000 SEK. These estimates come from looking at population-wide data available to me in the registers. The average unemployment rate as measured in this sample is somewhat higher than the official unemployment rate due

With respect to the diagnoses, 2.3% of males and 3.4% of females in my sample receive a mental health diagnosis in a given span of two years.[13] The most prominent diagnoses appear to be neurotic and stress-related disorders as well as depression and mood-related disorders. Disorders with an onset primarily in childhood or adolescence exhibit a low level of prevalence.[14]

3 Empirical Strategy

3.1 Specification and Identifying Assumptions

While one may observe a strong relationship between mental health and relative earnings, a direct comparison would not be informative about a causal relationship. Couples with different compositions of relative earnings likely also differ on a number of unobservable 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 by comparing couples around the threshold of 1/2, i.e. where one of the spouses just out-earns the other.

Identification of treatment effects in a regression discontinuity setting relies on the assumption of "local continuity" around the threshold. The assumption implies that couples found just short of the threshold are comparable to the ones just above it and would be similarly affected by the wife's income exceeding the husband's. Local continuity is more likely to hold in an administrative data setting, such as this one. As earnings data comes from the tax authority, individuals do not have the ability to under- or over-report their earnings to manipulate their position with respect to the threshold.[15]

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to the variable construction: namely, my indicator for unemployment receives a value of 1 if an individual collected *any* unemployment benefits in a given year.

[13]The share is 1.5% and 2.1% in the year of marriage, respectively.

[14]Thus, hyperactivity and conduct disorders afflict only 0.04% of the sample, while learning and socialisation disorders less than 0.01%. These levels of prevalence are somewhat lower than would be representative in the general population. The reason is that here it is measured in 2001, the first year of data availability. The rate of diagnostic discovery was steadily increasing throughout the years when the data is available. For comparison, in 2011 recorded prevalence of all mental issues is 2.7% for men and 4.2% for women. These rates would, in turn, be lower than those shown in survey data. This is likely due to the fact that the records only include diagnoses issued by specialists and not cases handled by primary care.

[15]Selective reporting has been suggested as a potential source of discontinuity in studies with a similar setup that rely on survey data. Having administrative data, therefore, helps mitigate that specific concern (Roth and Slotwinski, 2020; Kuehnle, Oberfichtner and Ostermann, 2021)

A significant concern for this empirical strategy is that couples on either side of the threshold are not directly comparable. This would impede a causal interpretation of between-couples variation. To address that issue, I rely on individual fixed effects. Effectively, I consider a within-individual variation with respect to the 1/2 threshold. Just under half of the individuals in my sample move around the threshold throughout the years when I observe them. 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 effects. I estimate the effects using local linear specifications with the bandwidth of 0.15, which encompasses more than 1/2 of my original sample.[16] The specification is shown in the following equation:

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

In the equation above, 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, $\frac{EarningsWife_{iy}}{EarningsWife_{iy}+EarningsHusband_{iy}}$; $I[WifeShare_{iy} > 0.5]$ is a binary indicator for whether the wife's share exceeds 1/2, i.e. if the wife out-earns the husband, and the parameter of interest; α_i represents individual fixed effects; $X_{iy}\gamma'$ is a vector of individual-level controls measured in a given year. Variables included in that vector are age, metrics of education, fertility, and metrics of prior mental and somatic health.[17] In a similar fashion to Hansen (2015), I cluster standard errors, ϵ_{iy}, by levels of wife's relative income.[18] Since one can expect residuals to correlate at different levels of relative income, this appears consistent with the suggestion by Abadie et al. (2017). The results are also highly comparable when I cluster those on the individual level.

3.2 Balancing Tests

Manipulation of the Running Variable. In this context, manipulation of the running variable could happen if couples were able to influence their reported or actual earnings. Pre-

[16] 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 appear robust to both of those parameters.

[17] In the specification with individual fixed effects, this vector is restricted to time-variant controls.

[18] There is a practical difference to clustering by level when compared to Hansen (2015). In both cases, the running variable is continuous. However, Hansen clusters by the minimal available increment to him, which, in practice, makes the variable discrete. In my case, there is no minimal increment. I address this issue by varying the number of decimal points in the relative income share when deciding how many clusters to create. My standard errors appear robust to the rounding decision and the number of clusters created.

vious findings in Swedish data do show a drop in the density around the threshold (Hederos and Stenberg, 2019). However, the authors show that the drop is associated with spouses that earn exactly the same and often work together or co-own a company. When excluding those couples, they did not detect a corresponding drop.[19]

In my data, I first manage to replicate this finding in Figure B.1. Similarly to Hederos and Stenberg (2019), I split my data into 1000 bins, yielding a 0.1 percentage-point increment. Consistently with their findings, I observe one bin that has a higher density, which corresponds to the bin that reflects exactly the same earnings. In my sub-sample, that comprises 2,105 observations. While this constitutes a small share of the sample, it is possible that it differs systematically from the main population, including in mental health status. Then the estimates could reflect compositional differences. This does not appear to be the case in my data. Firstly, when conducting a test for the running variable manipulation (McCrary, 2005), I do not find a statistically significant change in variable density ($p = 0.145$), even when including those with the same income.[20] The results are also virtually identical when excluding those individuals. I discuss several additional tests and checks to address this concern in Section 4.2. The results are generally robust to those checks.

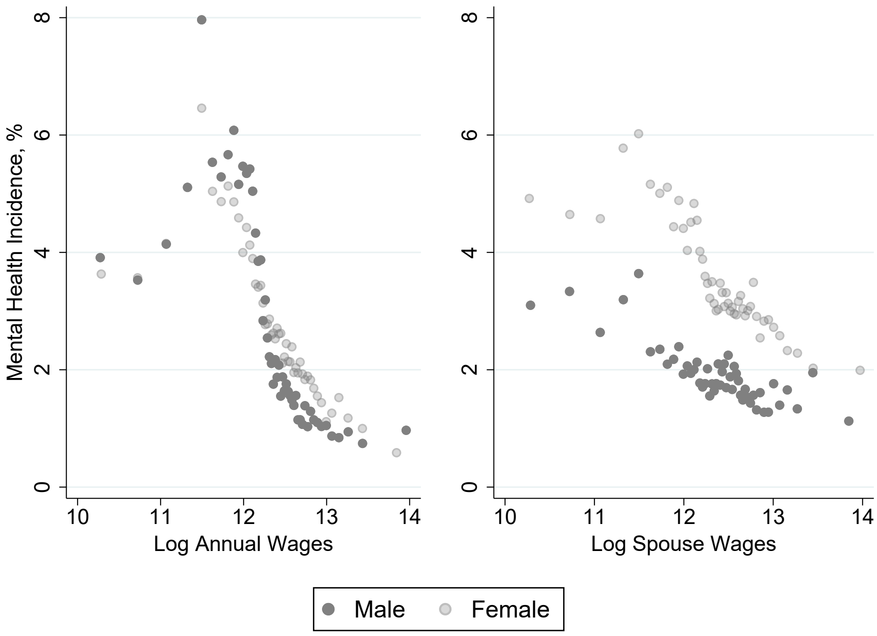
Background Characteristics. One concern that remains when using individual fixed effects is that couples could select into their respective positions around the threshold along other variables related to mental health. It is also possible that individuals sort into marriage based on their prior mental health. I conduct balancing checks for background variables which enter the vector of individual controls. The vector includes age, metrics of education (having a university degree and/or a STEM degree), having a foreign background, having a child in a given year, and a health index of somatic diagnoses. I measure all of those in the year when individuals get married to address the issue of selection into marriage.[21] 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 Table B.1 and shown

[19] In the original paper, the authors find that self-employed couples are substantially over-represented among those couples. The share of self-employed couples among equal earners is approximately 17%, as opposed to 3% in the general population. Using occupational indicators available to me, I find that approximately 21% of equal-earning couples share the same occupation. Therefore, it is broadly consistent with the idea that a disproportionate share of the couples reporting identical incomes are likely to work together.

[20] When excluding those individuals, $p = 0.265$.

[21] For these RD estimates, I use the specification from column (1) in Table 1 since most of the control variables are time-invariant and cannot be estimated using a specification with individual fixed effects.

Figure 2: Own and 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 logarithmized annual income for values above 10. The dots show the binned averages across 50 quantiles for each gender in each sub-plot.

graphically in Figure B.2. Out of all of these variables, only the dummy for having a university degree shows a statistically significant relationship with relative income. To address that issue, I control for that variable in my main specification.

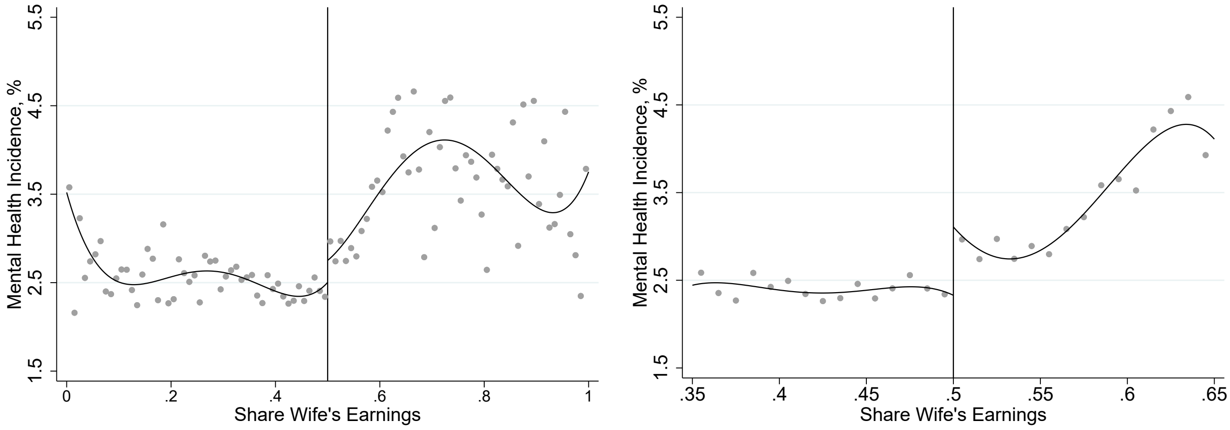
4 Results

4.1 Descriptives 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.[22] Mental health is depicted as incidence likelihood (in percentages). After an initial increase, there is a rather precipitous decline in the incidence with increasing income for both genders. The relationship between spousal income and own mental health is also positive and more linear than in the case of own income, albeit less pronounced.

[22]Each value is recorded as $ln(earnings_{iy}+1)$. Negative values are bottom-coded at 0 (only several hundred observations). Values under 10 (roughly corresponds to 23,000 SEK a year, or 200 EUR a month) are left out of the plot for scaling purposes.

Figure 3: Female Earnings Share around Threshold and Mental Health



(a) Full Distribution **(b) Within Bandwidth**

Note: The figure 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 (the point where the wife out-earns the husband). The sample in the figure corresponds to the one in Table 1. The figure on the left is a plot for the entire distribution. There, the dots show the binned averages across 100 quantiles. The figure on the right is zoomed in on the bandwidth used in the estimation.

In both panels, one can observe a generally positive relationship between earnings and mental health, i.e. the more either spouse makes the less likely either is to be diagnosed with a mental health problem. The relationship with spousal income could be partially mechanical: higher spousal earnings may imply higher own earnings, thus largely reflecting the same relationship as with own income. Importantly, however, 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. Figure 3 shows a granular plot of mental health incidence as a function of the wife's share of earnings in a given couple, with a discontinuity at the threshold of 1/2 as shown by the vertical line. The left figure shows mental health incidence for the full distribution of relative income. There, I plot the average incidence across 100 bins of relative income on either side of the threshold. There is a shift of approximately seven percentage points, or roughly 30 per cent, in the likelihood of a mental health diagnosis when crossing the threshold. The shift is corroborated by the figure on the right, where I focus on the bandwidth used in my estimation.[23]

[23]Here, I plot 15 bins on either side of the threshold, for the increment in each bin to be consistent with the first sub-figure.

Combined, figures 2 and 3 suggest a negative association between the share of wife's relative earnings and mental health that is likely not driven by absolute income. Incremental changes appear the largest in the middle of the distribution. This indicates the importance of the 1/2 threshold, emphasizing the role of the change in the main breadwinner. I show estimates of the effect of that change in Table 1. All coefficients are associated with the dummy variable of being above the 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. I use a local linear specification with the bandwidth of 0.15 for all estimates. This bandwidth encompasses just over a half of the original sample.[24] The first row 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), I add a vector of individual controls discussed previously. In columns (3) - (5), I incrementally include individual and year fixed effects, and individual time trends. Controls entering the preferred specification in column (5) are time-variant since other controls are collinear with individual fixed effects.

In the preferred specification shown in column (5), crossing the 1/2 threshold appears to increase the likelihood of a mental health diagnosis by around 0.22 percentage points, or approximately 8%. The effect appears primarily driven by males, for whom the increase corresponds to approximately 12% (0.26 percentage points). This increase is economically significant as it reflects a relatively minor change in both absolute and relative income and primarily describes a shift in the role of the primary earner. To provide some perspective on these magnitudes, in an earlier study using Swedish administrative data, we find that a concurrent parental mental health is associated with an approximately doubled likelihood of a mental health issue in adolescents (Getik and Meier, 2022). While I do not find statistically significant effects on females, the size of the estimates is only approximately 30% lower than those for males. Including individual fixed effects decreases the size of the estimates by approximately 1/3, which is likely related to relying on within-individual variation in crossing the threshold and where the estimates therefore capture the effects in the sub-population for which such variation is present. These estimates are still sizeable and statistically significant, and they are subsequently robust to including individual-level controls, year fixed effects,

[24]The results are robust to bandwidth and polynomial selection. See Section 4.2 for more details.

Table 1: Relative Spousal Income and Mental Health

	Mental Health Diagnosis [0,100]				
	(1)	(2)	(3)	(4)	(5)
All (2.85%)	0.31*	0.31**	0.21**	0.20**	0.22**
	(0.16)	(0.15)	(0.08)	(0.08)	(0.09)
Males (2.27%)	0.43**	0.42**	0.24**	0.23**	0.26**
	(0.17)	(0.17)	(0.10)	(0.10)	(0.10)
Females (3.42%)	0.20	0.21	0.18	0.17	0.18
	(0.19)	(0.18)	(0.13)	(0.13)	(0.13)
Controls		X	X	X	X
Individual FE			X	X	X
Year FE				X	X
Individual Trends					X
Observations	434,482	434,482	434,482	434,482	434,482
R-squared	0.00	0.01	0.53	0.53	0.71

Note: The table shows the estimated relationship between the share of 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 wife out-earns the husband). All the effects are measured using a local linear estimator with a bandwidth of 0.15. 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-squared come from the sample including both genders. Standard errors (in parentheses) are based on clustering at the closest 0.005 increment of the relative share. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

and individual time trends. I also obtain similar estimates when using only labor income for measuring relative earnings.[25]

4.2 Robustness

Varying the Bandwidth and Polynomial Degree. To further 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 Figure C.1. On the X-axis, I show a given bandwidth, and on the Y-axis the corresponding effect size using

[25] As a minor robustness check, I re-estimate the effects using only labor income as a measure of earnings. When estimating the main effects for the same bandwidth, in the preferred specification (column (5) in Table 1) $\beta = 0.17, se = 0.07$. In the specification corresponding to column (4), which does not include individual time trends, the estimate for females is $\beta = 0.23, se = 0.14$. These results are statistically significant at the 10% level.

the preferred specification. I include bandwidth sizes in the range between 0.05 and 0.2, in the increments of 0.005, thus conducting 30 separate regressions. As shown in the figure, the size of the estimates remains fairly constant throughout, even at significantly narrower bandwidths than the one used in the main regressions.[26] This suggests that the results are quite robust to bandwidth selection.

For all of my estimates, I follow the literature in relying on local linear specification (Hansen, 2015; Avdic and Karimi, 2018). This follows the results by Gelman and Imbens (2019), who suggest 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 Table C.1. The estimates are robust to the highest degree of the included polynomial.

Donut Regression. Conversely, individuals just to either side of the threshold might be different from each other, which could bias the estimates. To address that, I conduct a "donut" regression, where I estimate the effects in the preferred specification while leaving those individuals (as well as those right at the threshold) out of the sample. To comprehensively measure the sensitivity of my results, I vary the size of the gap between 0.001 and 0.015, with an increment of 0.001. Effectively, I start by excluding the observations right around the threshold and continuously expand the portion of the distribution excluded from the sample. The outcome of this exercise is shown in Figure C.2. The results are not highly sensitive to excluding individuals in the immediate vicinity of the threshold.

Sub-samples. To further address possible selection concerns outlined by Hederos and Stenberg (2019), I also replicate my main results in the preferred specification for several sub-samples. In the first one, I exclude individuals that earn exactly the same, with the estimates remaining virtually identical (see Table B.2). I then additionally control for one's occupation. The estimates remain very similar, particularly for males. In the third sub-sample, I exclude spouses who are in the same occupation.[27] The estimates for females in this sub-sample increase somewhat and are statistically significant. Finally, excluding self-employed individuals

[26]Incrementally narrowing the bandwidth reduces the sample size and therefore widens the confidence interval. However, it is worth noting that the size of the estimates is quantitatively stable at all shown bandwidths. The estimates are also significant at the 10% level even at bandwidths smaller than 0.1.

[27]These two checks are conducted for the sub-sample for whom occupational data is available. This constitutes approximately 90% of my sample.

does not seem to alter the original estimates. Jointly, these checks suggests that my results are not driven by compositional changes around the threshold, nor by self-employed individuals or couples in the same occupation. If anything, the results are more pronounced in couples that do not share an occupation.

4.3 Heterogeneity in Effects

Absolute Income. In Table D.1, I present the effects of relative earnings by income quintile, with income measured concurrently. The estimates suggest that the observed effects are mainly driven by the middle and upper-middle parts of the income distribution. Namely, the effects are more pronounced in the third and fourth income quintiles. There, crossing the threshold increases mental health incidence for men by 0.39 percentage points, or approximately 17%.

Age. I further split the individuals into 4 age groups that roughly correspond to decades.[28] These results are shown in Table D.2. Similarly to absolute income, the effects appear primarily driven by the middle and upper-middle part of the distribution. The effects are most pronounced for men in their forties, with a 0.46 percentage point increase in the likelihood of a diagnosis. This corresponds to an approximately 21% increase in relative likelihood.

Education and Residence. I also consider whether the effects are heterogeneous by education level and municipality size. Both of these aim to reflect heterogeneity by importance of tradition, as individuals with higher levels of education and those living in larger areas are perceived to place less emphasis on it. For education, I introduce a binary indicator for having a university degree; for residence, an indicator for whether one's municipality is above-median in size. The results are shown in Table D.3. It appears that having a university degree and living in a larger area significantly reduces the likelihood of a mental health diagnosis in men. Simultaneously, I observe the opposite trend for women. For both women with university degrees and those residing in larger areas, I observe a significantly higher mental health effect of out-earning their husbands. The magnitude of this effect, in fact, exceeds that

[28]I also include those age 18-19 in the first group, and those aged 60-64 in the last, for brevity and greater comparability of sample sizes.

of the general effect on males. This is a somewhat surprising finding which suggests that the effects are actually more prevalent among women in less traditional households.

Fertility. Finally, I check whether results differ based on having a child in a given year. If that were to be the case, the results could be driven by fertility decisions rather than more idiosyncratic changes in income. Fertility has previously been linked to significant drops in earning for women (Kleven, Landais and Søgaard, 2019; Adda, Dustmann and Stevens, 2017). I show the results in Table D.3. The estimates are quantitatively similar when restricting the sample to couples that do not have a child in a given year. This suggests that fertility is not a significant driving factor behind the results.

5 Mechanisms and Discussion

5.1 Effects by Specific Diagnoses

Table 2 shows which of the 7 diagnostic types drive the main results. For all of the estimates in the table, I use the preferred specification, shown in column (5) of Table 1.[29] The results for males are mainly driven by mental health disorders related to substance use. In addition, I observe an effect on behavioral disorders. For substance-related disorders, which comprise any mental health issue stemming from use of alcohol and other psychoactive substances, I observe a 25% increase in the relative likelihood of diagnosis. This is a rather sizeable effect when compared to economic effects on mental health in previous research.[30]

For behavioral disorders, which mainly comprise issues related to conduct and attention, being out-earned by the wife more than doubles the likelihood. It is worth noting, however, that this diagnostic category has a relatively low prevalence in the adult population. These issues typically have an onset earlier in life, but are not exclusive to adolescents. It is possible

[29]The WHO ICD classification includes 10 main diagnostic categories for mental health. In this table, I include 7 of them as the remaining 3 pertain to diagnoses with biological origins or early onset (please see section 4.2 for more details). Thus, I do not expect those to be affected by relative income. I confirm that by doing a robustness check where I estimate the effects on those diagnostic categories. The outcome of that exercise is shown in Table B.3.

[30]To provide some perspective on these magnitudes, in an earlier study using Swedish administrative data we find that a concurrent parental mental health is associated with an approximately doubled likelihood of a mental health issue in adolescents (Getik and Meier, 2022). In the same study, we estimated that a 10 percentage point increase in the share of female peers in a given classroom increases the likelihood of a mental health issue by approximately 4.7%.

that in this instance I observe an increase that is driven more by the likelihood of being diagnosed rather than an increased prevalence.[31]

Consistently with the results in Table 1, I do not find statistically significant effects for females. At the same time, I observe effects on neurotic and stress-related disorders that is of a larger magnitude than the effects on men mentioned earlier. This could be suggestive of relative income effects on this diagnostic category in females. This finding also aligns with the effects shown by Pierce, Dahl and Nielsen (2013). The category encompasses issues such as phobias, anxieties, compulsive behaviours, severe reactions to stress, and dissociative disorders. This disposition of the effects between the genders is in line with the general pattern of affliction.[32]

5.2 Divorce

One of the observed effects of the breadwinner dynamic is marriage longevity (Bertrand, Kamenica and Pan, 2015). Divorce could then be a driving force behind my results as it has been linked to negative mental health outcomes.[33] I designate the year in which a couple is no longer recorded to be married to be the year of divorce. Since I do not observe when exactly a couple files for divorce, in a separate metric I also incorporate the year prior to the one in which the divorce is recorded. I present the results for both of those metrics in Table E.2. The first row shows the effect of crossing the threshold on divorce in a given year. The second estimate maps divorces that occur concurrently or in the prior year to when relative income is observed. The results are shown for the specifications with individual fixed effects, which corresponds to columns (3) - (5) in Table 1. In my sample, I do not find a substantial effect of the wife earning more on divorce. This suggests that divorce in itself does not explain the observed increase in mental health diagnoses.

[31] In Getik and Meier (2022), we conduct an extensive discussion on diagnostic likelihood versus prevalence across diagnostic categories.

[32] In my sample, 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 (see Table A.1 for details). Similarly, women are twice as likely as men to be affected by an eating or a sleeping disorder, or a mood disorder.

[33] See, for instance, Richards, Hardy and Wadsworth (1997); Tosi and van den Broek (2020)

Table 2: Relative Spousal Income and Diagnosis Type

Diagnosis:	**All**	**Male**	**Female**
	(1)	(2)	(3)
Substance-Related Disorder	0.08***	0.15***	0.02
	(0.03)	(0.05)	(0.03)
Depression and Mood Disorder	-0.04	0.03	-0.10
	(0.06)	(0.07)	(0.09)
Eating and Sleeping Disorder	-0.01	-0.00	-0.02
	(0.02)	(0.02)	(0.04)
Neurotic and Stress Disorder	0.11	0.03	0.18
	(0.08)	(0.10)	(0.11)
Schizotypal Disorders	0.00	0.02	-0.01
	(0.01)	(0.01)	(0.01)
Behavioral Disorder	0.02	0.06**	-0.01
	(0.02)	(0.03)	(0.03)
Adult Personality Disorder	0.00	0.00	0.00
	(0.02)	(0.03)	(0.02)
Controls	X	X	X
Individual FE	X	X	X
Year FE	X	X	X
Individual Trends	X	X	X

Note: The table shows the estimated relationship between the share of 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 wife out-earns the husband). Column (1) shows the results for the sample with both genders (All). The next two columns show coefficient 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. Behavioral 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). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.3 Workplace Effects

One potential channel for the observed results is workplace. It is possible that workplace environment and culture shape one's attitude towards earnings and the importance of relative income. While it is difficult to proxy these metrics in register data, I evaluate two potential candidates: share of men and wage spread in one's firm.[34] With the former, I aim to gauge whether mental health effects 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 Table E.3. The first row shows a replication of my main results for individuals for whom workplace data is 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 appear to be no substantial effects of these interactions. This indicates that at least in these two dimensions, one's workplace is not primarily responsible for the effects. This also suggests that more male-dominated environments are not responsible for the norm propagation. This finding is particularly interesting in conjunction with the observed effects being larger for women with university degrees and those residing in larger municipalities.

5.4 Dynamic Effects

A shift around the 1/2 threshold could be a result of the wife being on an upward trajectory, or vice versa. To address this, I estimate mental health effects around the threshold by interacting them with lagged income variables. To that end, for each individual in the sample I derive the value of relative lagged income, which is measured as follows:

$$\Delta I_{iy} = (I_{i,y} - I_{i,(y-1)}) - (I_{s,y} - I_{s,(y-1)}) \tag{2}$$

In the equation above, $I_{i,y}$ represents own earnings in year y, and $I_{i,(y-1)}$ in year $y-1$. Similarly, $I_{s,y}$ and $I_{i,(s-1)}$ represent spousal earnings in years y and $y-1$, respectively. ΔI_{iy} then provides me with an estimate of a relative increase of own earnings over the last year as compared to the corresponding increase in spousal earnings. This serves as an indicator

[34] The data is aggregated on the level of a given organization.

of one's position on the earnings trajectory relative to their spouse. For instance, if both lagged incomes (values in parentheses) are negative, a positive ΔI_{iy} would indicate that own earnings dropped by a smaller amount than the earnings of the spouse. I then interact a dummy indicating whether ΔI_{iy} is positive with the preferred specification:

$$\begin{aligned} Y_{iy} = \beta_1 \times WifeShare_{iy} + \beta_2 \times I[\Delta I_{iy} > 0] + \\ \beta_3 \times I[WifeShare_{iy} > 0.5] \times I[\Delta I_{iy} > 0] + \alpha_i + \epsilon_{iy} \end{aligned} \tag{3}$$

In this specification, β_2 is the coefficient representing mental health effects of a higher lagged income than that of one's spouse. β_3 then shows the corresponding effect for those with a higher lagged income for males and females in households where the wife is the primary earner in a given year. By producing these interacted effects, I can assess the effects of the wife being the primary earner in conjunction with the relative dynamic income in the couple. The results of this exercise are shown in Table E.1.

The first row of the table replicates the pooled and gender-specific results from the specifications with individual fixed effects. In the second row, I show the estimated association between mental health and having a higher lagged income than one's spouse. The estimates are negative albeit small and not statistically significant, suggesting little association with diagnostic incidence. Finally, in the last row I interact the effect of crossing the threshold with the estimates of having a higher lagged income. Doing that does not appear to affect the effect size. This suggests that relative income trajectory likely does not play a substantial role with respect to relative spousal earnings. The effects that I observe are likely more attributable to static income differences.[35]

5.5 Direction of the Effects

While I observe a pronounced link between relative income and mental health within individuals, one potential concern is that mental health could be driving changes in relative income and affecting who is the primary earner in the family. This is a valid concern in my setup. In this section, I present a list of additional checks and arguments that make me conclude that it is not the primary driver of my results.

[35] I also do not find statistically significant results when the outcome is measured in years t+2 and t+3 instead of years t and t+1. The results are shown in Table C.4. This suggests that the effects are somewhat contemporaneous. However, they also underline the significance of the year when the wife starts to earn more.

Non-Concurrent Diagnoses. In my main specification, I consider the effects of relative income on mental health diagnoses received concurrently or in the following year. It is then possible that the effects could flow in the other direction. However, mental health issues recorded in the following year are less likely to be affecting relative income retroactively. Therefore, if the effects hold for only the non-concurrent diagnoses, it is unlikely that my estimates are fully explained by mental health effects on income. I show the estimates where I restrict the diagnostic horizon to only include the subsequent year in Table C.3. While the estimates are somewhat lower in absolute terms, they are comparable relative to the new baseline, which is lower since the observation period is now reduced.[36] In the preferred specification, crossing the threshold increases the likelihood of the diagnosis by approximately 7%. The estimate is also statistically significant.

Additionally, in Table C.3 I also show the results of a placebo test where I check mental health effects in the year t-1. There, I do not find any significant estimates, which is in line with the expected direction of the effects. Mental health in year t-1 does not appear strongly related with income in the year when relative income is measured. This indicates that my main estimates are unlikely to be explained by prior mental health affecting relative income.

Placebo Thresholds. If the primary earner hypothesis were adequate, one would expect that crossing other ("placebo") thresholds in the vicinity of 1/2 should not produce a substantial effect on mental health diagnoses. To test that, I replicate the results of my preferred specification whilst moving the discontinuity point within the range of 0.4 to 0.6 in increments of 0.005. I present the results for those 40 arbitrary cut-offs in Figure B.3. This finding supports the suggestion that it is the role of the primary earner that likely drives the mental health effects. It also suggests that reverse causality is less likely to be explaining my results, as one could expect a more uniform distribution of effects across placebo thresholds.

Effects by Diagnostic Categories As shown in Table 2, the effects are mainly clustered around several diagnostic categories. If one expected mental health to primarily affect relative

[36] When calculating the effects only in the following year, I consider only diagnoses received by those on either side of the threshold in the year after income was measured (t+1). Since the observation period is shorter for both groups, this implies lower prevalence as there is less time in which I could receive a diagnosis. The new prevalence level is 2%, with $\beta = 0.14$, compared to 2.85% and $\beta = 0.22$ in the preferred specification (column (5) in Table 1).

income rather than vice versa, one could expect a more even distribution of the effects across different categories.[37] I also examine mental health issues that have biological origins often determined at birth: organic disorders and mental retardation (Wittchen, 2001; Costeff, Cohen and Weller, 2008). In these diagnostic categories, one would expect the effects of relative income to be close to null as it is unlikely to affect mostly biologically determined issues. However, if the direction of the effects was the opposite, one could expect more pronounced effects since such issue would likely affect labour supply. I show the estimates for the two categories in Table B.3. I find no significant effects across all specifications, which does not appear consistent with a mental health effect on relative income.

Magnitudes and Sick Leave. In this paper, I focus on effects associated with minor changes in both absolute and relative income. I observe that these changes can already translate to sizeable mental health effects, even at narrower bandwidths. This suggests that the effects are present outside of more serious cases where one's working capacity and income would be more strongly affected. I conduct an additional check to verify this. There, I exclude individuals who received any sick leave compensation in the year when their income is measured (See Table C.2).[38] Doing that makes the estimates even somewhat more pronounced. This indicates that the effects are at least comparable for those whose mental health does not prompt them to take time away from work. Therefore, it is likely not the individuals that diminish their labor supply due to mental health issues that drive my results.

6 Conclusion

Across many countries, the likelihood of the wife being the primary earner has risen substantially, resulting in a more frequent violation of the male breadwinner norm. In this paper, I examine the implications of this dynamic for clinically diagnosed mental health. I find that the wife out-earning the husband results in higher incidence of mental health issues for both spouses. The effects are more pronounced for males, with a 12% increase in the probability

[37] For instance, one could expect effects by depression and mood disorders that has been previously linked to income (Blattman, Jamison and Sheridan, 2017).

[38] While I do not directly know the grounds the benefits, I observe that it is approximately 30% higher among individuals with a mental health diagnosis.

of a diagnosis. This relationship is present in spite of the fact that for both genders mental health is generally positively associated with both own and spousal earnings.

For males, the effects are mostly driven by mental health diagnoses related to substance use, as well as behavioral disorders. While I do not observe statistically significant effects for females, the magnitude of the effects on neurotic and stress disorders among them is higher than the effects detected for males. The effects are largely driven by the middle-age and middle-income individuals. Males with university education and living in larger areas are less responsive to the dynamic, while the opposite applies to females.

I also evaluate several potential mechanisms that could be responsible for the effects. Firstly, it does not appear that they are largely explained by an increased chance of divorce. Being on a higher income trajectory than one's spouse also does not significantly alter the main results. Finally, I do not find evidence of the effects being transmitted through one's workplace. Neither more male-dominated environments, nor those with higher wage spreads appear to drive the main effects.

Mental health has been previously linked to a host of economic and life outcomes. It could also be seen as a metric for life satisfaction that is more robustly clinically rooted and less susceptible to reporting issues. The evidence produced in this paper is diagnostic and pertains mainly to more serious issues that required specialist intervention. This suggests that there are tangible effects of relative income in couples on more serious manifestations of mental health issues, even in more institutionally egalitarian societies like Sweden.

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Appendix

Table of Contents

A Summary Statistics

Table A.1: Summary Statistics

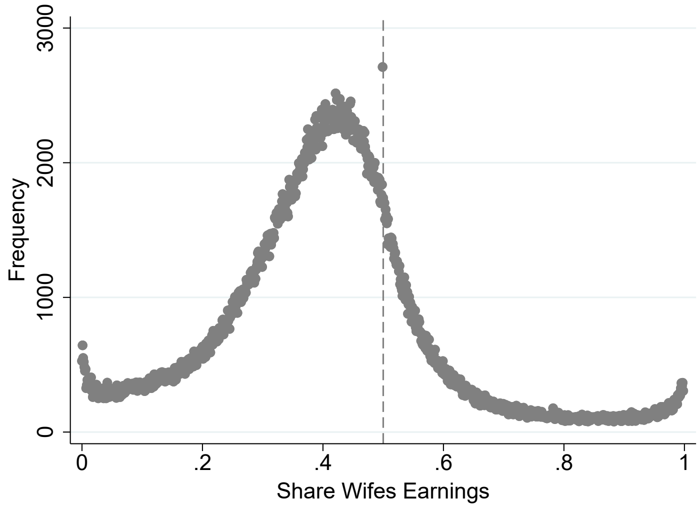
Variable	N	Mean	SD	N	Mean	SD
Background Variables		**Men**			**Women**	
Age	44,127	34.23	8.19	45,811	32.30	8.17
Immigrant	44,127	0.25	0.44	45,811	0.27	0.45
College Degree	44,127	0.19	0.39	45,811	0.28	0.45
STEM Degree	44,127	0.07	0.26	45,811	0.03	0.17
Annual Earnings	44,127	231.09	331.25	45,808	140.73	111.52
Unemployed	44,127	0.08	0.27	45,811	0.14	0.34
Had Child	44,127	0.06	0.23	45,811	0.06	0.23
Sick Leave	44,127	0.22	0.42	45,811	0.10	0.30
Share Wife's Earnings	41,210	0.41	0.25	42,999	0.41	0.25
Diagnoses, %						
Mental Health Disorder	44,127	1.54	12.31	45,811	2.11	14.36
Hyperactivity and Conduct Disorder	44,127	0.04	2.07	45,811	0.04	2.04
Substance-Related Disorder	44,127	0.53	7.26	45,811	0.30	5.50
Depression and Mood Disorder	44,127	0.34	5.84	45,811	0.67	8.16
Eating and Sleeping Disorder	44,127	0.05	2.33	45,811	0.18	4.25
Neurotic and Stress Disorder	44,127	0.62	7.83	45,811	1.06	10.22
Learning and Socialisation Disorder	44,127	0.01	0.82	45,811	0.00	0.66
Schizotypal Disorder	44,127	0.09	2.97	45,811	0.10	3.13
Adult Personality Disorder	44,127	0.06	2.38	45,811	0.08	2.88
Organic Disorder	44,127	0.04	1.96	45,811	0.02	1.24
Mental Retardation	44,127	0.01	0.82	45,811	0.00	0.00

Note: This table presents summary statistics for background and diagnoses received in the year of marriage. The number of observations is somewhat lower for the share of wife's earnings since it is reported as missing if annual earnings for both spouses are 0. The number of males and females is different since spouses are not counted in the main sample. This discrepancy occurs due to the age criterion applied to the sample (see Section 2.2). 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 diagnoses names and formal ICD definitions is the same as in Table 2. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B Balancing tests

B.1 Running Variable Manipulation

Figure B.1: Running Variable Density



Note: The figure shows the density distribution of the wife's share of total earnings in the family for the values between 0 and 1. The bin that sticks out from the distribution represents couples that earn exactly the same. The p-value of the McCrary test for the running variable manipulation is $p = 0.145$.

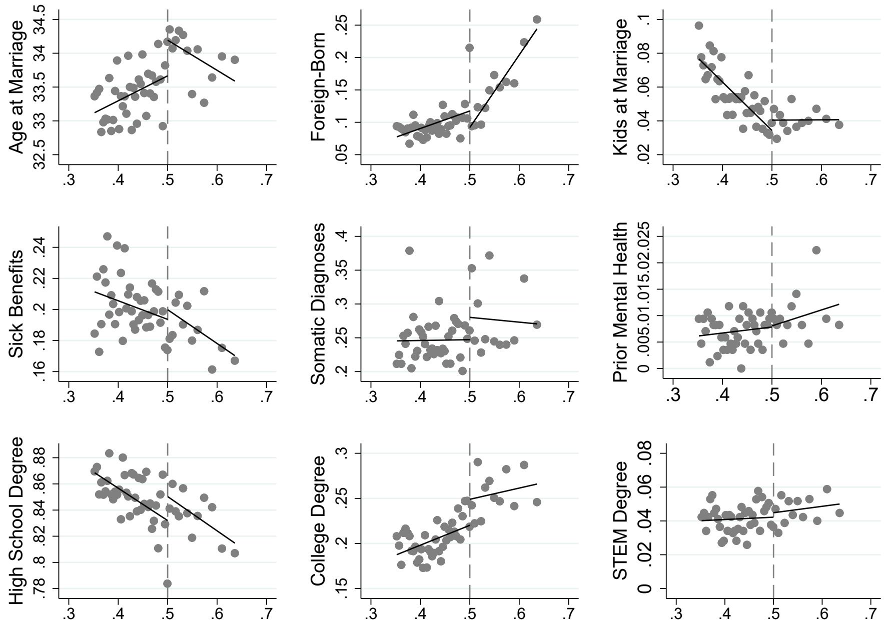
B.2 Balancing by Control Variables

Table B.1: Bivariate Balancing Tests

Dependent variable:	
Age (33.25)	0.00
	(0.01)
High-School Degree (.81)	0.02
	(0.01)
College Degree (.23)	0.03**
	(0.01)
STEM Degree (.05)	0.00
	(0.00)
Foreign-Born (.26)	-0.01
	(0.02)
Child in 2001 (.06)	0.01
	(0.01)
Prior Mental Health (.01)	0.00
	(0.00)
Health Index (.24)	0.03
	(0.02)
Sick Leave Benefits (.16)	0.00
	(0.01)
Observations	42,512

Note: The table shows the RD estimates of the relationship between the share of wife's earnings and background variables in the vector of controls, with a discontinuity applied at the threshold of > 0.5. The relationship is estimated in the year of marriage. The value in parentheses show the sample mean. All the effects are measured using a local linear estimator. I use the specification from column (1) in Table 1 with added year fixed effects since most of the control variables are time-invariant and cannot be estimated using a specification with individual fixed effects. For the health index, I measure the number of prior somatic diagnoses. The rest of the variables (except age) are a fraction between 0 and 1. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure B.2: Balancing by Control Variables



Note: The figure graphically represents the relationship between the share of wife's earnings and background variables in the vector of controls, which is numerically measured in Table B.1. The X-axis shows the earnings share for each variable. Each variable is plotted in 50 bins.

Table B.2: Running Variable Robustness Tests

Mental Health Diagnosis [0,100]	(1)	(2)	(3)	(4)
All (2.85%)	0.21**	0.18**	0.25***	0.21**
	(0.09)	(0.09)	(0.08)	(0.08)
Males (2.27%)	0.25**	0.24**	0.23*	0.24**
	(0.10)	(0.10)	(0.12)	(0.11)
Females (3.42%)	0.18	0.13	0.27**	0.17
	(0.13)	(0.13)	(0.13)	(0.13)
50/50 Dropped	X			
Occupation Control		X		
Same Occupation			X	
Self-employed				X
Observations	434,484	410,130	355,232	432,128
R-squared	0.71	0.71	0.71	0.71

Note: The table shows the estimated relationship between mental health incidence and the share of wife's earnings in a given household in a given year for several sub-samples. In the first column, I drop individuals who earn exactly the same. In the second, I control for one's occupation. In the third column, I drop spouses who are in the same occupation. In the final column, I leave out those who are self-employed. The coefficients demonstrate the effect of crossing the threshold of > 0.5 (i.e. where wife out-earns the husband). The specification used for all the estimates mimics the one in column (5) in Table 1. Standard errors (in parentheses) are based on clustering at the closest 0.005 increment of the relative share. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

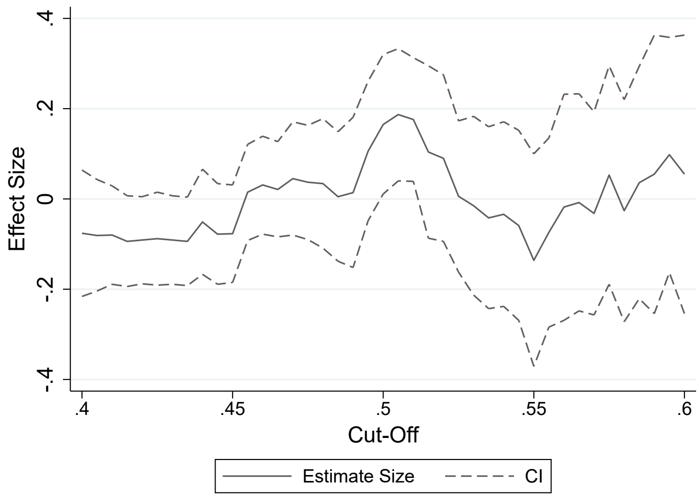
B.3 Placebo Tests

Table B.3: Relative Spousal Income and Mental Health Problems with Biological or Early-Onset Origins

Dependent variable: [0,100]	(1)	(2)	(3)	(4)	(5)
Mental Retardation(.01%)	-0.02	-0.02	0.00	0.00	0.00
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Organic Disorder (.04%)	0.02	0.01	0.01	0.01	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Controls		X	X	X	X
Individual FE/Trends			X	X	X
Year FE			X	X	X
Individual Trends					X
Observations	434,482	434,482	434,482	434,482	434,482

Note: The table shows the estimated relationship between the incidence of mainly biologically-driven mental health diagnoses and the share of wife's earnings in a given year. The layout and the specifications mimic those in Table 1 The first row shows the effects on organic disorders, which include disorders induced by cerebral disease, brain injury, or other to cerebral dysfunction (F00-F09); the second row shows diagnoses related to mental retardation (F70-F79). The number of observations and the corresponding R-squared come from the sample including both genders. Standard errors (in parentheses) are based on clustering at the closest 0.005 increment of the relative share. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure B.3: Effects Estimated at Different Thresholds

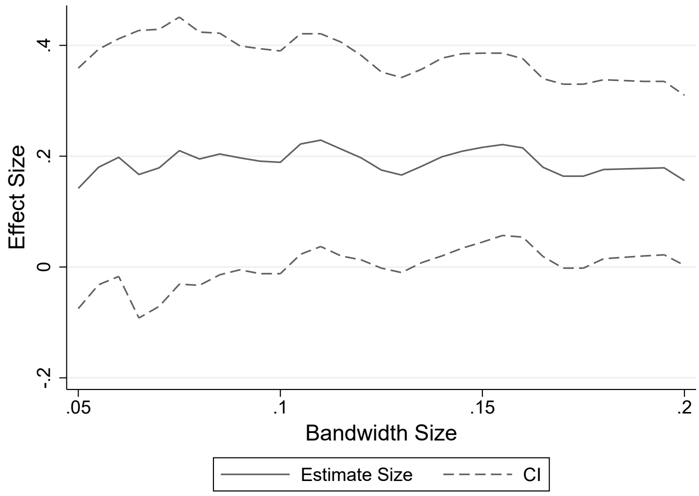


Note: The figure shows the relationships between the size of the main estimates and the chosen relative income threshold. The graph is based on 40 separate regressions, one for each 0.005 increment of relative income in the interval. The full line shows the estimate size, and the dotted lines the bounds of 95% confidence intervals for each regression.

C Robustness checks

C.1 Bandwidth Selection

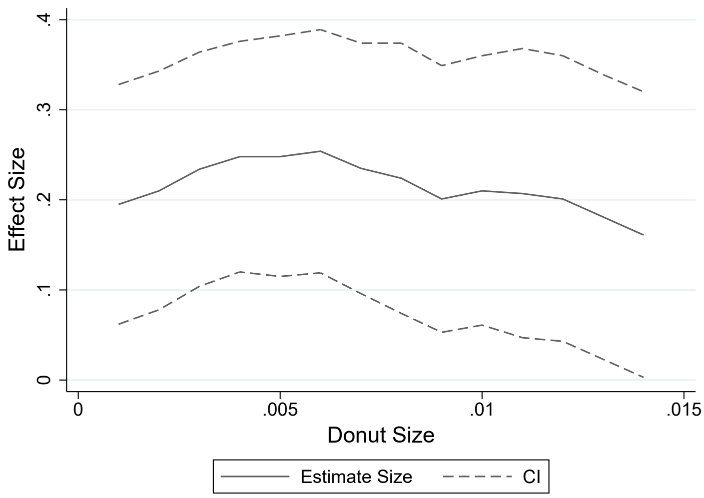
Figure C.1: Bandwidth and Effect Size



Note: The figure shows the relationships between the size of the main estimates and a given bandwidth of choice. Bandwidth are used in increments of 0.005, and the relationship is derived from 30 separate regressions. The full line shows the estimate size, and the dotted lines the bounds of 95% confidence intervals for each regression.

C.2 Donut Regression

Figure C.2: Female Earnings Share around Threshold and Mental Health



Note: The figure shows the relationships between the size of the main estimates and the size of the "donut", i.e. the interval left out of the observation pool around the threshold. Donuts are used in increments of 0.005, and the relationship is derived from 30 separate regressions. The full line shows the estimate size, and the dotted lines the bounds of 95% confidence intervals for each regression.

C.3 Polynomial Selection

Table C.1: Main Results, Including Higher-Order Polynomials

	Degree of Polynomial				
	(1)	(2)	(3)	(4)	(5)
All (2.85%)	0.22**	0.19**	0.20**	0.20**	0.20**
	(0.08)	(0.09)	(0.09)	(0.09)	(0.09)
Males (2.27%)	0.26**	0.25**	0.25**	0.25**	0.25**
	(0.10)	(0.12)	(0.12)	(0.12)	(0.11)
Females (3.42%)	0.18	0.14	0.15	0.15	0.16
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
Controls	X	X	X	X	X
Individual FE	X	X	X	X	X
Year FE	X	X	X	X	X
Individual Trends	X	X	X	X	X
Observations	434,482	434,482	434,482	434,482	434,482

Note: The table shows the estimated relationship between the share of 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 wife out-earns the husband). All the effects are measured using a local linear estimator with a bandwidth of 0.15. Each column represents the highest-order polynomial that enters the specification. The first row shows the results for the sample with both genders (All). The next two rows show estimates from separate regressions for males and females. Coefficients in parentheses indicate general prevalence in a given sub-sample. The number of observations and the corresponding R-squared come from the sample including both genders. Standard errors (in parentheses) are based on clustering at the closest 0.005 increment of the relative share. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.2: Relative Spousal Income and Mental Health in Those not on Sick Benefits

	Mental Health Diagnosis [0,100]				
	(1)	(2)	(3)	(4)	(5)
All (2.76%)	0.30*	0.30*	0.28***	0.27***	0.29***
	(0.18)	(0.16)	(0.08)	(0.08)	(0.09)
Males (2.2%)	0.47***	0.47***	0.38***	0.38***	0.35***
	(0.17)	(0.16)	(0.11)	(0.11)	(0.12)
Females (3.24%)	0.13	0.14	0.19	0.18	0.24*
	(0.22)	(0.20)	(0.14)	(0.14)	(0.13)
Controls		X	X	X	X
Individual FE			X	X	X
Year FE				X	X
Individual Trends					X
Observations	368,247	368,247	368,247	368,247	368,247
R-squared	0.00	0.01	0.55	0.55	0.73

Note: The table shows the estimated relationship between the share of wife's earnings in a given household in a given year and the incidence of mental health diagnoses in a given or the following year for those who do not take out sick leave benefits in that year. The coefficients demonstrate the effect of crossing the threshold of 0.5 (i.e. where wife out-earns the husband). All the effects are measured using a local linear estimator with a bandwidth of 0.15. The first row shows the results for the sample with both genders (All). The next two rows show estimates from separate regressions for males and females. Coefficients in parentheses indicate general prevalence in a given sub-sample. The number of observations and the corresponding R-squared come from the sample including both genders. Standard errors (in parentheses) are based on clustering at the closest 0.005 increment of the relative share. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.4 Non-Concurrent Diagnoses

Table C.3: Relative Spousal Income and Mental Health Diagnoses in the Following Year

Mental Health Diagnosis [0,100]	(1)	(2)	(3)
Current and Following Year (2.85)	0.21**	0.20**	0.22**
	(0.08)	(0.08)	(0.08)
Following Year, t+1 (1.99)	0.12*	0.11	0.14**
	(0.07)	(0.07)	(0.07)
Previous Year, t-1 (1.99)	0.07	0.06	0.05
	(0.07)	(0.07)	(0.07)
Controls	X	X	X
Individual FE	X	X	X
Year FE		X	X
Individual Trends			X
Observations	434,484	434,484	434,484

Note: The table shows the estimated relationship between the share of wife's earnings and mental health incidence in the following year. The coefficients demonstrate the effect of crossing the threshold of > 0.5 (i.e. where wife out-earns the husband). The first row shows the results for both the same and the following year, the second only for diagnoses received in the following year (t+1), and the third row only for those received in the previous year (t-1). Coefficients in parentheses indicate general prevalence in a given period of time. The specifications used for these estimates mimic those in in columns (3) - (5) in Table 1. The number of observations and the corresponding R-squared come from the sample including both genders. Standard errors (in parentheses) are based on clustering at the closest 0.005 increment of the relative share. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.4: Relative Spousal Income and Mental Health Diagnoses in Years t+2 and t+3

Mental Health Diagnosis [0,100]	(1)	(2)	(3)
Year t+2 (2.13)	-0.02	-0.02	0.05
	(0.09)	(0.09)	(0.10)
Year t+3 (2.36)	-0.08	-0.09	0.05
	(0.09)	(0.09)	(0.12)
Controls	X	X	X
Individual FE	X	X	X
Year FE		X	X
Individual Trends			X
Observations	358,952	358,952	358,952

Note: The table shows the estimated relationship between the share of wife's earnings and mental health incidence in the following year. The coefficients demonstrate the effect of crossing the threshold of > 0.5 (i.e. where wife out-earns the husband). The first row shows the results for diagnoses received in the year (t+2), and the third row only for those received in year (t+3). Coefficients in parentheses indicate general prevalence in a given period of time. The specifications used for these estimates mimic those in in columns (3) - (5) in Table 1. The number of observations and the corresponding R-squared come from the sample including both genders. Standard errors (in parentheses) are based on clustering at the closest 0.005 increment of the relative share. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

D Heterogeneity

D.1 Absolute Income

Table D.1: Relative Spousal Income and Mental Health by Income Quintile

Income Quintile:	Male	Female
	(1)	(2)
Quintile 1 (-252641 - 103946)	-0.212	0.109
	(0.551)	(0.421)
Quintile 2 (103947 - 198134)	-0.373	-0.182
	(0.388)	(0.279)
Quintile 3 (198135 - 260091)	0.387**	-0.262
	(0.180)	(0.240)
Quintile 4 (260092 - 343188)	0.392***	0.103
	(0.145)	(0.180)
Quintile 5 (343189 - 48013056)	0.139	0.243
	(0.138)	(0.211)
Controls	X	X
Individual FE	X	X
Year FE	X	X

Note: The table shows the estimated relationship between mental health incidence and the share of wife's earnings in a given household in a given year, by earnings quintile. The boundaries of a given bin in terms of the respective annual earnings are recorded in parentheses. The coefficients demonstrate the effect of crossing the threshold of 0.5 (i.e. where wife out-earns the husband). Each row illustrates the effect of the wife out-earning the husband on the likelihood of a mental health diagnosis in a given income quintile. The first column shows the results for the sample with both genders (All). The next two columns show estimates from separate regressions for males and females. The specification mimics that in column (4) in Table 1. Standard errors (in parentheses) are based on clustering at the closest 0.005 increment of the relative share. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

D.2 Age

Table D.2: Relative Spousal Income and Mental Health by Age Group

Age Group:	**Male**	**Female**
	(1)	(2)
Under 30	-0.59	-0.15
	(0.44)	(0.52)
30-40	0.26**	-0.05
	(0.13)	(0.15)
40-50	0.46**	0.38
	(0.22)	(0.23)
50-64	-0.04	-0.23
	(0.28)	(0.47)
Controls	X	X
Individual FE	X	X
Year FE	X	X
Individual Trends	X	X

Note: The table shows the estimated relationship between mental health incidence and the share of wife's earnings in a given household in a given year, by age group. The coefficients demonstrate the effect of crossing the threshold of > 0.5 (i.e. where wife out-earns the husband). The specification for all the estimates mimics that in column (5) in Table 1. Standard errors (in parentheses) are based on clustering at the closest 0.005 increment of the relative share.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

D.3 Other SES Variables

Table D.3: Relative Spousal Income and Mental Health by Other SES Variables

Mental Health Diagnosis [0,100]	**Male**	**Female**
	(1)	(2)
Everyone	0.26**	0.18
	(0.10)	(0.13)
No Child in Given Year (.96)	0.28**	0.20
	(0.11)	(0.14)
Above-Median Municipality (.5)	0.01	0.31*
	(0.17)	(0.18)
College Degree (.24)	0.18	0.34*
	(0.21)	(0.20)
Controls	X	X
Individual FE	X	X
Year FE	X	X
Individual Trends	X	X

Note: The table shows the estimated relationship between mental health incidence and the share of wife's earnings in a given household in a given year, by education level, residence, and fertility. The values in parentheses provide mean shares for each given SES variable. The coefficients demonstrate the effect of crossing the threshold of > 0.5 (i.e. where wife out-earns the husband). The specification used for all the estimates mimics the one in column (5) in Table 1. Standard errors (in parentheses) are based on clustering at the closest 0.005 increment of the relative share. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

E Mechanisms

E.1 Dynamic Effects

Table E.1: Relative Spousal Income and Mental Health

Mental Health Diagnosis [0,100]	**All**	**Males**	**Females**
	(1)	(2)	(3)
Wifeshare >0.5	0.22**	0.26**	0.18
	(0.09)	(0.10)	(0.13)
Own Lag Higher	-0.05	-0.04	-0.05
	(0.05)	(0.06)	(0.06)
Wifeshare >0.5 × Own Lag Higher	0.01	-0.00	0.04
	(0.09)	(0.12)	(0.13)
Controls	X	X	X
Individual FE	X	X	X
Year FE	X	X	X
Individual Trends	X	X	X
Observations	434,482	212,914	221,568
R-squared	0.71	0.71	0.71

Note: The table shows the estimated relationship between the share of wife's earnings in a given household in a given year, own or spousal lagged income in the year, and the incidence of mental health diagnoses in that or the following year. The first row demonstrate the effect of crossing the threshold of > 0.5 (i.e. where wife out-earns the husband); the second shows the effect of having a higher lagged income than the spouse; finally, the third row shows the interaction of those two variables. The first column shows the results for the sample with both genders (All). The next two columns show estimates from separate regressions for males and females. The specification used for all estimates mimics that in column (5) in Table 1. Standard errors (in parentheses) are based on clustering at the closest 0.005 increment of the relative share. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

E.2 Divorce

Table E.2: Relative Spousal Income and Divorce

Divorce [0,1]	(1)	(2)	(3)
Current Year (.03)	0.000	-0.000	0.002
	(0.002)	(0.002)	(0.003)
Current/Prior Year (.07)	0.000	-0.000	0.000
	(0.002)	(0.002)	(0.002)
Controls	X	X	X
Individual FE	X	X	X
Year FE		X	X
Individual Trends			X
Observations	434,482	434,482	434,482

Note: The table shows the estimated relationship between the share of wife's earnings, and the likelihood of divorce. The coefficients demonstrate the effect of crossing the threshold of > 0.5 (i.e. where wife out-earns the husband). The first row shows the results being divorced in the same year, while the second for both the same and the following year. Coefficients in parentheses indicate general likelihood of divorce in that period. he specifications used for these estimates mimic those in in columns (3) - (5) in Table 1. The number of observations and the corresponding R-squared come from the sample including both genders. Standard errors (in parentheses) are based on clustering at the closest 0.005 increment of the relative share. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

E.3 Workplace

Table E.3: Relative Spousal Income and Divorce

Mental Health Diagnosis [0,100]	**All**	**Male**	**Female**
Wifeshare >0.5	0.23***	0.27**	0.18
	(0.08)	(0.10)	(0.12)
Wifeshare >0.5 × Share Men	0.28	0.05	0.48
	(0.19)	(0.38)	(0.34)
Wifeshare >0.5 × Wage Spread	0.02	-0.04	0.09
	(0.09)	(0.13)	(0.14)
Controls	X	X	X
Individual FE	X	X	X
Year FE	X	X	X
Individual Trends	X	X	X
Observations	387,145	191,933	195,212

Note: The table shows the estimated relationship between the share of wife's earnings in a given household in a given year, share of males and the wage spread on one's workplace, and the incidence of mental health diagnoses in that or the following year. The first row demonstrates the effect of crossing the threshold of > 0.5 (i.e. where wife out-earns the husband); the next two rows show the interaction of those effects with the male share and the wage spread in one's workplace, respectively. The first column shows the results for the sample with both genders (All). The next two columns show estimates from separate regressions for males and females. The specification used for all estimates mimics that in column (5) in Table 1. Observations include only the individuals for whom workplace data is available. Standard errors (in parentheses) are based on clustering at the closest 0.005 increment of the relative share. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$