Household Leverage and Mental Health Fragility *

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Abstract

We use detailed administrative records to show that high household leverage increases mental health fragility, with persistent negative economic effects. After adverse life events, e.g. heart attacks or job losses, individuals with higher ex ante leverage experience larger increases in mental health problems. The effects are long-lasting and stronger in times of financial crisis. Parallel pre-trends, robustness to non-parametric controls, and IV estimation suggest the results are not driven by confounding unobservables. High leverage is also associated with worse long-run earnings dynamics at the time when loan arrears and mental health problems emerge, suggesting tenacious scarring effects of leverage.

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1 Introduction

One of the most salient long-run trends in developed economies in the post-war period is the rise in household debt.[1] While access to credit has important benefits by allowing households to smooth consumption through income shocks and over the life-cycle, economists are increasingly emphasizing the adverse effects of high private debt levels. At the macro level, it has been shown that household leverage may contribute to the severity and persistence of economic downturns (e.g. Jordà, Schularick, and Taylor 2016; Mian, Sufi, and Verner 2017). At the micro level, there is evidence that access to credit can be the cause of financial difficulties rather than a remedy (e.g. Melzer 2011a; Gathergood, Guttman-Kenney, and Hunt 2018).

In this paper, we analyze the effects of household debt on mental health fragility, and the associated economic effects. The effect on mental health is an important question in its own right: mental illness has been emerging as one of the most important health and welfare challenges in modern society (Layard and Clark 2014; WHO 2011; Biasi, Dahl, and Moser 2020).[2] Further, if high debt is associated with increased risk of mental illness, it may contribute to the broader adverse effects of debt in the economic domain and help explain why these effects tend to be so persistent.

The most plausible mechanism through which a high level of debt may raise the risk of mental illness is by creating financial fragility that reduces the emotional resilience to negative life events.[3] For instance, a cancer diagnosis, a job loss or the death of one's spouse may trigger more anxiety and emotional distress in highly indebted individuals because it lowers their ability to pay installments, and thus raises the risk of a default with severe personal consequences. The adverse effect on mental health may, in turn, lower the individual's earnings capacity and, therefore, deepen the financial and economic implications of the initial adverse event.

Exploring this mechanism empirically presents several challenges. First, the data requirements are formidable: Researchers need to be able to identify individuals experiencing negative life events, track their mental health over time and combine it with financial information about their balance sheets. Second, mental health problems may cause higher indebtedness due to lower income and higher expenditure; hence, the research design needs to address the issue of

[1] In the United States, aggregate household debt rose from around 20% of GDP in 1950 to around than 80% in 2020 and a similar pattern emerges in many other countries (IMF 2022).

[2] Layard (2020) finds that the most important single factor for happiness is mental health. Recent results from the Global Burden of Diseases, Injuries, and Risk Factors Study suggest that mental disorders account for 14.6% of global years lived with disability (GBD 2019 Mental Disorders Collaborators 2022).

[3] For example, in the United Kingdom, the National Health Service argues that debt problems are an important source of mental health problems: `https://www.nhs.uk/mental-health/advice-for-life-situations-and-events/how-to-cope-with-financial-worries/`.

reverse causality. Further, individuals more prone to mental health problems may be more likely to have a high level of debt even before the problems materialize, so the research design must also address the issue of selection on unobservables.

To address these challenges, we combine individual-level data from several administrative registers covering the entire Danish population from 2000-2011. Health records allow us to identify somatic as well as mental health problems for a large sample of individuals. Our main outcome variable is a comprehensive measure that indicates whether the individual in a given year has any consultations with a psychiatrist or psychologist, gets treatment of any kind for a diagnosis related to depression or other mental health problems, or receives any type of care at psychiatric hospitals.[4] Moreover, we match the health records with information from tax returns about debt, income and assets. Focusing on homeowners, we measure an individual's leverage by the loan-to-value (LTV) ratio, defined as the individual's total debt divided by the total value of their home(s). Finally, we also use matched government administrative data on area of residence, gender, age, household structure, and employer-employee linkages.

Our empirical framework exploits adverse shocks that affect the individual's ability to service debt and compares the incidence of mental health problems around such events for individuals with high vs. low ex ante leverage. Our main specifications focus on adverse somatic (non-mental) health shocks that require inpatient hospitalization (including heart problems, cancer, etc.). Such shocks can have important economic consequences (Dobkin et al. 2018), thus affecting the ability to repay debt and they can happen to everyone irrespective of leverage. We also analyze other adverse shocks: spouse's health problems or death, and unemployment triggered by mass layoffs.

Our results show that individuals with high and low ex ante leverage follow parallel trends in mental health outcomes in the years before experiencing an adverse shock. However, there is a sharp divergence after the adverse shock, with the incidence of mental health problems rising much more sharply for high-leverage individuals. The effect of leverage is large and highly persistent: Over the two years following a somatic health shock, the increase in mental health problems is 30% larger for high-leverage individuals and the difference remains statistically significant even seven years after the shock. Further, the differential increase is more pronounced for severe manifestations, such as psychiatric hospitalization as compared to psychologist consultations, and it extends beyond mental health outcomes to the incidence of suicides.

[4] A potential worry is that mild cases may go untreated and therefore also undetected with our approach to measurement. However, the fact that health care, including psychiatric treatment, is universal and provided free of charge in Denmark alleviates this concern.

We provide evidence suggesting that debt-induced stress is a key mechanism underlying these results. First, we find strong differential effects on loan delinquency after adverse shocks: A sharp rise in the incidence of loan arrears among high-debt individuals, indicating mounting financial difficulties, but only a modest increase for those with low debt. Second, we find larger differential effects on mental health problems when the adverse shock occurs during the Global Financial Crisis, where the supply of credit to households was tightened (Jensen and Johannesen 2017).

A key question is whether a high level of debt, through its impact on mental health fragility, can turn transitory episodes of adversity into severe events with persistent, long-lasting economic effects. Analyzing earnings dynamics around adverse somatic health shocks, we find evidence consistent with such "scarring" effects. Before the adverse shock, individuals with high and low leverage are on parallel trajectories and when the adverse shock occurs, earnings fall steeply for both groups. But two years later, the two groups diverge: The earnings of low-leverage individuals gradually recover, while those of high-leverage individuals continue to decline throughout our seven-year time window. These results suggest a mechanism from high debt through mental health problems to medium and long-run income losses.

We take several steps to address potential endogeneity concerns. First, we control extensively for observable characteristics that correlate with ex-ante debt and could influence mental health responses to shocks. We also show that households with high and low leverage experience very similar types of somatic health shocks, as indicated by the diagnosis category associated with the hospitalization event, and we control flexibly for differences in this dimension. Thus, we effectively compare individuals with different ex ante debt levels who are similar in other observable dimensions and experience the same type of health shock. Moreover, we show that our estimates are insensitive to progressively including observable controls as well as unobservables (e.g. household fixed effects) that massively raise the model's explanatory power (R-squared), suggesting that the results are not driven by selection on unobservables (Altonji, Elder, and Taber 2005; Oster 2019).

To further strengthen the causal interpretation of our results, we adopt an instrumental variables strategy that isolates plausibly exogenous variation in ex ante leverage. We exploit the fact that leverage declines mechanically over time as households pay back their mortgages and instrument the ex-ante loan-to-value ratio with the number of years since the individual's first home purchase. In our preferred specification, we control for age at the time of the purchase so that identification comes from variation in the timing of the adverse shock. In other words,

we effectively compare individuals who purchase homes at the same age and experience the same health shock, but at different ages.[5] We find that the first-stage is very strong, reflecting that leverage indeed has an important mechanical component that declines with the passage of time since the first home purchase, and that the second-stage results support the conclusions from the OLS analogue.

Overall, our results suggest that a high level of debt can leave individuals susceptible to mental health problems in the face of adverse shocks. Existing studies show that excessive household borrowing can have negative economic consequences for the individual borrower (e.g. Melzer 2011b; Jappelli, Pagano, and Maggio 2013), as well as for society at large (e.g. Eggertsson and Krugman 2012; Mian, Rao, and Sufi 2013; Mian, Sufi, and Verner 2017). We contribute to this literature by highlighting the negative consequences in the domain of health.[6] Furthermore, our results suggest a mechanism leading to higher persistence of negative economic shocks in high-leverage economies. With high household leverage, adverse aggregate shocks may have long-lasting consequences for the mental well-being of large parts of the population, in turn amplifying their initial impact – both in intensity and in persistence – on the economy.

We also contribute to the literature that documents an association between debt and mental health problems (e.g. Bridges and Disney 2010; Gathergood 2012; Drentea and Reynolds 2012; Hojman, Miranda, and Ruiz-Tagle 2016). Studies in this literature typically rely on surveys – many of them with small sample sizes – and self-reported measures of both debt and mental health, and most of them do not uncover the causal mechanism behind the positive association. The richness of our administrative data allows us to identify individuals experiencing adverse shocks, as well as to have individual level balance sheet components (including debt) and mental health illnesses, and we are therefore able to study a specific causal mechanism through which household leverage can affect mental health outcomes. Our results highlight the persistence in mental health problems and point towards enduring economic and mental health effects of high leverage.

Finally, our paper contributes to the literature on the relationship between household financial circumstances and health in general. Richardson, Elliott, and Roberts (2013) provide a literature review and meta-analysis of the effects of unsecured debt and find that it is related

[5]We also analyze a different implementation of the strategy in which we control for age at the time of the adverse shock. In this case, we effectively compare individuals who purchase houses at different ages but experience the adverse shock at the same age and, therefore, tend to have different levels of leverage when the shock occurs.

[6]See also the seminal correlational study by Brenner (1973) that points to significant deterioration in mental health of individuals in periods of instabilities in the national economy. Note also that Ruhm (2000) shows evidence to the contrary of recessions improving health outcomes.

to a broad range of undesirable health outcomes. Currie and Tekin (2015) and Tsai (2015) focus on foreclosures and find positive associations with unscheduled hospital visits and a broad range of negative health outcomes, respectively. Ramsey et al. (2016) document higher mortality risk among lung cancer patients filing for bankruptcy. Morrison et al. (2013) document higher mortality rates following cancer diagnoses among individuals with more debt. Schwandt (2018) documents that wealth shocks increases the risk of hypertension. We contribute to this literature by focusing on mental health problems and the associated negative economic effects, in particular, loan arrears, financial crisis effects and reduction in earnings. Importantly, our results highlight the interplay between household leverage and mental health fragility and the long-lasting scarring economic effects that may ensue.

2 Institutional background

Health care in Denmark The Danish health care system is universal and financed almost entirely through general taxes. All residents have equal access to services, which are generally provided free of charge.

Most health care services are provided by five regional governments that are responsible for both somatic and psychiatric hospitals, and for reimbursing GPs and specialists for services provided in private practice. [7]

When in need of non-acute health care, the general practitioner is the patient's primary contact, and the GP acts as gatekeeper between the primary health care system and more specialized treatment. If a health problem requires specialist treatment, the GP can refer the patient to treatment in hospitals or non-hospital specialist clinics. In clinics operated by medical doctors, such as psychiatrists, treatment is provided free of charge for the patient.

In contrast, non-hospital specialist services performed by other types of health professionals, such as psychologists, require partial or full payment by the patient, depending on whether the patient has a referral from a GP or not. In the former case, the regional government pays a 60% subsidy.[8]

Household debt and borrowing Danish households are among the world's most indebted but also own large assets (OECD 2020). This is in large part due to the Danish mortgage financ-

[7]Non-hospital health clinics typically function as privately owned companies that, based on collective agreements between the regions and the practitioners, get a specific reimbursement for each service they provide. However, there are also health clinics run directly by the regional governments.

[8]GPs can refer the patient to psychologist treatment under specific circumstances. These include cases where the patient has had serious illness, lost a relative, suffered from mild to moderate depression or anxiety, or attempted suicide.

ing system, which grants homeowners easy and cheap access to credit, thereby also increasing house prices (Campbell 2012).

Mortgage debt accounts for about 70% of total household debt in Denmark. Mortgage loans are offered only by specialized mortgage banks and are financed by covered bond issues. At origination, all mortgage borrowers face the same interest rates determined by current rates on the covered bond market.

Homeowners can borrow up to 80% of their home value on the mortgage market. The proceeds from loans can be used for any purpose, including consumption. In addition, households may borrow from non-specialized retail banks that offer a wide range of credit facilities. Loans from such banks account for about 25% of total household debt, while the remaining 5% mostly consist of student loans, store credit, and other debt to non-financial companies.

3 Data sources and sample selection

We use data from several government administrative registers covering the entire Danish population. Common to all registers is a unique personal identifier that all Danish citizens receive at birth (or date of first residence for immigrants). This allows us to link information from the various sources at the level of the individual.

For health outcomes, we rely on three registers: First, information on hospitalizations comes from the National Patient Register, which contains detailed records of all contacts between hospitals and their patients. The information in this register is recorded by staff at the treating hospital and reported to the Ministry of Health for accounting and monitoring purposes. Each record contains information on the type of care provided (inpatient, outpatient or emergency room), the type of hospital (somatic or psychiatric), and a diagnosis indicating the disease or condition for which the patient received treatment (ICD-10 classification). We use this information to identify individuals who experience somatic health shocks or receive hospital treatment for mental health problems.

Second, we use data on consultations with psychiatrists and psychologists from the Health Insurance Register. The data in this register come from primary healthcare providers who, for reimbursement purposes, report information to regional governments about the services they have provided to patients.

Third, the Cause of Death Register contains information about the date and cause of death for deceased individuals. We use this to identify individuals who commit suicide as well as those who experience the loss of a spouse.

We combine the health data with individual-level data on income, debt, and assets from annual tax returns. This data is highly reliable because it is almost completely based on third-party reported information from employers, government agencies and financial institutions, and evasion is minimal (Kleven et al. 2011; Alstadsæter, Johannesen, and Zucman 2019). On the asset side, we have information on bank account deposits, financial securities, and the value of all homes owned by the individual as assessed by the tax authority for taxation purposes. Data on liabilities include all debt owed to financial institutions, and to the government (e.g. student loans). Financial institutions and other credit providers must also report delinquent loans to the tax authority, and we use this data to construct an end-of-year indicator for loan arrears for each individual.

Finally, we add individual background characteristics from a number of registers provided by Statistics Denmark. From the population register, we extract data on municipality of residence, gender, and age. This register also contains information on household structure, thus allowing us to link individuals to their spouses in the data. From the Integrated Database for Labour Market Research (IDA), we add information linking employees to employers. The data base also contains information on individuals' main source of income and employment status.

From these sources, we compile an individual-level data set with annual observations for each person in the Danish population in the years 2000-11. We then construct a number of indicators for mental health problems. Our main outcome variable is a comprehensive measure that indicates whether the individual in a given year has any consultations with a psychiatrist or psychologist, gets treatment of any kind at somatic hospitals for a diagnosis related to depression, or receives any type of care at psychiatric hospitals. We also construct separate indicator variables for each of these separate outcomes. Finally, we generate an indicator for whether the individual committed suicide or received hospital treatment of any kind for attempted suicide or intentional self-harm.

We measure an individual's *leverage* by the loan-to-value (LTV) ratio, defined as the individual's total debt divided by the tax value of their home(s). Figure 1 illustrates the raw correlation between an individual's within-year rank on this measure among all working-age homeowners and our comprehensive measure of mental health problems described above. Consistent with the existing literature, we find a strong positive correlation between indebtedness and mental health problems in this population.

We impose a number of sample restrictions to obtain our analysis sample. Most importantly, we focus exclusively on individuals who experience some adverse shock. In our main analysis,

we focus on *health shocks* and the description below explains how we select our sample for this analysis. However, we also report results from supplementary analyses where we focus on other adverse shocks. We describe the sample selection procedures for these analyses in section 6.

We define individuals experiencing *health shocks* in a given year as those who i) were admitted to a somatic hospital for inpatient care due to a non-mental, non-pregnancy-related disease or condition in that year, and ii) had not received inpatient care at a somatic hospital in the three previous years. We then limit our sample to individuals who experience such a shock in some year between 2003 and 2011. Further, since our interest is in homeowners in the adult working-age population, we also require that individuals are between 30 and 60 years old and that they own at least one home in each of the three years prior to the year of hospitalization

We follow each individual for up to seven years before and after the health shock. This produces a baseline sample of 546,750 individuals,with a total of 4,631,685 individual-year observations.

A key feature in our analysis is the distinction between individuals with high vs. low debt before the health shock. We define the high-debt individuals as individuals whose LTV ratio in the year before the event places them in the top 25% among all homeowners in the full population in that year. Conversely, low-debt individuals are defined as those with LTV ratios below the 75th percentile threshold in the year before the event.

Table 1 shows descriptive statistics for high vs. low-debt individuals in our sample, measured in the year before the health shock. By construction, high-debt individuals have more debt than low-debt individuals. They are also younger and more likely to have children, which is consistent with younger homeowners being more levered because they have only recently entered the housing market. There is virtually no difference in income between the two groups but high-debt individuals are about four times more likely to be in arrears on at least one of their loans. That is unsurprising, given their higher leverage.

Despite these differences, the two groups are reasonably similar in terms of mental health outcomes before the health shock. For example, the share of individuals who consult a psychiatrist in the year before the shock is exactly 1% in both groups. For the comprehensive measure, there is a difference of 0.5 percentage points in the share of people receiving some type of mental health care. Thus, as in the full population, we find a modest *ex ante* correlation between debt and mental health problems within our sample.[9]

[9]Controlling for differences in observable characteristics between high and low-debt individuals, as explained in the following section, reduces the ex ante difference to 0.2 percentage points.

4 Empirical strategy

The aim of our main analysis is to study the role of debt in shaping mental health outcomes following adverse health shocks. To do that, we estimate a standard event study model allowing for heterogeneous responses across individuals with different levels of indebtedness.[10] Specifically, we estimate the following model:

$$\begin{aligned} y_{it} = &\sum_{j \neq -1} \mathbb{1}[e_{it} = j] \times (\lambda_j + \beta_j HighDebt_i + \boldsymbol{X_i}\alpha_j) \\ &+ \delta HighDebt_i + \boldsymbol{X_i}\mu_j + \gamma_t + \varepsilon_{it} \end{aligned} \tag{1}$$

where i indexes individuals, t indexes years, y_{it} is an outcome of interest, $HighDebt_i$ is the indicator for high debt before the event, $\boldsymbol{X_i}$ is a vector of individual-specific controls, γ_t is a year fixed effect, and ϵ_{it} is an error term.

The variable e_{it} measures the number of years since the event year, with negative values indicating that the health shock has not yet occurred in year t. Thus, the term $\sum_{j \neq -1} \mathbb{1}[e_{it} = j]$ denotes a set of indicators for event time with $e_{it} = -1$, the year before the event, as the omitted category. To allow different responses to the health shock for individuals with different ex ante leverage, we interact these indicators with the indicator for high debt. The high-debt indicator also appears uninteracted with event time to capture any level difference between individuals with high vs. low debt.

We estimate Model (1) with ordinary least squares, with standard errors clustered at the level of the individual. The outcomes of main interest are the measures of mental health problems described in section 3, but we also consider a number of economic outcomes to explore potential mechanisms behind the mental health responses.

For each outcome, the λ_j and α_j coefficients jointly summarize the dynamic response to adverse health shocks for low-debt individuals. The coefficients of main interest to us, however, are the β_j, which summarize the *difference* in outcome responses to the adverse health shock between high and low-debt individuals. For example, β_2 expresses the change in the outcome variable from one year before to two years after the event for high-debt individuals, *over and above* the corresponding change for low-debt individuals.

We take several steps to address potential concerns about whether the β_j reflect the *causal* effect of high debt on mental health responses to health shocks. First, to address the concern

[10] Dobkin et al. (2018) and Fadlon and Nielsen (2019) use similar designs to study responses to hospital admissions and health shocks to family members, respectively, but do not focus explicitly on response heterogeneity. In another context, Kleven, Landais, and Søgaard (2019) use a design similar to ours to study gender differences in the impact of children on labor market outcomes.

that high- and low-debt individuals would have had different mental health developments even in the absence of the somatic health shock, we follow individuals for several years before the shock arrives to assess whether the two groups display parallel pre-trends. In practice, this amounts to checking whether the β_j coefficients are small and statistically insignificant for negative values of j.

Second, to address concerns about omitted variable bias, we control non-parametrically for a broad range of potential confounders. The vector $\boldsymbol{X_i}$ contains categorical control variables for gender, children, income (decile group), municipality of residence (98 categories) and age (31 categories), all measured in the year before the event. We also control for the nature of the health shock in the event year, as indicated by the diagnosis recorded in the National Patient Register.[11] Importantly, we interact all these controls with the event time indicators so as to capture differences in mental health responses to somatic health shocks across each dimension. This has important implications for the interpretation of the β_j coefficients. For example, adding controls for age and diagnosis type implies that the β_j capture the difference in mental health responses between individuals who have different levels of debt but have the *same age* and experience the *same type of health shock*.

Third, we apply instrumental variable estimation techniques to address any remaining endogeneity concerns. Exploiting the fact that leverage declines mechanically over time as households pay back their mortgages, we instrument the indicator for high debt in the year before the event with the number of years between the individual's first purchase of a home and the arrival of the adverse health shock. In constructing this instrument, we make use of the fact that information on income and assets from tax records goes as far back as 1987. Thus, for most individuals in our sample, we can pinpoint the exact year when they first became homeowners.[12,13]

With controls for age at the time of the health shock included, identification in the IV regression comes from comparing mental health responses of individuals who are the same age when they experience the adverse health shock but purchased their first home at different ages.

[11] Specifically, we apply the 99-grouping in the ICD-10 classification and include a dummy for each of the 99 categories (except for a reference category). Appendix Table A.1 shows the distribution of diagnosis types (aggregated into 18 groups) among high-debt and low-debt individuals within our sample.

[12] For individuals who experience the health shock in 2003, the measured number of years since first purchase is right-censored at 16. To ensure uniformity across individuals with different event years, we therefore censor the instrument at this value for everyone in the sample.

[13] To illustrate the mechanics of the instrument, we regress the indicator for high debt in event year -1 on the control variables in $\boldsymbol{X_i}$ and indicator variables representing the number of years since the first home purchase. The results, illustrated in Appendix Figure A.1, show that the share of high-debt individuals does indeed fall monotonically with time since first purchase among individuals in our sample, conditional on our baseline set of controls.

All other sources of variation in leverage, including subsequent decisions on debt repayment or new borrowing, are disregarded. This is desirable, since such decisions could in principle be influenced by emerging mental health problems that are not yet observable in the year before the health shocks.

However, one may still worry that the instrument correlates with subsequent mental health problems through some other channel than leverage. In particular, one could speculate that individuals who purchase a home at a young age have different character traits (e.g. matureness, groundedness) than those who are older when they purchase first their home, and that it is these differences in character, rather than their lower debt, that make them more mentally robust in the face of adverse health shocks. In addition to the IV regression with the baseline set of controls, we therefore also estimate a version where we sacrifice controlling for age at the time of the health shock and instead control for age at the time of the first home purchase.[14] In this version, identification comes from comparing mental health responses between individuals who purchased their first home at the same age but experience the same type of health shock at different ages.

Fourth and finally, we perform a number of auxiliary tests of the hypothesis that debt causally influences the mental health impact of somatic health shocks. One such test involves analysing the impact on economic variables. If debt-induced stress is the cause of a differential response across high and low-debt individuals, we should expect to see a larger increase in indicators of financial distress for the former group. Another test involves studying whether the difference between high and low-debt individuals varies over time. If excess leverage is the root cause of this difference, we should expect it to be larger in years with tight credit supply where high initial leverage is more likely to lead to binding constraints and financial distress.

5 Main Results

In this section, we present the results from our estimations of Model (1) for health shocks. We present results for other types of shocks in section 6.

5.1 Mental health outcomes

Figure 2 shows estimation results for Model (1) with our comprehensive summary measure of mental health problems as the outcome variable. We illustrate the results in two ways: In

[14]Note that we cannot simultaneously control for age at both points in time, since age at purchase, age at the time of the shock, and the number of years from purchase to shock are perfectly collinear.

the left panel, we plot the average dynamic effects of the health shock for high vs. low-debt individuals.[15] The vertical distances between the two graphs correspond exactly to the estimated β_j coefficients, which we plot in the right panel.

Starting in the left panel, the figure shows that individuals in both groups experience a sharp and persistent increase in mental health problems in the year of the health shock. The share receiving treatment for such problems increases by 1.2 percentage points in the year of the shock, rising to 1.4 percentage points in the next year for low-debt individuals. Five years after the health shock, the share with mental health problems is still elevated by around half a percentage point. Compared to the baseline share of 3% (Table 1) in the year before the event, these are large effects.

However, the effects are even larger for high-debt individuals. At its peak in year 1 after the shock, the share of individuals experiencing mental health problems is 1.8 percentage points above the pre-shock level, which is 30% (0.4 percentage points) larger than the corresponding increase for low-debt individuals. As shown in the right panel, this difference is highly statistically significant, and it remains large in the subsequent years. Cumulated over event years 0-7, the effect of the health shock is 45% larger for high-debt individuals than for low-debt individuals.[16]

Figure 2 also shows that the share of individuals with mental health problems is on an upward trend before the health shock for both groups. One reason for this may be that the hospitalization in the event year in some cases reflects a culmination following a protracted period of somatic illness, rather than acute disease. In such cases, it is possible that mental health problems would have become more prevalent even in the absence of the shock, although the steepness of the increase in the event year suggests that this is not the full story.[17] Most important for our purposes, however, is the fact that high and low-debt individuals display almost completely parallel trends before the event, after which they diverge. Thus, conditional on our controls, we find no significant differences in mental health developments between individuals

[15] Note from equation (1) that the partial effect of event time indicator j is individual-specific and equal to $\lambda_j + \boldsymbol{X_i}\alpha_j$ for low-debt individuals and $\lambda_j + \beta_j + \boldsymbol{X_i}\alpha_j$ for high-debt individuals. To construct the left panel of Figure 2, we compute averages of both these values across all individuals in the sample and plot them for each value of $j \neq -1$.

[16] We calculate the cumulated effects by summing the coefficients on the event time indicators since year 0. At year 7, the cumulated effect is 5.9 percentage points for low-debt individuals and 8.6 percentage points for high-debt individuals.

[17] Appendix Figure A.2 shows results for a subsample of individuals who are hospitalized with specific circulatory diseases characterized by their acute nature. We find no upward trends in mental health outcomes prior to the event year when we limit the sample to such cases, but sharp and persistent increases in the event year. The differences between high and low-debt individuals are qualitatively the same as in the full sample but statistically weaker due, in part, to the smaller number of observations.

with high vs. low debt *before* the shock. This strongly suggests that the subsequent divergence between the two groups does indeed reflect differences in the causal effect of the health shock.

Figure 3 shows results for the various indicators of mental health problems underlying our main comprehensive measure. We find qualitatively similar results across all outcomes, but with some variation in magnitude and statistical strength. Panel A shows a clear increase in the share of individuals who consult a psychologist, peaking in year 1 at 0.9 percentage point above the pre-event level for low-debt individuals. For high-debt individuals, the increase is 0.2 percentage points higher, and the difference is statistically significant at the 5% level. Panel B shows similar results for psychiatrist consultations, but here the difference between the two groups is smaller and statistically insignificant.

Turning to the outcomes indicating severe mental health problems, we find sharp increases in the share of people receiving hospital treatment for depression or psychiatric hospital care, as shown in panels C and D, respectively. For both outcomes, the response to the health shock is significantly stronger for high-debt individuals, and the difference compared to low-debt individuals is even clearer than in panels A and B. This is especially true for psychiatric hospital care, where the difference in year 1 is nearly 0.3 percentage points. In line with these results, we also find a stronger responses in mental health problems among high-debt individuals if we consider the strongest indicators for severe mental health problems: suicides, suicide attempts and intentional self-harm (see Appendix Figure A.3).

5.1.1 Controlling for potential confounders

A potential concern with our results is that the difference in mental health responses between high and low-debt individuals could be driven by confounding factors other than leverage. As we explain in section 4, we address this issue by interacting the event time indicators with a set of controls for potential confounders. Table 2 explores how our main result varies with the exact composition of this set. To present this information in a compact way, we estimate simplified versions of Model (1) where we have replaced the full set of event time dummies with a binary indicator, $post_{it}$, that takes the value one if $e_{it} \geq 0$. Table 2 reports the coefficient on the interaction term between this indicator and $HighDebt_i$. We include observations from event years -3 to 2 in the estimations. Thus, the model allows us to estimate the average increase in mental health problems in years 0-2 after the health shock, relative to the three preceding years, and the reported coefficient captures the *difference* in this response between high and low-debt individuals, conditional on the included controls.

We begin with a simple version with no controls in column (1) and then gradually add controls until we reach our baseline set, shown in column (3). The coefficient is remarkably stable across columns and always significant at the 1 percent level, demonstrating that our main result is insensitive to the composition of the set of controls.

In columns (4) to (8), we go beyond our baseline. A specific concern is that the stronger mental health response for high-debt individuals could be due to higher financial vulnerability in some broader sense, rather than leverage per se. For example, one could imagine that self-employed individuals - who often invest heavily in their own businesses and face considerable income risk - are both more indebted and more vulnerable to adverse shocks than wage earners. Similarly, high-debt individuals are plausibly more likely to have few liquid assets and low net wealth, and it may be these features, rather than their indebtedness, that make them mentally vulnerable to adverse shocks. To address these concerns, we sequentially add controls capturing various dimensions of financial vulnerability that may correlate with indebtedness: Self-employment, low liquid assets, a high share of unsecured debt, and high net wealth. All are measured in the year before the event.[18] In all four cases, the coefficient on $post_{it} \cdot HighDebt_i$ is largely unaffected by the addition of the extra control variable. This corroborates the view that the observed differences between high and low debt really do reflect differences in ex ante leverage, rather than a correlated dimension of financial vulnerability (Altonji, Elder, and Taber 2005; Oster 2019).

Finally, we add individual fixed effects to our model to capture time-invariant characteristics affecting mental health. This raises the model's explanatory power substantially without affecting the key coefficient much.

5.1.2 Instrumental variable estimation

Columns (9) and (10) report results from IV regressions in which we instrument the indicator for high debt with the number of years since first home purchase, as described in section 4. In column (9), we use our baseline set of controls, which includes the age at the time of the health shock. The coefficient estimate on $post_{it} \cdot HighDebt_i$ is larger than in our baseline OLS regressions but so is the standard error. Thus, while the coefficient is statistically significant at the 10 percent level (p-value of 0.06), we cannot reject the null that it is equal to the coefficient

[18]The indicator for self-employment is based on the individual's primary source of income. Individuals are defined as having low liquid assets if their end-of-year bank deposit balances are less than 1/6 of their annual disposable income. We define individuals as having a high share of unsecured debt if the balances on their non-mortgage loans exceeds 20% of their total debt. High net wealth is defined as belonging to the top 25 % of the net wealth distribution in the year in question.

from our baseline specification shown in column (3).

In column (10), we sacrifice controlling for age at the time of the health shock in order to control for age at the time of the first home purchase. Compared to column (9), this increases the precision of the key estimate considerably. The coefficient estimate is strongly significant and even larger than in our OLS regressions. It suggests that the share of individuals suffering from mental health problems increases by a full percentage point *more* for high debt than for low-debt individuals following an adverse health shock. One possible reason for the difference in magnitude compared to the OLS estimate is that the OLS and IV estimates capture average treatment effects for different groups of individuals. In particular, the IV estimate captures the average treatment effect for the *compliers*, i.e. those who actually bring down their LTV values as time since the first home purchase passes. It may be that these individuals tend to worry more about financial troubles - that is that makes them compliers - and therefore are more affected by the level of debt when adversity strikes. But the main take-away from the IV results is that the difference in mental health responses between high and low-debt individuals remains when we base our estimates on a plausibly exogenous source of variation in debt.

5.1.3 Other robustness checks

Our main results described above are also robust to a number of other variations of our baseline specification. Appendix Figure A.4 shows that they do not hinge on the specific choice of cut-off between high and low-debt individuals. Appendix Figure A.5 shows that we can change the sample restriction on age with no change in results. Finally, Appendix Figure A.6 shows that the results are insensitive to controlling for the occurrence of a second hospitalization in the event year: In our main specification, we control for the nature of the first hospitalization in the year, as indicated by the diagnosis type. However, an individual may be re-admitted later in the year with the same or a different diagnosis. We therefore add controls capturing the diagnosis type of any second hospitalization and note that this does not change our main result.

5.2 Economic outcomes

To explore possible mechanisms behind our main result, we now turn our attention to the dynamic effects of health shocks on a range of economic variables.

Existing literature has shown that health shocks are costly both in terms of direct health expenditures and indirectly via income losses (Mohanan 2013; Fadlon and Nielsen 2020; Dobkin et al. 2018). Since health insurance coverage is universal in Denmark, the direct costs are of

minor importance in our context. Income losses, on the other hand, could be substantial, not only due to foregone earnings while hospitalized, but also in the longer term due to, for example, lost promotions or reduced productive capacity. To the extent that such income losses lead to financial distress, this could have adverse consequences for mental health.

We explore this potential channel in Figure 4. Panel A shows results from estimating Model (1) with labor market earnings (in DKK) as the outcome. Both high and low-debt individuals are on a clear downward earnings trend in the years before the health shock. With a drop of about DKK 11,000 (USD 1,750), the earnings decline clearly accelerates in the year when the shock occurs, and then flattens out. There is virtually no difference between the two groups until year 2 after the shock, suggesting that the initial impact of the health shock on income is the same for high and low-debt individuals.

Interestingly, however, the earnings paths of the two groups then diverge, with continued declines for high-debt individuals and stable or even moderately increasing earnings for low-debt individuals. One explanation could be a feedback mechanism from mental health problems: As our main results show, the share of individuals suffering from severe mental health problems rises more sharply after the shock among those with high debt, and this may be causing the continued decline in earnings for this group.

Panel B shows results for loan arrears. Here, we see strikingly different patterns between high vs. low-debt individuals. For the low-debt group, the share of individuals who are in arrears on their loans barely moves in the year of the health shock, and then increases moderately in subsequent years. In stark contrast, the share of delinquent borrowers among high-debt individuals increases considerably in the year of the health shock and continues to do so in the following years, reaching a level more than 2 percentage points above the pre-event baseline after 7 years.[19]

Together, these results suggest a mechanism through which high debt amplifies the mental health consequences of somatic health shocks: High and low-debt individuals initially suffer similar income losses due to the health shock, but the implications of these losses in terms of loan arrears are much more severe for high-debt individuals. Being in arrears is an indicator of financial stress, which can trigger negative emotions such as anxiety and guilt (Tsai 2015; Ramsey et al. 2016). This source of distress adds to the emotional effects of the health shock itself, thus providing a plausible explanation for the larger increase in mental health problems for individuals with high ex ante debt.

[19]Similarly, Morrison et al. (2013) find larger increases in mortgage defaults, foreclosures and bankruptcy filings for high-debt homeowners than for low-debt homeowners following a cancer diagnosis.

5.3 Heterogeneous effects

High debt can become an emotional stress factor when it turns into a binding constraint on consumption possibilities or the ability to stay in one's home. This is more likely to happen during times when credit supply is tightened, such as during a financial crisis.[20] We should therefore expect larger debt-related differences in mental health responses to health shocks in 2008-09 when the Danish financial sector was hit by the international crisis than in other years.

Figure 5 documents such a pattern. The difference in mental health responses between high and low-debt individuals is 2-3 times larger among those who suffered a health shock in 2008 or 2009 compared to other years. [21]

Figure 5 also illustrates results from heterogeneity analyses across individuals with vs. without children (Panel B) and gender (Panel C). We find no significant differences in either dimension. This suggests that the amplifying effect of debt on mental health problems following somatic health shocks is present for both men and women, and among individuals with or without children.

6 Results for other adverse shocks

In this section, we show that our results are not specific to somatic health shocks but hold across different types of adverse shocks.

First, rather than shocks to the individual's own health, we focus on adverse health shocks for the spouse. To do that, we redefine our sample to include individuals whose spouse experiences an adverse health shock - defined in the exact same way as in the main analysis. All other sample restrictions are unchanged. We then estimate Model 1 with our usual comprehensive measure of mental health problems as the outcome, only now with e_{it} denoting the number of years since the *spousal* health shock.

The results from this analysis are shown in Panel A of Figure 6. As in the case of own health shocks, we see a sharp increase in the share of people suffering from mental health problems at the time of the shock for individuals with low debt, but an even sharper increase for high-debt individuals. The relative difference between the two groups' estimated responses is about 30% but it is only borderline statistically significant, as seen from the right graph.

[20] Indeed, existing evidence suggests that household leverage played a key role in explaining the sharp drop in consumption in the U.S. during the Great Recession of 2007-09 (Mian and Sufi 2010; Mian, Rao, and Sufi 2013).

[21] The β_1 and β_2 estimates in the two graphs are significantly different at the 10 and 5 percent levels, respectively.

The results are even stronger in Panel B where we look at mental health responses to experiencing the death of a spouse. Here, the sample consists of people who have lost their spouse in some year between 2003 and 2011, with all other sample restrictions unchanged. The share of people who receive some mental health treatment rises by no less than 10 percentage points for both groups in the year of the shock. For high-debt individuals, it increases even further in the next year at which point the impact is again about 30% larger than for low-debt individuals. These large increases are primarily due to a sharp increase in the share of people consulting a psychologist. If we remove this particular outcome from our comprehensive measure, we find increases of 0.8 and 1.1 for low and high-debt individuals, respectively.

Finally, we explore the effects on mental health when the individual loses her job during a mass layoff event. We define a mass layoff event as a year where at least 30% of the employees at a workplace leave from one year to the next.[22] We then confine our sample to homeowners who become unemployed after experiencing such an event at some point between 2003 and 2011, while not having experienced any unemployment during the three preceding years. Compared to health shocks, the number of people experiencing mass layoff events is much lower, and we obtain a sample of 3,831 individuals between 30 and 60 years of age. Perhaps because of the small number of observations, the mental health responses are not statistically significant for either group, but - consistent with our other results - the point estimates do suggest a sizeable differential increase of 1 percentage point in the high-debt group.

Summing up, the results presented in this section suggest that the mental health consequences of other types of adverse shocks are also more severe for high-debt individuals. The statistical power of this evidence is generally lower than for the case of adverse shocks to the individual's own health but, overall, the results are consistent with and corroborate our main finding that high debt poses a risk factor for mental health problems when individuals face difficult circumstances.

7 Concluding remarks

In this paper we provide novel evidence on the link between debt and mental health. We study the effects of various adverse shocks on mental health and find an amplifying effect of having a high initial level of debt. Focusing on adverse health shocks requiring hospitalization, we

[22]More precisely, we define that an individual experiences a mass layoff in year t if i) he/she works for an employer that employs at least 50 people in year t-1, ii) at least 30% of the employees leave the employer from year t-1 to year t, and iii) no more than 50% of those who left the employer move on to work for the same new employer.

show that the peak increase in the share of individuals who receive some type of treatment for mental health problems is 30% larger for individuals with high ex ante debt than for those with low debt. Similar effects appear for spousal health shocks and job loss related to mass layoffs. Consistent with debt-induced financial distress lying at the root of these findings, we show that individuals with high debt experience a much larger increase in loan arrears than low-debt individuals following an adverse health shock, despite initially similar declines in income. Long-run income dynamics after an adverse shock are significantly worse for individuals with higher ex ante leverage, suggesting a mechanism from high debt through mental health problems to long-run income losses.

Our findings provide lessons for financial regulators, social insurance policymakers, and health care professionals. Financial regulators should be aware of the potentially enormous personal costs of excessive borrowing when designing regulation governing households' access to credit. Social insurance policymakers should pay attention to trends in household debt levels when assessing the costs and benefits of programs that insure households against the financial consequences of adverse shocks. Finally, health care professionals must recognize that financial leverage is a relevant risk factor for developing mental health problems following somatic disease.

Table 1 – **Pre-event characteristics** Notes: The table shows the sample means of basic characteristics for our estimation sample, measured in the year prior to the event. Gross income and housing wealth are measured at 2015 price level and winsorized at the 2.5 and 97.5 percentiles within each year.

	Low debt	High debt	All
Sample mean at t-1			
Age	50.683	42.616	48.604
Children	0.436	0.635	0.487
Gross income, 1000 DKK	389	394	391
Household debt, 1000 DKK	760	1215	877
Loan arrears	0.006	0.027	0.012
Consultation with psychiatrist	0.010	0.010	0.010
Consultation with psychologist	0.010	0.014	0.011
Depression treatment	0.002	0.003	0.003
Psychiatric hospital	0.010	0.010	0.010
Any mental health treatment	0.028	0.033	0.030
N	405,832	140,918	546,750

Table 2 – Sensitivity to controls Notes: The table reports results from simplified versions of Model 1 in which the set of indicators for event time has been replaced by a single post-event dummy variable. Each column reports the coefficient estimate on the interaction term between this dummy and the indicator for high debt. In all columns, the dependent variable is our comprehensive measure of mental health problems. Observations from years -3 to +2 relative to the event year are included in the estimation. Columns (1) to (8) report OLS estimates with different sets of controls. Column (3) corresponds to our baseline specification. Columns (9) and (10) report results from IV regressions where we instrument the dummy for high debt with the number of years since first real estate purchase. The F-statistic reported in these columns refers to the cluster robust Kleibergen-Paap rk Wald F-statistic of weak identification. Std. errors are estimated allowing for clustering at the level of the individual.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
High debt x post	0.00324***	0.00298***	0.00288***	0.00283***	0.00256***	0.00272***	0.00223***	0.00313***	0.01446*	0.00980***
	(0.00059)	(0.00061)	(0.00061)	(0.00061)	(0.00062)	(0.00064)	(0.00068)	(0.00061)	(0.00783)	(0.00293)
Controls:										
Year fixed effects	X	X	X	X	X	X	X	X	X	X
Gender x post		X	X	X	X	X	X	X	X	X
Children x post		X	X	X	X	X	X	X	X	X
Age at health shock x post		X	X	X	X	X	X	X	X	
Age at purchase x post										X
Municipality x post			X	X	X	X	X	X	X	X
Income x post			X	X	X	X	X	X	X	X
Diagnosis x post			X	X	X	X	X	X	X	X
Self-employed x post				X						
Low liquidity x post					X					
High unsecured debt x post						X				
High wealth x post							X			
Individual fixed effects								X		
Estimation method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	IV	IV
First stage F-statistic	-	-	-	-	-	-	-	-	1314.72	9086.28
R^2	0,00229	0,00723	0,02588	0,02600	0,02589	0,02589	0,02589	0,49420	-	-
N	2.409.549	2.409.549	2.408.442	2.407.965	2.408.442	2.408.442	2.408.437	2.385.654	2.234.554	2.234.554

Figure 1 – Correlation between mental health problems and leverage Notes: The figure shows a binned scatter plot of our comprehensive measure for mental health problems against within-year percentile ranks of the loan-to-value ratio. The sample is homeowners aged 30-60 years with non-zero debt.

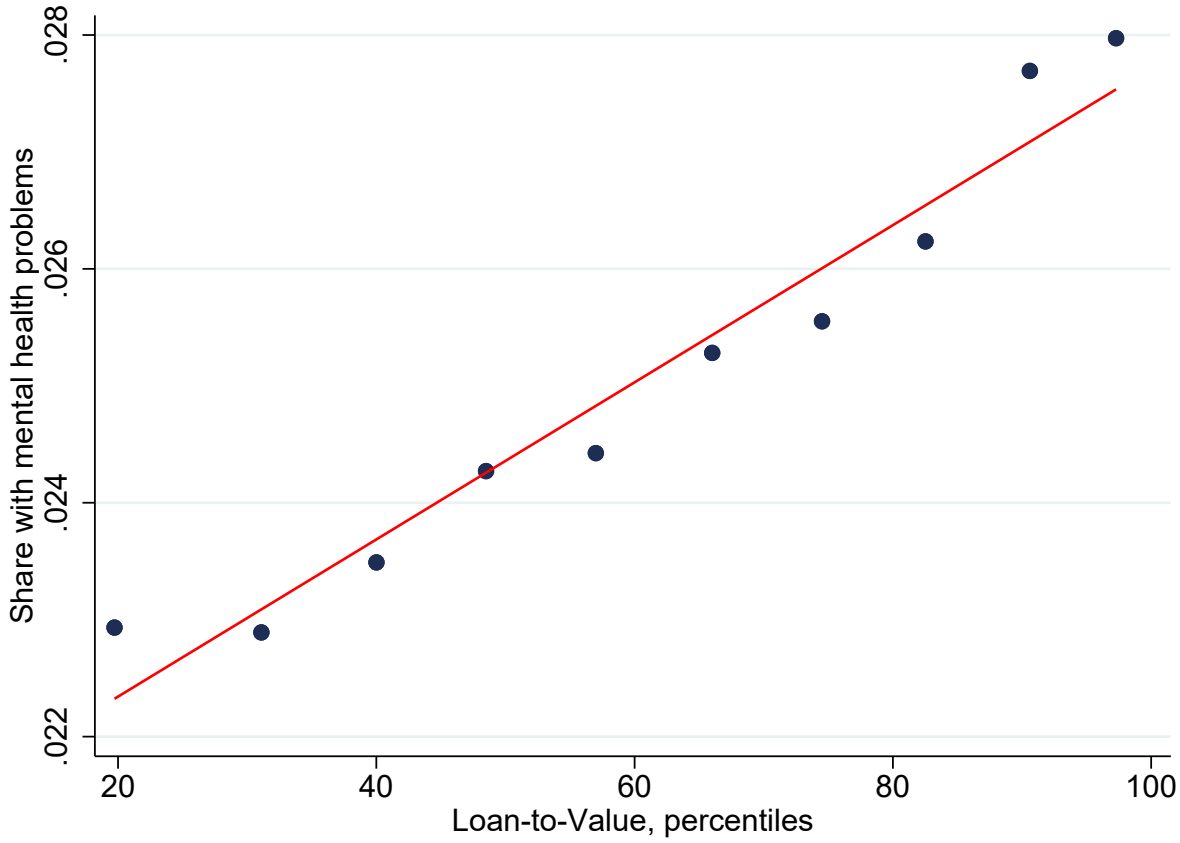


Figure 2 – Mental health responses to health shocks, high- vs. low-debt individuals
Notes: The figure shows the impact of an inpatient hospitalization on mental health problems for individuals with different ex ante degrees of leverage. The dependent variable is our comprehensive measure of mental health problems. The left graph shows dynamic responses separately for high- and low-debt individuals. These are constructed by estimating Model (1) and plotting sample averages of $\hat{\lambda}_j + \boldsymbol{X_i}\hat{\alpha}_j$ (red graph) and $\hat{\lambda}_j + \hat{\beta}_j + \boldsymbol{X_i}\hat{\alpha}_j$ (blue graph) for each value of $j \in \{-7; 7\}$. The right graph shows the difference in responses between high- and low-debt individuals, corresponding to the estimated $\hat{\beta}_j$ from Model (1). Vertical bars indicate 95% confidence intervals. Standard errors are clustered at the level of the individual.

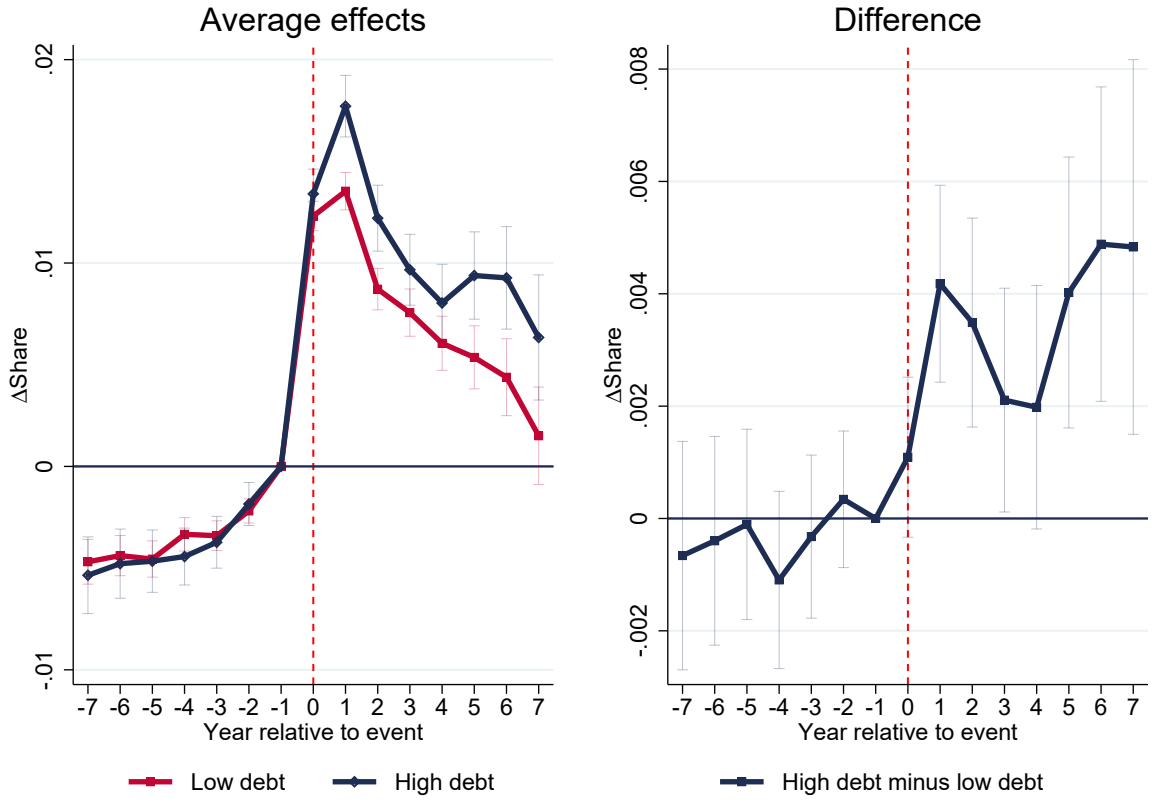


Figure 3 – Mental health components Notes: The figure shows the impact of an adverse health shock requiring hospitalization on various measures of mental health problems. The dependent variables are indicators for whether the individual had any consultations with a psychologist (Panel A); had any consultations with a psychiatrist (Panel B); received hospital treatment for depression (Panel C); received any type of care at a psychiatric hospital (Panel D). Graphs on the left show dynamic responses separately for high- and low-debt individuals while graphs on the right show differences between the two groups, corresponding to the estimates of the β_j in Model (1). Vertical bars indicate 95% confidence intervals. Standard errors are clustered at the level of the individual.

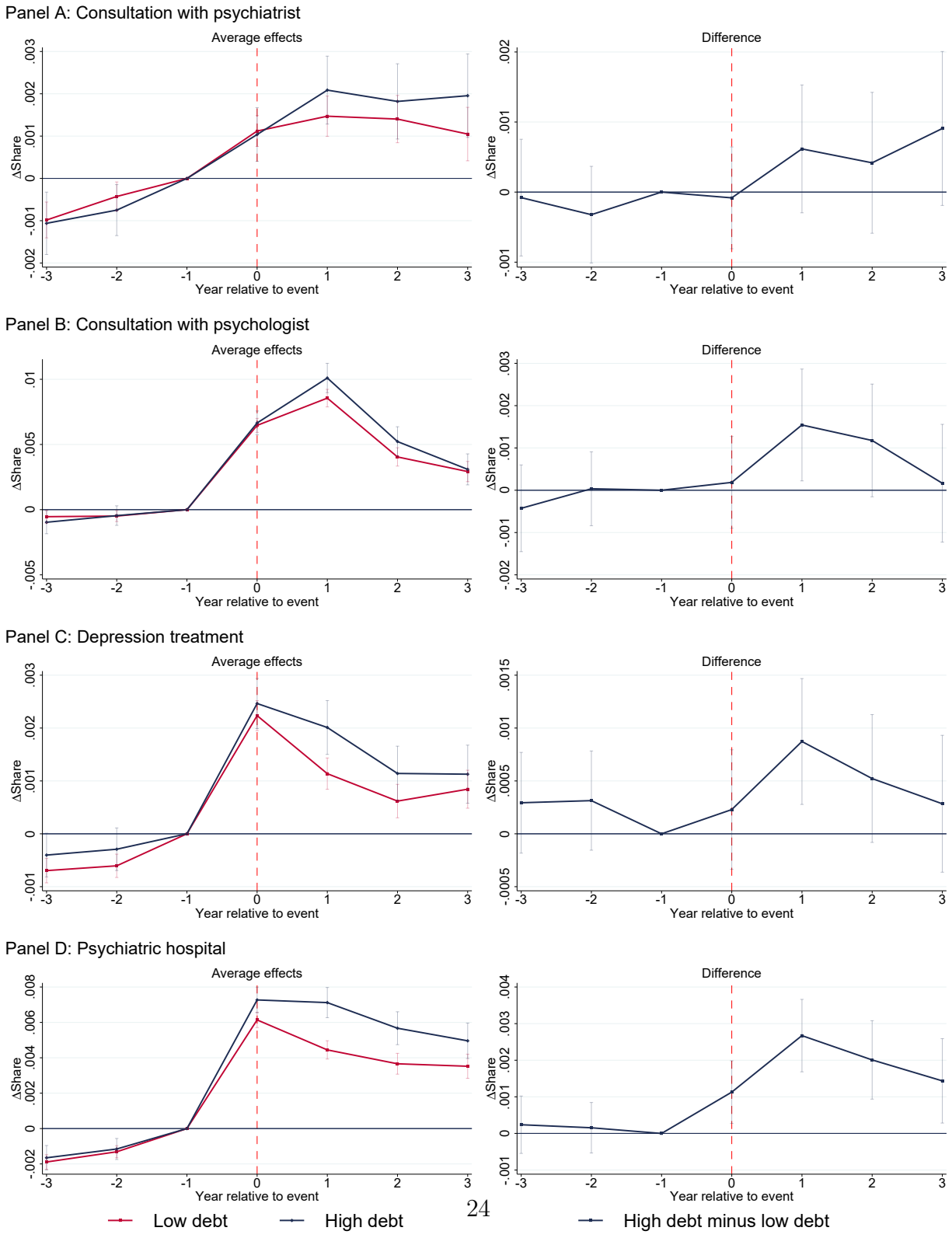


Figure 4 – Economic consequences of a health shock Notes: The figures shows the impact of an inpatient hospitalization on earnings (panel A), and on the share of individuals in loan arrears (panel B). Graphs on the left show dynamic responses separately for high and low-debt individuals while graphs on the right show differences between the two groups, corresponding to the estimates of the β_j in Model (1). Vertical bars indicate 95% confidence intervals. Std. errors are clustered at the individual level.

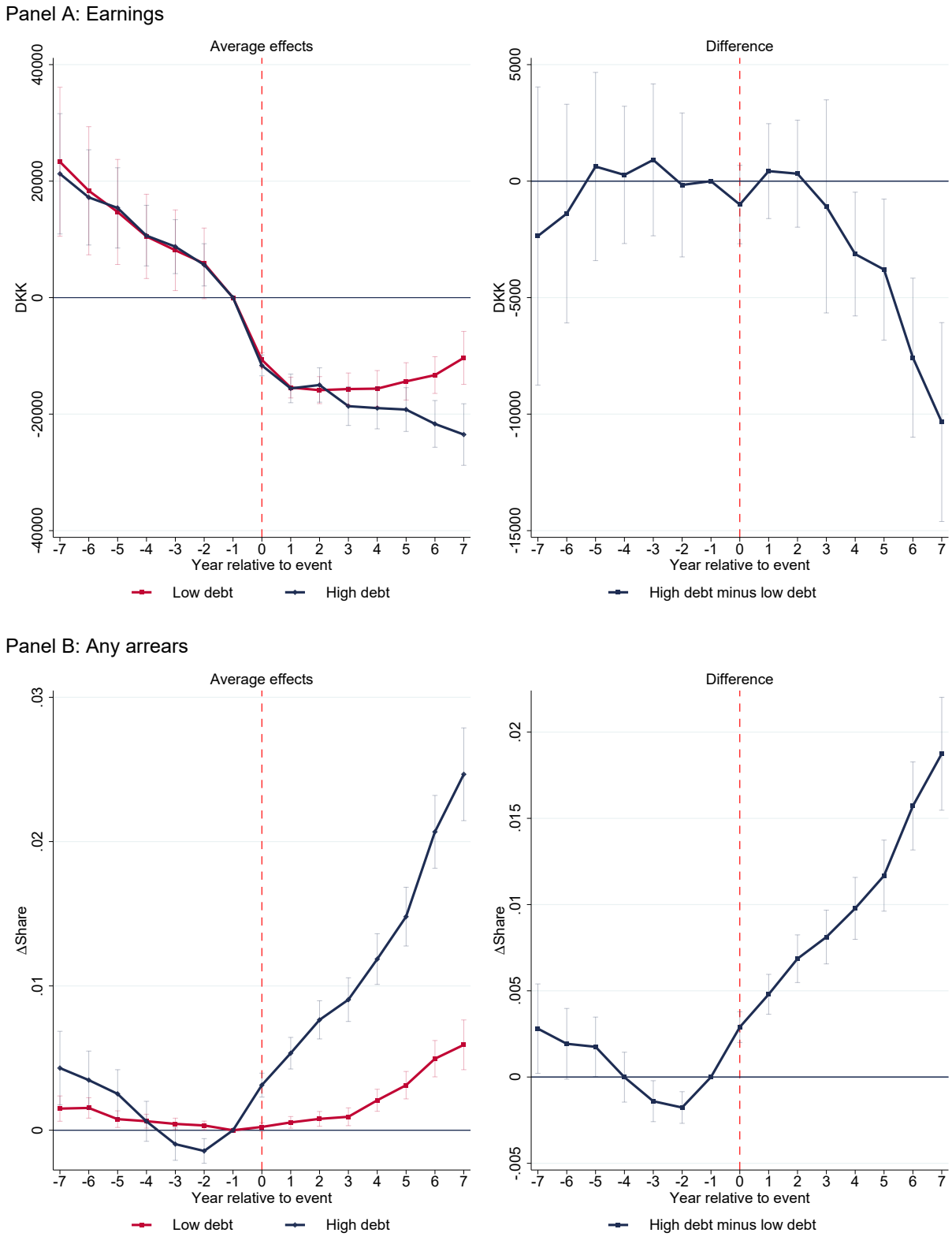


Figure 5 – Heterogeneous effects of debt on mental health responses to health shocks
Notes: The figure shows results from split-sample estimations of Model (1) for adverse health shocks. The dependent variable is our comprehensive measure of mental health problems. Each graph shows differences in effects between high and low-debt individuals, corresponding to the estimates of the β_j. In Panel A, the sample is split by whether the event happens during the financial crisis in 2008-09 or not. In Panel B, the sample is split by whether the individual has children in the year before the event. In Panel C, the sample is split by gender. Std. errors are clustered at the level of the individual.

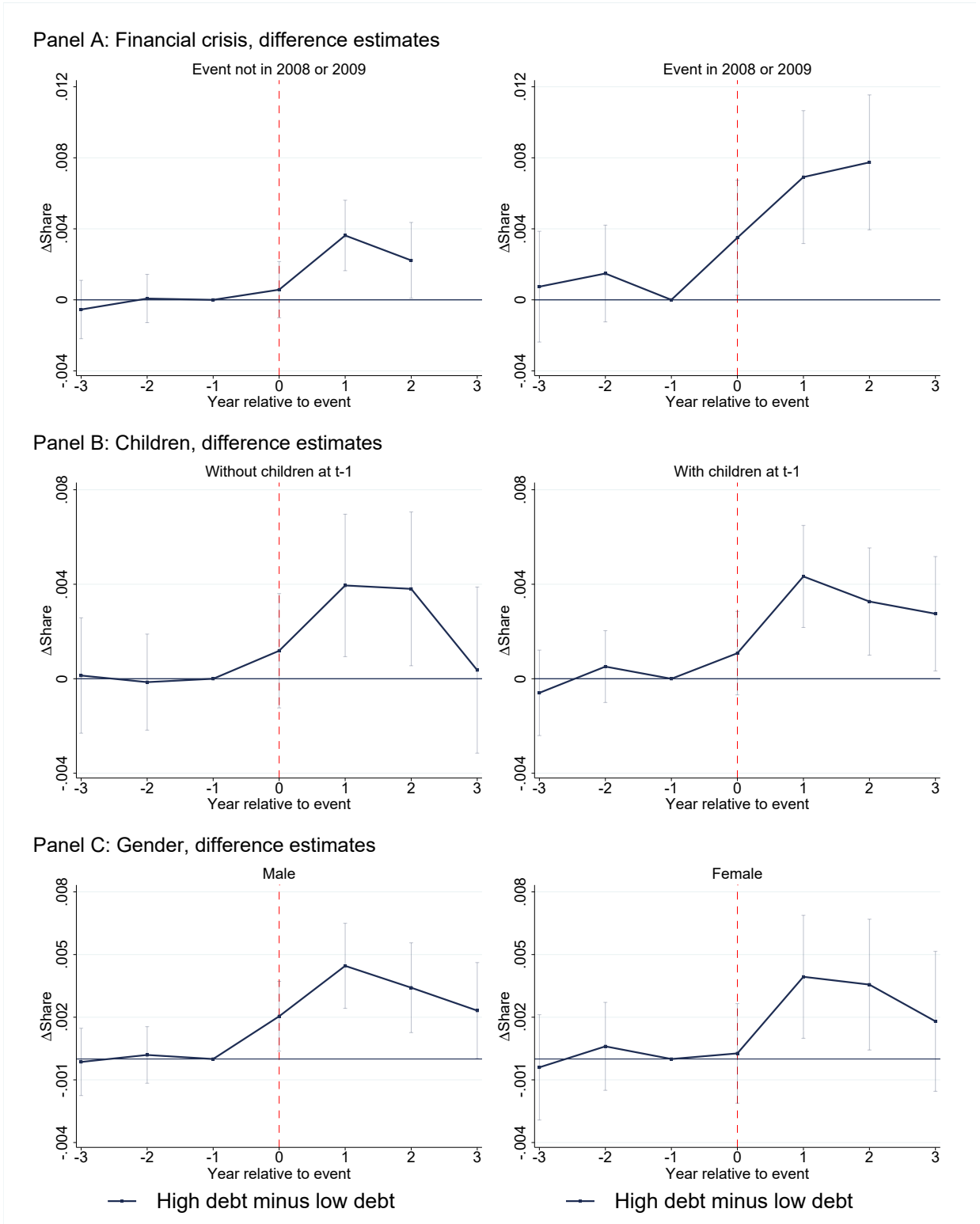
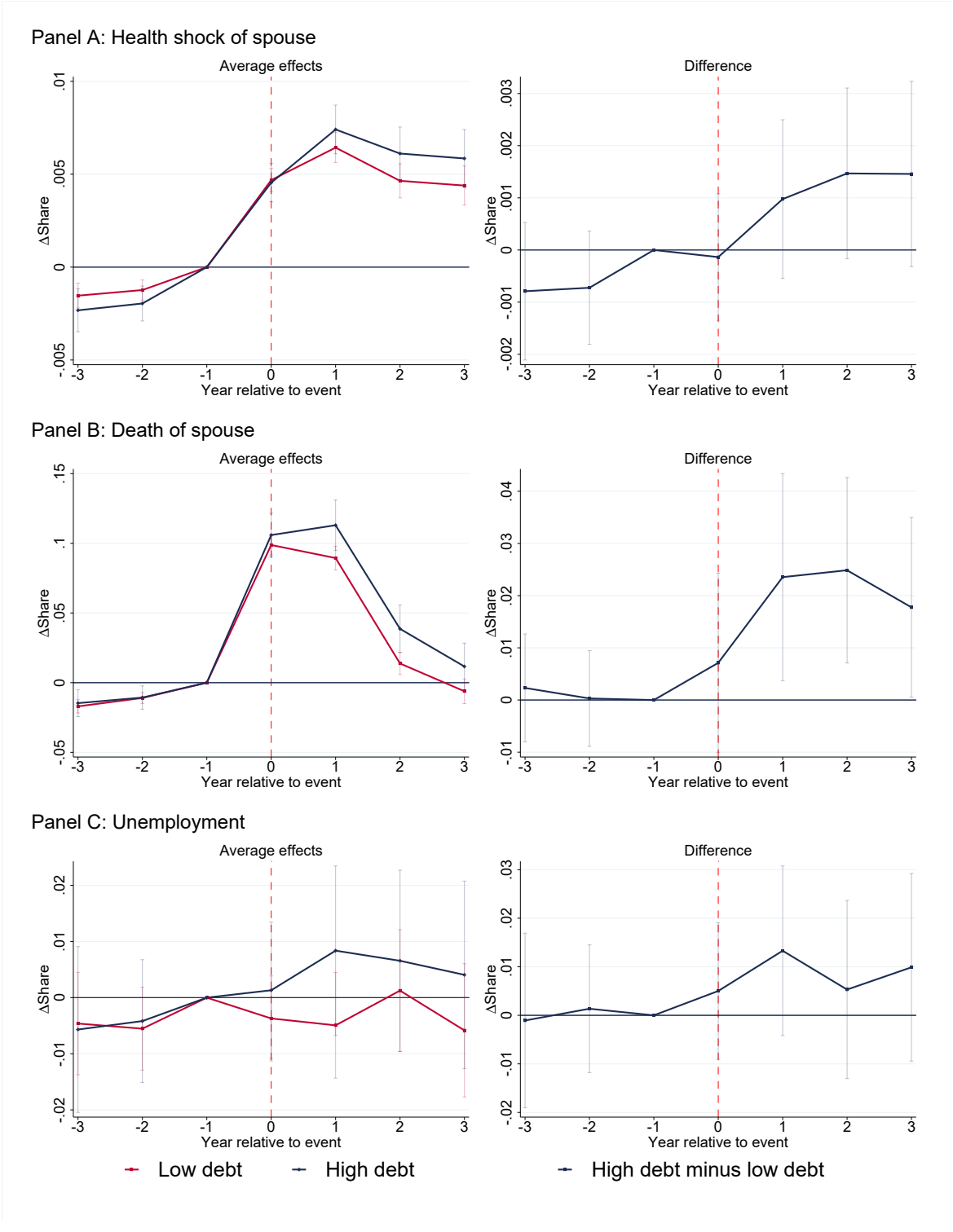


Figure 6 – Mental health responses to other adverse shocks Notes: The figure shows dynamic responses for our comprehensive mental health measure around the time of various adverse shocks. Graphs on the left show responses separately for high- and low-debt individuals, while graphs on the right show differences between the two groups. The adverse shocks are: a somatic health shock to the individual's spouse (Panel A), the death of a spouse (Panel B), and unemployment following a mass layoff event (Panel C). In panel (a) and (b) we include the same controls as in Model (1) except for the controls capturing the type of diagnosis. In panel C, we control for age and gender interacted with event time, and year fixed effects. Std. errors are clustered at the level of the individual in all panels.



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Appendix: Additional Tables and Figures

Table A.1 – Distribution of diagnosis types at inpatient hospitalization event Note: The table shows the diagnosis type associated with the first inpatient hospitalization in the event year.

	Low debt		High debt	
	Share	*Frequency*	*Share*	*Frequency*
Infectious and parasitic diseases	0.02	8,117	0.02	3,100
Neoplasms	0.09	37,337	0.06	8,314
Endocrine, nutritional and metabolic diseases	0.02	8,928	0.02	3,382
Diseases in blood and blood-forming organs	0.01	2,029	0.01	705
Diseases in nervous system	0.03	11,363	0.03	3,664
Diseases of the eye and adnexa	0.01	3,652	0.01	986
Diseases of the ear and the mastoid process	0.01	3,247	0.01	986
Diseases of the circulatory system	0.13	53,976	0.10	13,387
Diseases of the respiratory system	0.05	20,697	0.06	7,891
Diseases of the digestive system	0.10	41,801	0.11	15,078
Diseases of the genitourinary system	0.09	35,713	0.09	12,964
Diseases of the skin and subcutaneous tissue	0.02	8,117	0.03	3,523
Diseases of the muschuloskeltal system and connective tissue	0.11	43,424	0.10	13,669
Congenital malformations, deformations and chromosal abnormalities	0.01	2,029	0.01	705
Symptoms and undefined conditions	0.11	45,859	0.13	17,756
Broken bones and joint damages	0.07	27,597	0.07	9,442
Lesions, wounds and other traumas (external causes)	0.09	34,902	0.10	14,092
Examination, preventive care etc. w/o symptoms or diagnosis	0.04	17,451	0.08	11,273
N	1	405,832	1	140,918

Figure A.1 – Years since first purchase and probability of having high debt Notes: The figure illustrates the relevance of the instrument used in the IV regressions reported in Table 2. To produce the graphs, we regress the indicator of high debt in the year before the event on a set of indicator variables for the number of years between the first home purchase and the somatic health shock (right-censored at 16 years), as well as a set of controls. In each panel, we plot the estimated coefficients on the indicators for time since first purchase, with 3 years as the omitted category. Panel A shows results for a specification including the same controls as in Model 1, including age at the time of the health shock. In Panel B, we instead control for age at the time of the first home purchase. Both panels show that individuals who bought their first home only a few years before they experience the somatic health shock are more likely to have high debt in the year before the shock than individuals who purchased their first home many years before the shock. Std. errors are clustered at the level of the individual.

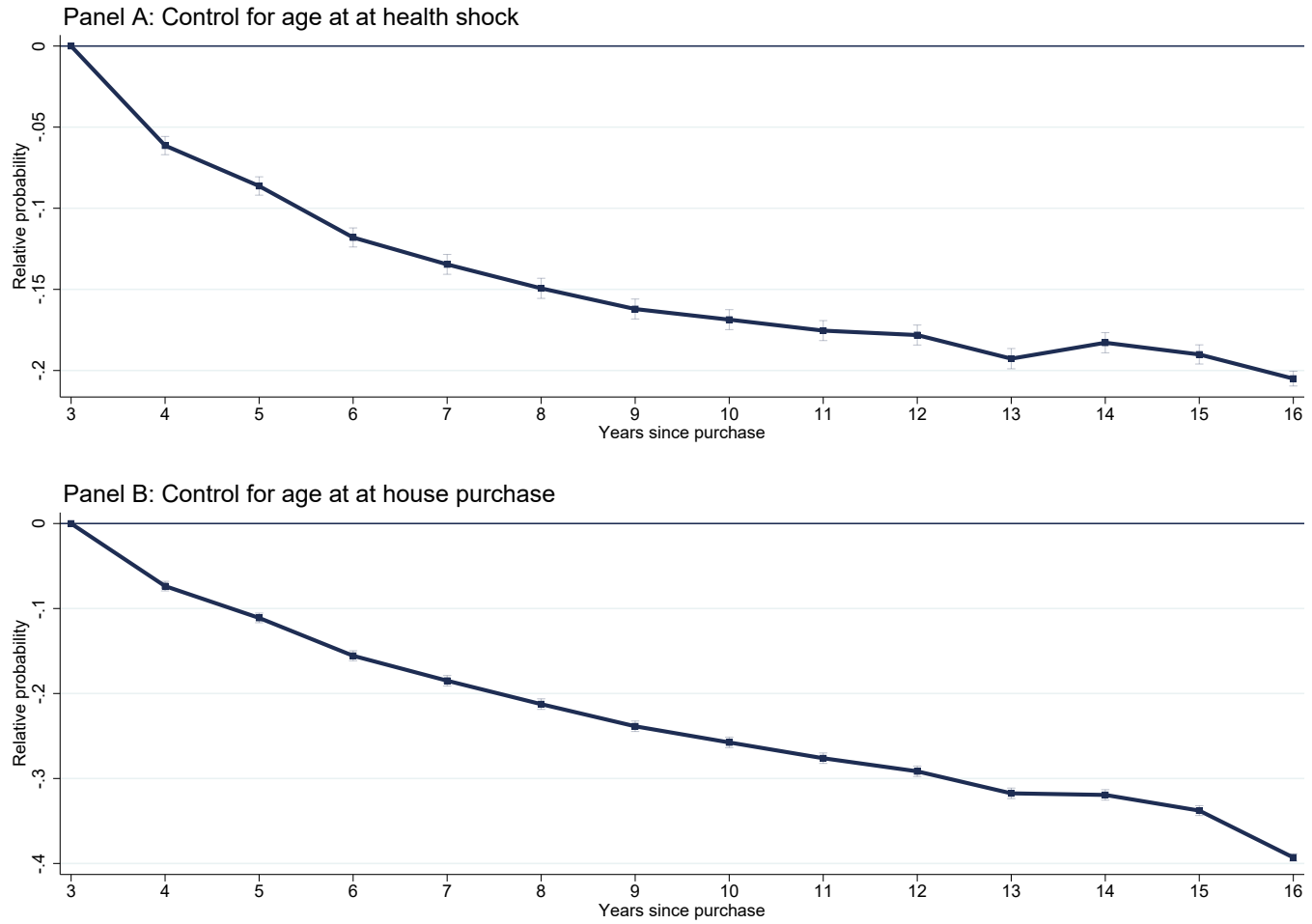

Figure A.2 – Impact of specific circulatory diseases on mental health by ex ante leverage Notes: The figures shows the effect on mental health and components of our comprehensive mental health measure of a more specific health shock by ex ante leverage. In this figure a health shock is limited to inpatient hospitalizations with the diagnoses: Acute myocardial infarction , other ischaemic heart diseases, symptomatic heart disease, other heart diseases, and cerebrovascular diseases corresponding to ICD-10 codes: I20-I69. The dependent variable is a dummy for suffering from mental health problems (Panel A), having any consultations with a psychologist (Panel B), and having any contact with a psychiatric hospital (Panel C). Std. errors are clustered at the individual level.

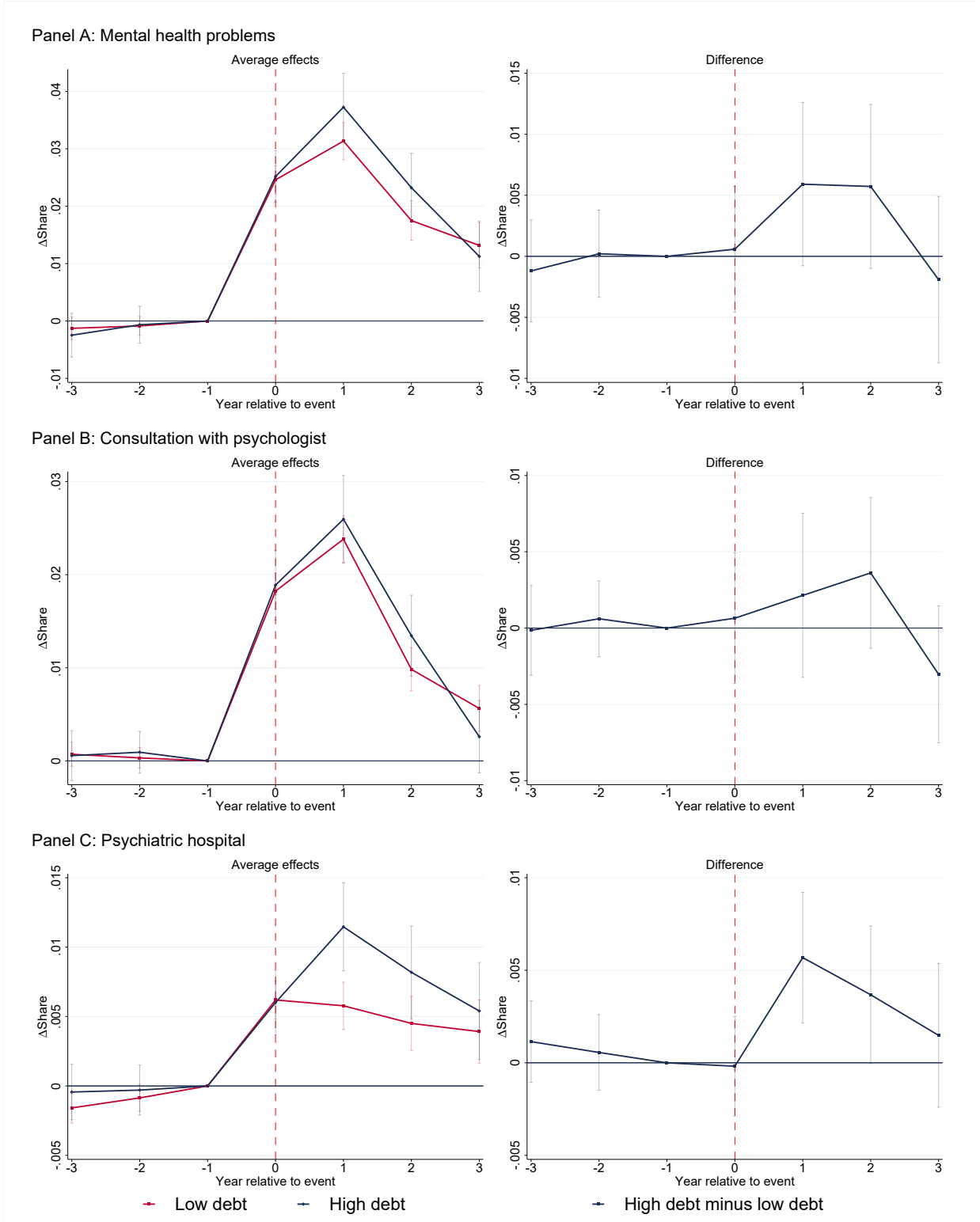

Figure A.3 – Impact of a health shock on suicide and intentional self-ham by ex ante leverage Notes: The figures shows the effect on suicides (attempts with and without death) and intentional self-ham of a health shock by ex ante leverage. The dependent variable is a dummy that takes the value one if the individual has committed suicide, attempted to commit suicide or committed other intentional self-harm time t and zero otherwise. Suicide attempts and intentional self-harm are defined by the ICD-10 codes X60-X87. Std. errors are clustered at the individual level.

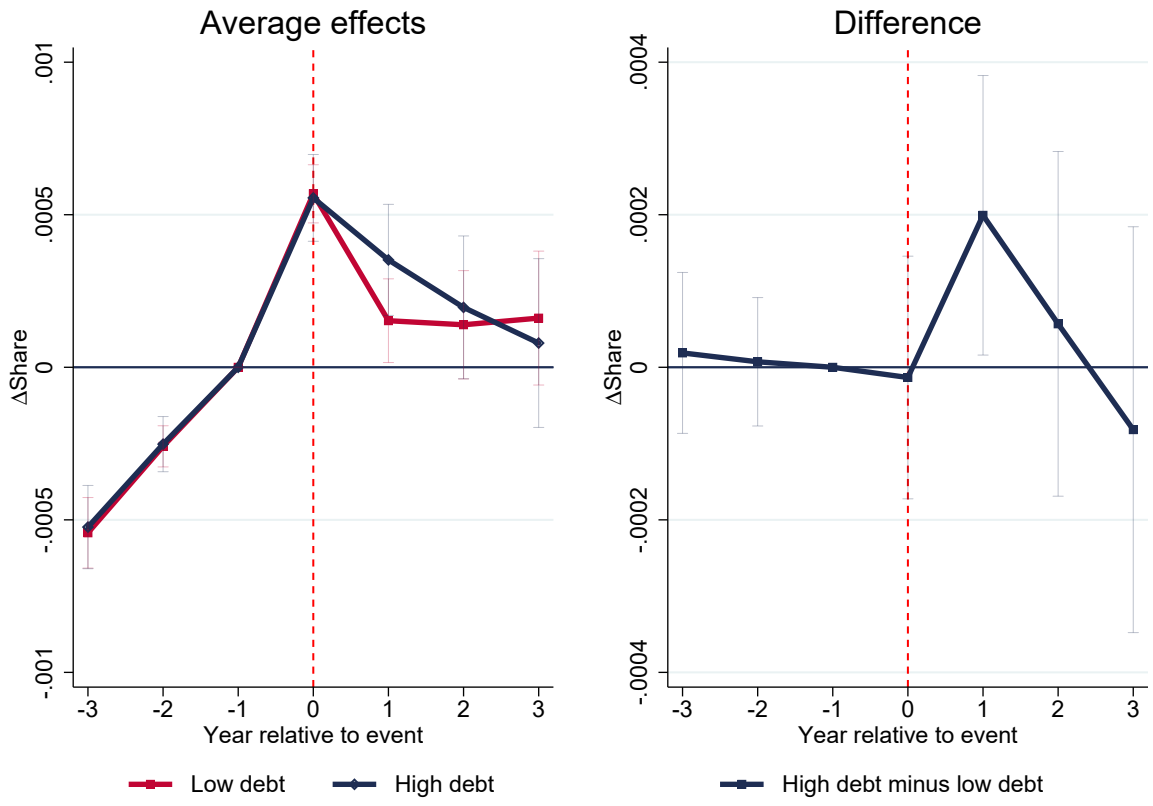

Figure A.4 – Robustness: Measurement of high and low debt Notes: The figure shows the impact on mental health of a health shock by various definitions of ex ante high and low debt. In panel (a) high-debt individuals are home-owners in the top 10% of the LTV distribution in the year prior to event and low debt are the remaining home-owners. In panel (b) the high-debt individuals are home-owners who are both in the top 25% of the distribution of LTV and DTI in the year prior to the event and low-debt individuals are the other home-owners. In panel (c) we define high-debt individuals as the homewoners in the top 25% of the LTV distribution and low-debt individuals as home-owners in the bottom 25% of the LTV distribtion. Std. errors are clustered at the individual level.

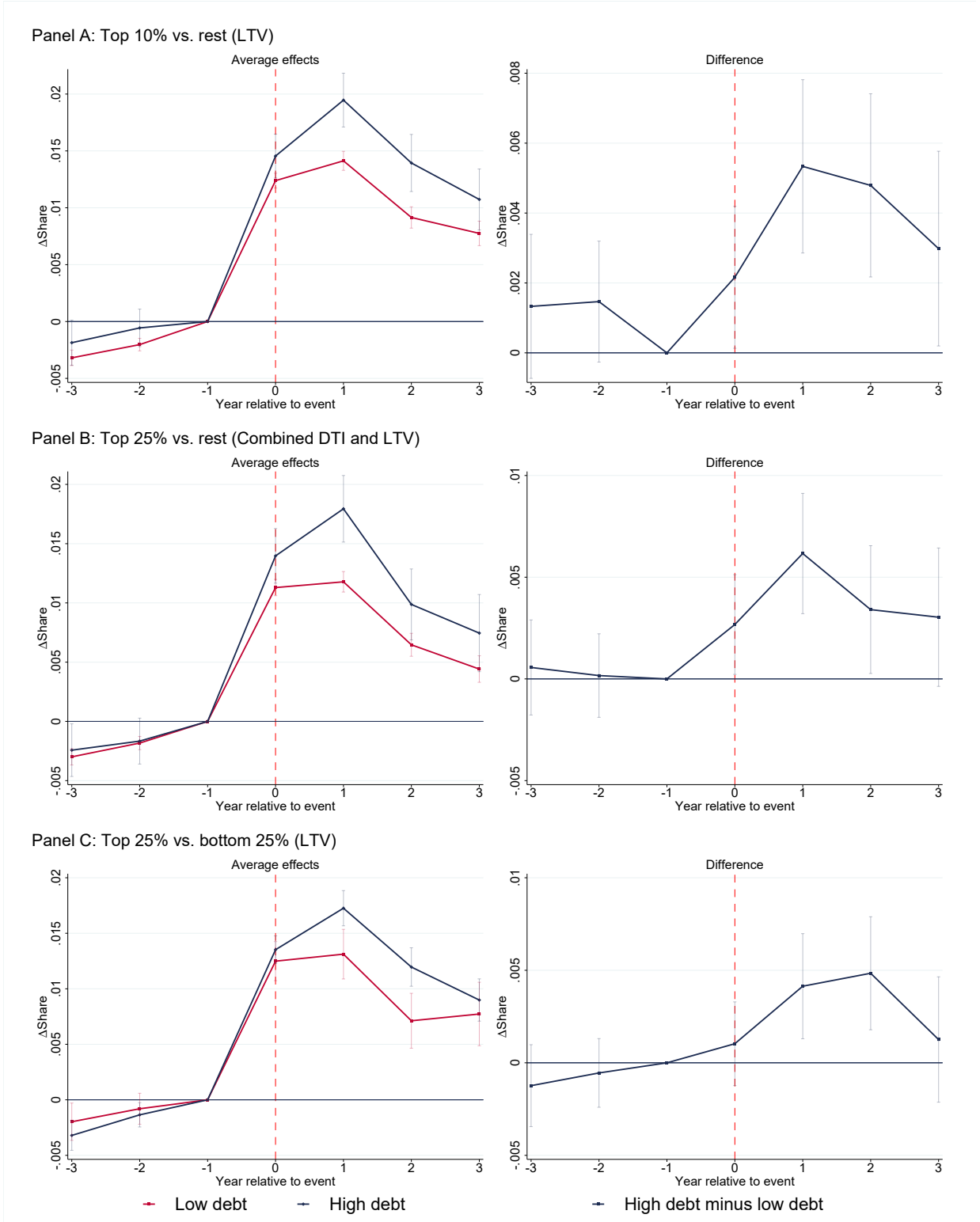

Figure A.5 – Robustness: Different age restrictions on sample Notes: The figure shows the impact on mental health of a health shock by ex ante leverage for different age restrictions on the sample. Std. errors are clustered at the individual level. Individuals are included in the estimation when they are within 30-70 years of age (panel A), 30-80 years of age (panel B), 40-60 years of age (panel C) and 50-70 years of age (panel D). Std. errors are clustered at the individual level

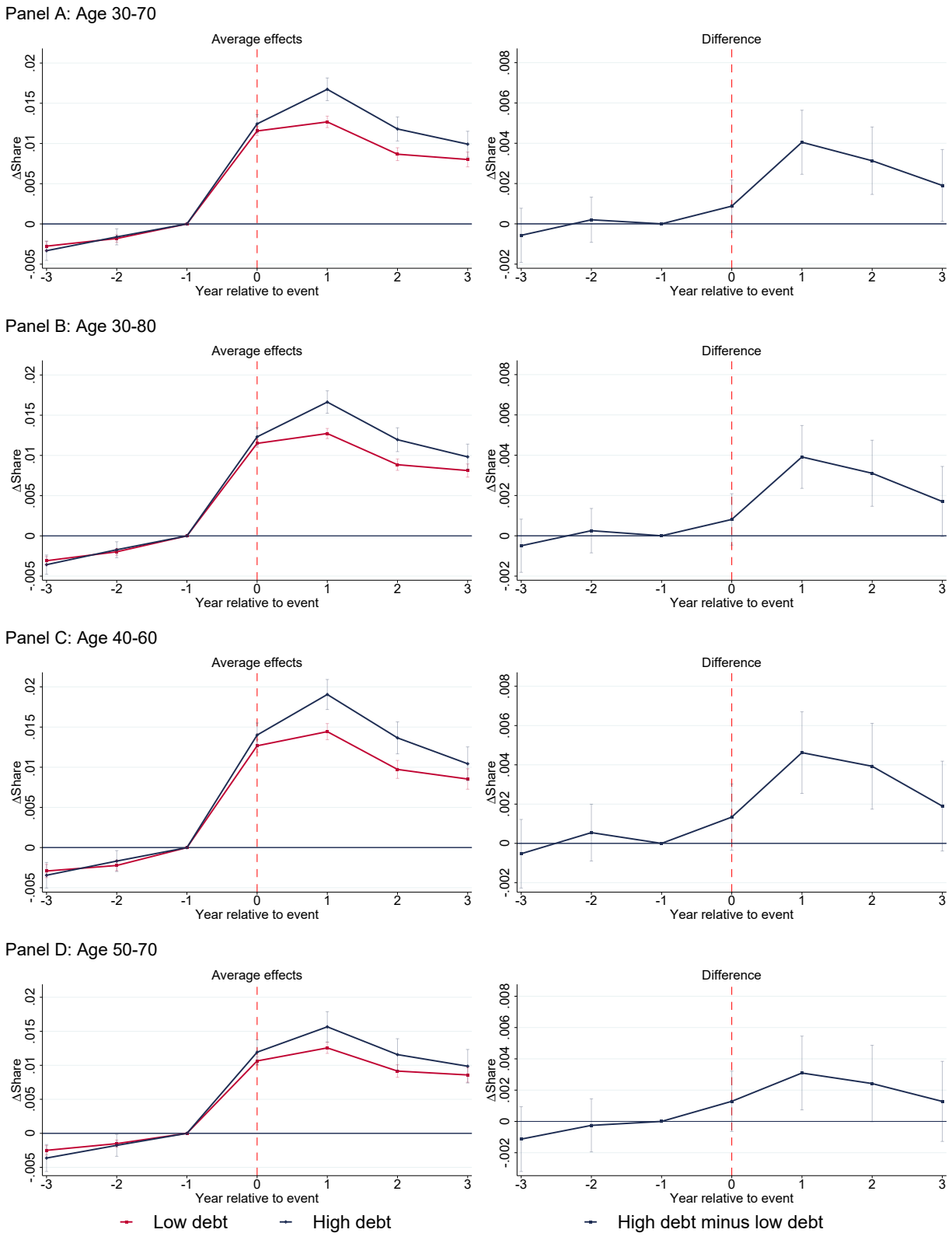

Figure A.6 – Robustness: Further controls for diagnosis Notes: The figure shows the impact on mental health of a health shock by ex ante leverage including controls for all diagnoses associated with subsequent inpatient hospitalizations in the event year. Std. errors are clustered at the individual level.