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Labor supply and informal care responses to health shocks within couples: Evidence from the UK

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Abstract

Shocks to health have been shown to reduce labor supply for the individual affected. Less is known about household self-insurance through a partner's response. Previous studies have presented inconclusive empirical evidence on the existence of a health-related Added Worker Effect, and results limited to labor and income responses. We use UK longitudinal data to investigate within households both the labor supply and informal care responses of an individual to the event of an acute health shock to their partner. Relying on the unanticipated timing of shocks, we combine Coarsened Exact Matching and Entropy Balancing algorithms with parametric analysis and exploit lagged outcomes to remove bias from observed confounders and time-invariant unobservables. We find no evidence of a health-related Added Worker Effect but a significant and sizable Informal Carer Effect. This holds irrespective of spousal labor market position or household financial status and ability to purchase formal care provision, suggesting that partners' substitute informal care provision for time devoted to leisure activities.

KEYWORDS

added worker effect, health shocks, informal care, labor supply, matching methods, panel data

JEL CLASSIFICATION

C14, I10, I13, J14, J22

1 | INTRODUCTION AND BACKGROUND

Health shocks represent a major source of economic risk. An established literature shows how shocks reduce labor supply for an individual, entailing a significant reduction in earnings (e.g., Flores et al., 2019; Jones et al., 2020; Lenhart, 2019 and literature cited therein).[1] Depending on healthcare financing arrangements, the economic consequences of health shocks might extend to an increase in health-related expenditures, leading to the risk of catastrophic payments, reduced access to credit and consumer borrowing, as recently shown for the US by Dobkin et al. (2018).

Wealth deteriorations, consumption smoothing and other spillover effects inevitably extend to other family members. Partners in particular,[2] might provide an important source of informal insurance against this economic risk, both in terms of acting as alternative or additional earners, and in terms of informal care providers, in conjunction with any formal protection available. While interest in family and partners' responses is growing (e.g., Dobkin et al., 2018; Fadlon & Nielsen, 2021; Jeon & Pohl, 2017; but also Gathmann et al., 2020 on the reverse issue of job loss and health spillovers in couples), the existing literature has produced mixed results and evidence limited to labor and family income outcomes. We extend this literature by combining the study of labor supply adjustment to that of the informal care response of household partners, exploiting panel data drawn from the Understanding Society survey, conducted in the UK since 2009.

Under a collective household theoretical framework (Apps & Rees, 1997; Chiappori, 1997) the effect of a health shock on spousal labor supply is ambiguous. The income effect arising from the loss of earnings by the person whose health deteriorates (only partially compensated by disability benefits or pension entitlements, given prevailing replacement rates) might increase spousal labor supply, in the spirit of what has been called the Added Worker Effect (AWE) (Lundberg, 1985; Mincer, 1962). While the income effect is diminished if a health shock affects individuals living on pension or non-labor income, additional consumption needs arising from disability might occur, for example, in terms of transport, heating, formal care or other extra-costs of disability. In addition to an income effect, in countries such as the USA, where employment-contingent health insurance plays a major role, the importance of extending healthcare coverage to the individual experiencing the health shock creates an additional incentive for a partner to seek suitable employment (Bradley et al., 2013).

In contrast to a positive AWE, the event of a health shock might also be expected to lead to a reduction in the labor supply of a partner. A shock-induced disability might limit home production necessitating additional spousal involvement at the expense of time devoted to work. Home production in the form of informal care provision (the so-called Caregiver Effect) would appear particularly relevant in these circumstances. Also, complementarity of partners' leisure, enhanced by newly acquired health information possibly indicating a shortening lifespan might contribute to reducing, rather than increasing, spousal labor supply. Indeed, complementarity in the non-market time of older husbands and wives is documented by Kneisner (1976), and confirmed by Hamermesh (2002) and Hallberg (2003) who find that partners prefer consuming leisure at the same time of the day and adjust work duties and schedules accordingly. Complementarity in leisure has also been identified as one of the main drivers of joint retirement decisions (Gustman & Steinmeier, 2000; Stancanelli & Van Soest, 2016).

At the empirical level, studies on partners' adjustments are scarce. As discussed in Jeon and Pohl (2017) the research question requires addressing the combined challenges of adequate data availability (where family relationships are typically captured in household surveys, offering small sample numbers, rather than in larger administrative datasets) and endogeneity of health shocks which hamper causal identification. In addition, existing evidence is inconclusive on a partner's labor supply response.[3] Some studies (Garcia-Gomez et al., 2013; Jeon & Pohl, 2017; van Houtven et al., 2013, for the US, Netherlands and Canada respectively) have found no empirical support for an AWE, or even a reduction in labor supply following a health deterioration. In these studies, home production needs and the complementarity of leisure jointly appear to dominate the income effect, especially for men who are less exposed to major income losses should their partner's health deteriorate. Lack of an economically significant AWE for non-fatal heart attacks or strokes has recently been confirmed by Fadlon and Nielsen (2021), who use Danish administrative records and attribute the absence of an AWE to the lack of need for self-insurance, given the generous social insurance coverage available in Denmark which almost fully compensates the earnings loss.[4] In a strikingly different institutional context, a recent contribution by Dobkin et al. (2018) documents the lack of an AWE following hospitalizations in the US. Despite comparable (to Denmark) drops in earnings suffered by hospitalized individuals (about 20% of previous earnings on average), in the US only about 10% of this reduction is compensated by social insurance; yet no AWE is detected.

A remaining limitation of these empirical studies, that we seek to overcome, is that they acknowledge the importance of distortions to home production following a health shock but discuss these indirectly,[5] rather than measuring the Caregiver Effects, possibly due to a lack of information on informal care provision in the underlying data. Ultimately, existing research focuses exclusively on labor supply and income outcomes, leaving questions on other time allocation adjustments unaddressed. Alternative (to labor) time uses might include both informal care/home production and, as a complement to one's time endowment, leisure. Enhancing knowledge on such adjustments, in addition to labor supply, is relevant to forming a comprehensive household-level view of the overall effects of health deteriorations. Any adjustments to a partner's use of time impacts their own and their partners wellbeing. Partners are generally known to offer an important source of informal care provision (OECD, 2017) which complements formal care provided either privately or publicly. Informal care might be the preferred choice for the couple, as suggested by growing evidence on the complementarity between formal and informal care (Fischer & Müller, 2020; Rapp et al., 2022) and partners' reported feeling of fulfillment related to caring (Baji et al., 2019; Brower et al., 2005). However, informal care is also known to result in worsening health (Do et al., 2015), particularly in terms of spousal mental health (Bom et al., 2019), which on top of the physical strain of caring, and the decreased time available for leisure activities, might also lead to the so-called *family effect*, (i.e., the effect of caring about other family members, regardless of whether providing informal care to them, see Bobinac et al., 2010)—all contributing to a loss in wellbeing and quality of life.

In this paper, we are able to consider more broadly time use adjustments to health shocks due to our data providing direct measures of informal care responses collected over time for all adult household members, covering both informal care provided to a partner who has experienced a health shock, and care to other household members. The identification strategy follows previous contributions in the field that exploit acute health shocks, such as heart attack, stroke and cancer, as a source of unanticipated variation in the timing of health deteriorations (e.g., Datta Gupta et al., 2015; Jeon & Pohl, 2017; Jones et al., 2020; Smith, 1999, 2005; Trevisan & Zantomio, 2016). Conditioning on a wide range of observable individual characteristics for both partners, as well as household- and couple-level characteristics, we assume that the chance that a partner experiences an acute health shock at any particular point in time is conditionally random, and—as in a quasi-experimental framework—match household couples where one partner experiences the health shock, with observationally identical household couples where neither partner experiences a health shock. Following Jones et al. (2020), matching is performed through a combination of Coarsened Exact Matching and Entropy Balancing. This approach is suited to a setting that offers a much larger number of controls than treated units (Iacus et al., 2012). ATTs are then obtained through parametric modeling on the matched sample. We do this separately for each of the outcomes: employment, hours worked, informal care provision and hours of care for the non-shocked partner.

Our work relates to the strands of literature that investigates the relationship between labor supply and informal care provision along the two possible directions of causation that is, labor activity as a determinant of caregiving (e.g., He & McHenry, 2016) and caregiving as a determinant of labor supply (e.g., Jacobs et al., 2017). However, here we consider how both labor supply and informal care are jointly affected by the onset of a health shock suffered by a partner. We contribute to the existing literature on the health-related AWE by providing rigorous causal evidence on partners' overall time allocation adjustment to health deterioration. A novel aspect of our work is the direct testing and measurement of the Caregiver Effect which, combined with the measured adjustment in time devoted to work, also allows inference on leisure adjustments. Our results for labor supply show no evidence of a health-related AWE, but a sizable increase in the probability of acting as a caregiver. Together with a lack of a significant change in spousal working hours, the increase in spousal time devoted to informal care—detected irrespective of affordability of formal care, as proxied by household income—suggests a substitution to personal involvement in caring, at the expense of time devoted to other non-work activities, such as leisure. While enhancing our understanding of time allocation responses to a partner's health shock, our evidence is relevant as alternative usages of time are likely to impact on a wellbeing (Coe & Van Houtven, 2009; Stokel & Bom, 2022).

2 | DATA

We use nine waves of Understanding Society, the UK Household Longitudinal Study that, starting in 2009, builds on the previous British Household Panel Study (BHPS), but offers a larger sample size of about 40,000 households and 100,000 individuals (at wave 1). While the BHPS has been widely used to study health and labor dynamics, the larger Understanding Society sample is important as it allows analysis of sub-populations previously regarded as too small for research (Buck et al., 2012): such as couples experiencing one of the three types of health shocks that we select (heart attack, stroke or cancer).

While the fieldwork of each Understanding Society wave lasts about 2 years, all individuals aged 16 or above living in a target household are interviewed yearly, allowing us to use up to nine interviews undertaken by the same person between 2009 and 2019. During the first interview, individuals are asked about their past life history and their health history in terms of diagnoses and events.[6] This allows us to observe whether an individual had already experienced an acute health shock of the type we select. During subsequent interviews individuals report any new diagnosis or onset of health problems that occurred since the previous interview, so that an annual life history of health shocks can be constructed and updated. In addition, an advantage of these survey data (over administrative data sources) is the collection of a wider set of characteristics informative of underlying health risks: for example, diagnoses of coronary heart disease, angina, diabetes and high blood pressure, all related to cardiovascular risk (Braunwald, 2015); the presence of a long-standing illness or disability, limitations in activities of daily living (ADLs); information about past and current smoking and intensity; and parents' longevity (whether each parent was alive when the respondent was aged 14), indicative of relevant genetic characteristics.

Demographic information covers age, gender, race, marital status, number of children, and household size. Detailed information collected on individual labor market activity includes employment status (both employment and self-employment), hours worked and earnings. Available socioeconomic indicators cover education (the highest qualification achieved), various income sources (labor, pension, investment and transfers including different types of benefit income e.g., disability-related, means-tested), and home ownership. Individual level and source-specific income information provides indicators of household income composition (e.g., income sources which would not be exposed to health risk, such as pension income and investment

TABLE 1 Descriptive statistics

	Treatment couples (n = 484)		Potential controls couples (n = 48,723)		
	Mean	SD	Mean	SD	p val (diff)
Shocked/non-shocked partner					
Partner's age	50.28	9.51	42.11	11.54	0.000
Partner' gender: Male	0.48	0.50	0.47	0.50	0.431
Partner's race: White	0.87	0.34	0.81	0.39	0.001
Partner's education	3.57	1.79	4.25	1.63	0.000
Partner's LM participation ($t-1$)	0.57	0.50	0.79	0.40	0.000
Partner's father dead when aged 14	0.06	0.25	0.03	0.17	0.000
Partner's mother dead when aged 14	0.01	0.11	0.01	0.11	0.779
Partner's natural children ($t-1$)	2.02	1.60	1.66	1.39	0.000
Partner's current smoker	0.26	0.44	0.20	0.40	0.001
Partner's regular smoker past	0.26	0.44	0.21	0.40	0.003
Partner's heavy_smoker (current/past)	0.14	0.35	0.07	0.26	0.000
Partner's number of limitations ($t-1$)	0.46	1.13	0.20	0.70	0.000
Partner's long standing illness/disability ($t-1$)	0.40	0.49	0.23	0.42	0.000
Partner's shock ($t-1$)	0.22	0.41	0.03	0.17	0.000
Partner's risk ($t-1$)	0.44	0.50	0.20	0.40	0.000
Potential added worker					
AW age	53.22	8.19	46.65	9.57	0.000
AW male	0.49	0.50	0.52	0.50	0.162
AW education	3.65	1.75	4.26	1.62	0.000
AW labor market participation ($t-1$)	0.65	0.48	0.81	0.39	0.000
AW hours of work ($t-1$)	23.38	20.19	30.29	19.26	0.000
AW hours of work ($t-1$), conditional	36.05	13.08	37.45	13.80	0.073
AW provides informal care to partner ($t-1$)	0.15	0.35	0.03	0.16	0.000
AW hours of care ($t-1$)	6.15	18.68	2.05	11.75	0.000
AW hours of care ($t-1$), conditional	32	31.55	34.19	34.75	0.549
Couple level characteristics					
Household size ($t-1$)	3.13	1.36	3.51	1.29	0.000
Household equivalent income ($t-1$)	2106	1406	2359	1461	0.000
Home Tenure: social renter	0.16	0.37	0.09	0.30	0.000
Home Tenure: homeowner	0.78	0.41	0.82	0.39	0.054
Elapsed months between t and ($t-1$)	12.68	0.14	12.33	0.01	0.001
Wave (t)	4.73	2.32	5.06	2.27	0.002

Note: Variables in bold if t test of equality of means between treated and controls rejected at the conventional 5% level.

Source: UKHLS, waves 1-9.

income) and each partner's contribution to overall household income. These serve the purpose of assessing the level of household economic exposure to the monetary impact of a partner's health shock.

Finally, individuals are interviewed yearly on care provided to other household members, and their identity, as well as on the intensity of care provided to each, measured by the number of hours provided (in bands: 0–4; 5–9; 10–19; 20–34; 35–49; 50–99; 100 or more).[7] Care received by other informal caregivers living outside the household is also traced.[8] Wider types of home production, such as a variety of household chores, are covered only in specific waves, and for this reason cannot be exploited in our analysis. Descriptive statistics on the full list of variables employed in our study, on the sample selected for analysis, are reported in Table 1, and discussed in Section 3.2.

3 | EMPIRICAL METHODS

3.1 | Research design

The main challenge for identifying the causal effect of a health shock stems from potential selection bias with respect to the outcomes of a partner, in the labor market (see e.g., Siegel, 2006) and beyond. Empirically documented mechanisms such as assortative mating (Greenwald et al., 2014) and its reflection in terms of partners' health-relevant behaviors such as smoking, diet and exercise (e.g., see Clark & Etilé, 2006) and labor supply; comorbidity in couples (Guner et al., 2018); joint determination of partners' labor supply and home production decisions, all contribute to concerns about unobserved heterogeneity. Systematic differences between couples who experience a health shock compared to couples who do not could arise even before the occurrence of a shock, for example, in terms of time preferences or daily behaviors potentially correlated to both health investments and labor supply. Reverse causality could also play a role, for example, if the labor circumstances of one partner, such as unemployment, contribute to the other partner's health deterioration through, again, joint behavioral choices (e.g., smoking).

A way to address such concerns is to exploit some source of unanticipated variation in health. Previous authors have, for example, exploited road injuries and commuting car accidents (Dano, 2005; Halla & Zweimüller, 2013), unplanned hospitalizations (Belloni et al., 2019; Garcia-Gomez et al., 2013) or the onset of acute health shocks (e.g., Datta Gupta et al., 2015; Jeon & Pohl, 2017; Jones et al., 2020; Smith, 1999, 2005; Trevisan et al., 2016). We follow this last approach and use the onset of a heart attack, stroke or cancer experienced by one partner in a household to study the spousal (i.e., the unaffected partner and potential added worker) behavioral response. We focus on these conditions for the following reasons. Cancer, although a progressive condition, is often asymptomatic and typically becomes known upon diagnosis which has often been exploited for causal identification (e.g., Bradley et al., 2002, 2005, 2013). However, as cancer might be subject to diagnosis bias (i.e., individuals finding out they have cancer because of higher medical care use), it is important to include the other two types of health shocks, heart attack and stroke. As discussed in Tanaka (2021), these are cardiovascular events occurring suddenly at an identifiable, yet unpredictable, point in time (Braunwald, 2015). While individuals might reasonably be expected to anticipate their own health risk, in the light of known risk factors, the timing of an acute health shock is likely to be unanticipated. Moreover, the focus on major health conditions minimizes the scope for misreporting and recall bias that might be present in analyses based on milder or other progressive conditions.

Our research design aims to mimick a quasi-experimental setting (see Imbens & Wooldridge, 2009 for identification of causal effects under the potential outcomes approach) and is illustrated in Figure 1. We study the behavior of individuals (potential added workers [AW]) whose partner experiences an acute health shock between time $t-1$ and time t: these couples represent our treatment group. The treated couples are compared to a control group of couples, selected (through techniques explained below) so that both partners are individually observationally equivalent (up to the time of the shock) to those in the treatment group, except that neither experiences an acute health shock between time $t-1$ and time t. The potential AW's responses are observed, and contrasted, from time t onwards.

In this setting, identification of the effects of a health shock relies on a conditional independence assumption (CIA), which is standard in approaches based on selection on observables characteristics. CIA assumes that conditioning on the observed variables is sufficient to regard a time-specific acute health shock as being random, so that unobserved characteristics that might otherwise jointly affect the probability of a partner experiencing a time-specific health shock and the spousal adjustment

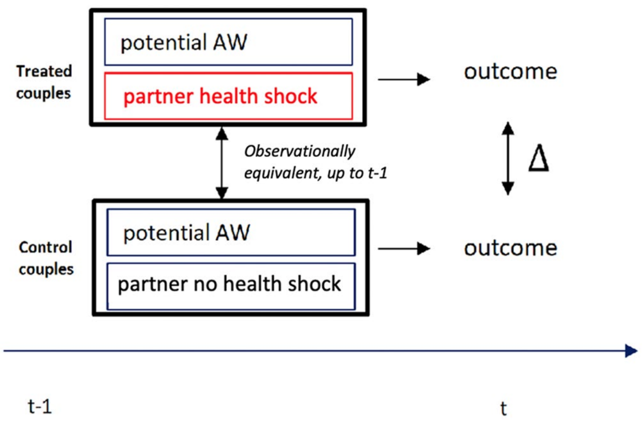

FIGURE 1 Research design [Colour figure can be viewed at wileyonlinelibrary.com]

observable from time t onwards, can be eliminated. The plausibility of CIA, which remains untestable, rests on the use of a rich set of observed variables available in the Understanding Society survey, for which observational equivalence between treatment and control couples can be attained: they include a broad set of individual and household variables that accounts for demographic and socioeconomic characteristics, labor market activity, health risks, and past acute health shocks. In addition, we further balance on lagged outcomes to mitigate against potential remaining differences in time-invariant unobservable individual characteristics (e.g., see O'Neill et al., 2016).

To achieve observational equivalence between treatment and control couples, we adopt the preprocessing approach discussed by Ho et al. (2007). This first uses matching methods to balance the distribution of confounders between treated and control units, which in turn reduces model dependence. Then, parametric modeling operates on the matched (i.e., preprocessed) data, to tackle any remaining imbalance. This preprocessing approach is doubly robust to either less than ideal balancing in the matching algorithm, or misspecification of the subsequent parametric model.

In practice, to implement preprocessing, we follow Jones et al. (2020),[9] who model individual responses to health shocks based on the same Understanding Society data and show how a combination of Coarsened Exact Matching (Iacus et al., 2012) and Entropy Balancing (Hainmueller, 2012) allows attaining a tight balancing of confounding covariates, as combining these two matching methods retains the advantages of each. In more detail, Coarsened Exact Matching (CEM) aims at achieving exact matching through stratification followed by exclusion of strata where either only treated or only control units are found. CEM corresponds to exact matching for binary variables, but coarsens continuous variables into intervals and is less data hungry than exact matching for these variables. CEM has the monotonic imbalance bounding property of improving the balance on each covariate without worsening that of others, although at the cost of reducing the sample size available for estimating causal effects as the set of included confounders increases (Iacus et al., 2011). A further implication is that CEM balances the joint distribution of confounding covariates, including interactions and nonlinearities. For this reason, it is used here to attain common support and tight balancing for a limited set of key covariates.

Once extreme units are discarded from the common support through CEM, Entropy Balancing (EB) balances the full set of confounders. EB operates by minimizing an entropy distance metric subject to balance constraints (e.g., equality of means between treated and matched controls) and normalizing constraints, generating weights to be applied in the following regression analysis. While EB operates on univariate distributions for each confounder separately, it is possible to extend the algorithm so that balancing extends to interactions and co-moments. Both CEM and EB were implemented in STATA using the *cem* and *ebalance* routines.

After preprocessing by CEM and EB, average treatment effects on the treated (ATTs i.e., potential added workers' effect responses to the treatment of having a partner experiencing an acute health shock) are obtained through parametric regression models using the preprocessed data. The estimation equation can be written as:

$$y_i = \alpha + \beta \text{treated}_i + \gamma X_i + \varepsilon_i$$

where y_i is the outcome of interest (labor supply, informal care provision) of the potential added worker, treated_i is a dummy variable equal to one if the potential added worker's partner experienced an acute health shock between time $t-1$ and time t, and zero otherwise; β captures the average treatment effect on the treated (ATT), while X_i are additional control variables included to tackle possible remaining imbalances in potential confounders. OLS or probit regressions were estimated according to the continuous or binary nature of the underlying outcome variable.

3.2 | Implementation

The sample for analysis is restricted to couples where both partners are observed, and are cohabiting, for at least two points in time, t and $t-1$, which could correspond to any two interviews across the nine waves available. In the vast majority of cases (91.18%) though these are two consecutive waves.[10] Also, we select couples where at least one partner (the potential added worker) is aged below the gender-specific state pension age, regardless of whether employed or not. After discarding couples with missing information on relevant variables, the number of couples in our sample is 49,207.

Treatment assignment operates dynamically, and at the level of the couple, accounting for each partner's history of health shocks. In more detail, all couples begin as untreated in the first wave they are interviewed. At any later wave, a couple is assigned to the treatment group if at least one acute health shock is observed for one of the partners (the shocked partner), and the other partner is under the state pension age (the potential added worker). The wave that the shock occurs is considered as time t, where outcome measurement begins.

TABLE 2 Outcomes of coarsened exact matching

	#Treated	#Controls	*by stratum*:	#Treated	#Controls
All	484	48,723	Mean	6.26	616.68
Matched	482	47,484	Median	3	153
Unmatched	2	1239	min	1	4
			10th perc.	1	13
			25th	1	32
			75th	8	388
			90th	14	1456
			Max	52	6875

Source: UKHLS, waves 1–9.

For treated couples where multiple health shocks are observed (possibly to both partners), we consider only the first shock recorded in the UHKLS observational window, and recode their treatment status to missing in any following wave (so that we study their adjustment to the first observed shock). Couples where a health shock is observed, but the partner is older than the state pension age as of time t, are discarded, as our interest lies in the combination of labor supply and informal care responses. We further drop couples where both partners experience a contemporaneous health shock (three cases) and couples where the two respective health shocks happen in consecutive years (eight cases), for which no credible causal effect measurement could be attained. In total, we observe 484 unique couples assigned to the treatment group.

The potential control group includes all couples where no shock is observed during the Understanding Society observational window, as long as one partner is aged below the gender-specific state pension age. Couples who are observed in the data at multiple time points may act as controls at each wave interviewed and hence might be used multiple times as potential controls. At any given time point they can potentially be used to form a counterfactual for multiple treated couples in that wave. This is in the spirit of “matching with replacement”, a standard specification option in the matching literature allowing control units to be “reused” and matched to multiple treated units. Treated couples are used only once (at time t, the year of reported shock for one partner in the couple), and never serve as potential controls. After dropping couples with missing information on relevant variables, there are 48,723 potential control couples, that is, approximately 100 couples, on average, for each treated couple.

Table 1 reports descriptive statistics for the treated and potential control sub-samples, showing that characteristics are highly unbalanced. In terms of potentially shocked partner characteristics (top panel of Table 1), partners that actually experience an acute health shock are on average older, less educated, more likely to be (past or present) heavy smokers, less healthy according to a variety of general health and disability indicators, exhibit a higher prevalence of specific CVD risk factors, and have fathers with lower longevity. Considering the potential added worker characteristics (mid panel of Table 1), individuals whose partner experiences an acute health shock are on average older, less educated, less likely to be active in the labor market and more likely to be providing informal care to their partner. For household level characteristics, significant differences are apparent in household size, equivalent income, probability of social renting and wave of interview (bottom panel of Table 1).

To control for selection bias arising from observables, we first implement CEM to achieve common support and exact matching on AW-gender, labor market activity and informal care provision as of $t-1$; as well as on (potentially shocked) partners' gender and diagnosis of a CVD risk factor.[11] On top of these binary variables, CEM includes (potentially shocked) partner's age, as a key predictor of risk of health shock, coarsened into five bands (with cut-offs at age 28, 43, 58 and 73 years). These variables were selected based on known risk factors (Braunwald, 2015); or because they are key predictors of the AW time allocation decision. Importantly, exact matching on AW's lagged outcomes (in terms of extensive margins) contributes to removing bias from time-invariant unobservables.

CEM stratifies treated and potential control couples into 142 strata, and retains only the couples found in a subset of 77 strata where at least one treated and one potential control couple are found. This corresponds to discarding from further analysis two treated couples, and 1239 control couples, as shown in Table 2. In each matched stratum, the number of treatment couples is systematically lower than the number of potential control couples. CEM weights account for this while maintaining exact matching on the relevant binary variables, and on the coarsened age groups.

EB aims at balancing (in terms of means) the univariate distribution of all remaining potential confounders, as listed in Table 1, along with the (health shocked) partner's exact age, rather than relying solely on balancing achieved though CEM. We further include in the EB minimization function the first order interactions between each conditioning variable and each of the binary variables included in the CEM step to balance co-moments. For continuous variables, we include quadratic and cubic terms, so that even if the EB distance minimization targets only the first moments of included variables, in practice balancing

TABLE 3 Balancing of observables

	Mean difference		Bias	
	Unbalanced	**Balanced**	**Unbalanced**	**Balanced**
Shocked/non shocked partner				
Partner's age	8.622	0.000	88.9	0
Partner' gender: Male	0.039	−0.002	7.8	−0.3
Partner's race: White	0.057	0.000	15.7	0.1
Partner's education	−0.6791	−0.002	−39.7	−0.1
Partner's labor market participation ($t-1$)	−0.223	0.000	−49.3	−0.3
Partner's father dead when aged 14	0.021	0.001	10.4	0.9
Partner's mother dead when aged 14	−0.087	−0.008	2.2	−0.0
Partner's natural children ($t-1$)	0.362	−0.005	24.1	−0.6
Partner's current smoker	0.064	0.002	17.7	0.4
Partner's regular smoker past	0.079	0.000	18.2	0.2
Partner's heavy smoker (current/past)	0.092	0.001	27.2	0.4
Partner's number of limitations ($t-1$)	0.754	0.016	48.4	1.0
Partner's long standing illness/disability ($t-1$)	0.262	0.001	55.1	0.4
Partner's shock ($t-1$)	0.186	0.003	58.8	1.0
Partner's risk ($t-1$)	0.247	0.001	54.8	0.3
Potential added worker				
AW age	6.563	−0.061	73.7	−0.7
AW male	−0.032	0.006	−6.4	1.1
AW education	−0.607	−0.010	−35.8	−0.6
AW labor market participation ($t-1$)	−0.160	−0.004	−36.5	−1.0
AW hours of work ($t-1$)	−6.898	−0.025	−35.0	−0.1
AW provides informal care to partner ($t-1$)	0.119	0.004	43.2	1.3
AW hours of care ($t-1$)	4.102	0.037	26.3	0.2
Couple level characteristics				
Household size ($t-1$)	−0.435	−0.006	−33.5	−0.5
Household equivalent income ($t-1$)	−252.8	1.1	−17.6	0.1
Home tenure: social renter	0.069	0.003	20.8	1.0
Home tenure: homeowner	−0.034	−0.003	−8.5	−0.8
Elapsed months (t)	0.359	−0.003	13.0	−0.1
Wave (t)	−0.328	−0.003	−14.3	−0.1

Source: UKHLS, waves 1–9.

extends to the second and third moments (Hainmueller & Xu, 2013). Table 3 reports the mean differences between matched couples, and the standardized difference in means or percentage bias, which are systematically lower than 1.5%.

4 | RESULTS

Table 4 reports, for each outcome, the estimated ATT and relative size effect (RSE)[12] at time t (top panel) and at $t+1$ (bottom panel). In both cases, no significant adjustment in the (potential AW) partner's labor supply emerges, neither along the extensive nor intensive margins. The lack of a partner's labor supply response holds across the three types of conditions we consider (Table A1 in Appendix).

However, partners significantly increase their involvement in informal care provided to the shocked spouses.[13] The ATT amounts to a 14% point increase in the probability of providing informal care in the year of the shock, which is double the counterfactual probability. This effect persists in the following year, although now at half the effect size (7.5% point increase) which

TABLE 4 ATT in the short run, full sample

	n (treated)	*n* (controls)	ATT	Std. Err.	*p* val	RSE
Potential AW outcome, as of *t*						
Labor market participation	481	47,449	−0.002	0.016	0.898	−0.003
Hours, unconditional on LMP	478	47,035	0.091	0.680	0.893	0.004
Hours, conditional on LMP	300	37,802	0.121	0.727	0.868	0.003
Informal care provision to partner	481	47,460	**0.137**	0.030	0.000	1.015
Hours of care, unconditional on providing care	478	47,427	**3.443**	1.152	0.003	0.525
Hours of care, conditional on providing care	132	2764	6.483	4.902	0.188	0.172
Potential AW outcome, as of $t+1$						
Labor market participation	408	39,492	−0.027	0.022	0.228	−0.044
Hours, unconditional on LMP	404	39,080	−0.996	0.897	0.267	−0.046
Hours, conditional on LMP	259	31,551	−1.169	1.214	0.336	−0.035
Informal care provision to partner	399	39,338	**0.075**	0.026	0.005	0.573
Hours of care, unconditional on providing care	399	39,304	2.225	1.277	0.082	0.362
Hours of care, conditional on providing care	112	2229	0.099	5.341	0.985	0.003

Note: ATT estimate in bold if significant at the conventional 5% level.

Source: UKHLS, waves 1–9.

represents a 57% increase in the counterfactual probability. The expected number of hours of informal care also increases, particularly in the year of the health shock, by about 3.5 h a week, which is a 50% increase on the counterfactual average. However, conditional on providing informal care, no significant increase in hours is observed, suggesting that the effect on the unconditional number of hours reflects an adjustment on the extensive margin.

Results by type of health condition (Appendix Table A1) show that the informal care response is entirely attributable to cases of stroke and cancer, with no response for myocardial infarction. Despite stroke being known as particularly disabling conditions (Trevisan & Zantomio, 2016 detect the largest personal labor supply reduction for individuals affected by a stroke, as compared to the two other conditions) the largest increase in informal care emerges from cancer, where updated expectations on remaining lifespan spent together as a couple might be particularly salient.

Table 5 shows estimated ATTs and RSE on the same outcomes, but measured at later points in time, that is, $t+2$, $t+3$ and $t+4$. Expanding the post-shock time horizon offers an indication of the dynamic pattern of response, which is displayed in Figure 2. However, these estimates, obtained on progressively reduced samples suffer from a lack of precision. They are also possibly biased by non-random attrition as treated couples are more likely to leave the panel, leading to a downward bias in estimated ATTs over time. Bearing this limitation in mind, estimates reported in Table 5 suggest that the results obtained in the very short term, in terms of lack of a labor supply response and increase in informal care, do show some persistence.

4.1 | Health shocks while active in the labor market

The lack of a positive health-related AWE might be attributable to the income loss following a health shock being of limited relevance. For example, if the shocked partner had already retired from the labor market or was relying on non-labor income sources. To investigate this possibility, we consider a restricted subset of couples where the shocked partner was active in the labor market in the year prior to the shock (i.e., in $t-1$). Descriptive statistics for basic demographics and lagged outcomes in this subsample are reported in Appendix Table A2. These reveal how these potential AWs are, on average, slightly younger, and more likely to be women. Table 6 reports ATTs for this subsample. While health shocks induce a significant increase in labor market exits for shocked individuals, together with a consequent income loss,[14] even in this sub-sample no AWE is detected. In fact, the point estimates on labor supply outcomes becomes negative in the year following the shock. Evidence suggesting that the loss of household labor income following a health shock does not result in a positive AWE also emerges when we further restrict the sample to couples where, in the year prior to the shock, the shocked partner's labor income contributed more than 50% of household income (results reported in Appendix, Table A3).

As in the full sample, we find a striking behavioral response in informal care provision in the year of shock: the ATT on the likelihood of providing informal care is 7.4 times the counterfactual value (reduced to 2.8 in the following year). The significant

TABLE 5 ATT in later years, full sample

	n (treated)	*n* (controls)	ATT	Std. Err.	*p* val	RSE
Potential AW outcome, as of $t + 2$						
Labor market participation	336	32,237	−0.028	0.026	0.287	−0.047
Hours, unconditional on LMP	333	31,869	−1.563	1.075	0.147	−0.076
Hours, conditional on LMP	213	25,787	−1.791	1.490	0.230	−0.057
Informal care provision to partner	321	31,977	0.047	0.025	0.057	0.370
Hours of care, unconditional on providing care	318	31,943	1.786	1.392	0.200	0.312
Hours of care, conditional on providing care	86	1757	2.685	6.638	0.687	0.092
Potential AW outcome, as of $t + 3$						
Labor market participation	271	25,549	−0.019	0.031	0.543	−0.033
Hours, unconditional on LMP	268	25,192	−1.684	1.243	0.176	−0.086
Hours, conditional on LMP	174	20,401	−1.906	1.754	0.278	−0.065
Informal care provision to partner	254	25,266	0.055	0.030	0.071	0.455
Hours of care, unconditional on providing care	252	25,241	1.494	1.277	0.402	0.228
Hours of care, conditional on providing care	64	1377	7.369	5.341	0.930	0.023
Potential AW outcome, as of $t + 4$						
Labor market participation	215	19,121	0.018	0.033	0.589	0.033
Hours, unconditional on LMP	211	18,814	−0.611	1.378	0.658	−0.033
Hours, conditional on LMP	136	15,232	−0.348	1.964	0.860	−0.013
Informal care provision to partner	200	18,849	0.043	0.033	0.202	0.355
Hours of care, unconditional on providing care	199	18,823	0.072	1.665	0.966	0.012
Hours of care, conditional on providing care	52	988	−2.786	8.759	0.752	−0.090

Note: ATT estimate in bold if significant at the conventional 5% level.

Source: UKHLS, waves 1–9.

ATT on the (unconditional) number of hours of care provided amounts to more than a doubling of the counterfactual value in the year of shock, but loses statistical significance in the following year. Again, this behavioral response relates to the extensive margin rather than the conditional number of hours of care provided.

4.2 | Gender effects and shock-induced disability

Table 7 and Figure 3, report results separately for men and women whose partner experienced an acute health shock.[15] In previous studies, when considering gender-specific responses to a partner's health shock, contrasting results have emerged. A reduction in men's labor supply is found in Berger (1983), Blau and Riphahn (1999), Charles (1999) and Nahum (2005). However, a small increase in men's labor supply is found by Coile (2004) and confirmed by Johnson and Favreault (2001), the latter in terms of a reduction in the probability of retirement. For women, Charles (1999) found an increase in labor supply in response to a shock to their male partner's health using US data, but a decrease in a male partner's labor supply in response to a female partner's health shock. This is interpreted as consistent with the idea of a relative gender specialization in income production (men) and home production (women) and a partner's response aimed at compensating for the reduction in time use of the partner who experiences a health shock. Several studies report heterogeneity in the responses of women, reflecting baseline labor market attachment (Berger, 1983; Blau and Riphahn, 1999; Jimenez Martin et al., 1999), and in response to disability insurance eligibility and generosity (Berger & Fleisher, 1984; Chen, 2012).

In our study, neither men nor women adjust their labor supply in the year of shock or the following year. While the ATTs are never statistically significant, the point estimate for women, who may be vulnerable to larger income losses when the male partner experiences a health shock, is systematically negative, suggesting that any income effect, which would induce an increase in labor supply, is outweighed by other factors. Indeed, both women and men significantly increase their informal care provision when their partner experiences a health shock. In the year of the shock this amounts to a 60% increase in the probability of caring for women and more than doubles (150%) for men who have lower baseline probabilities of caring than women (13.5%

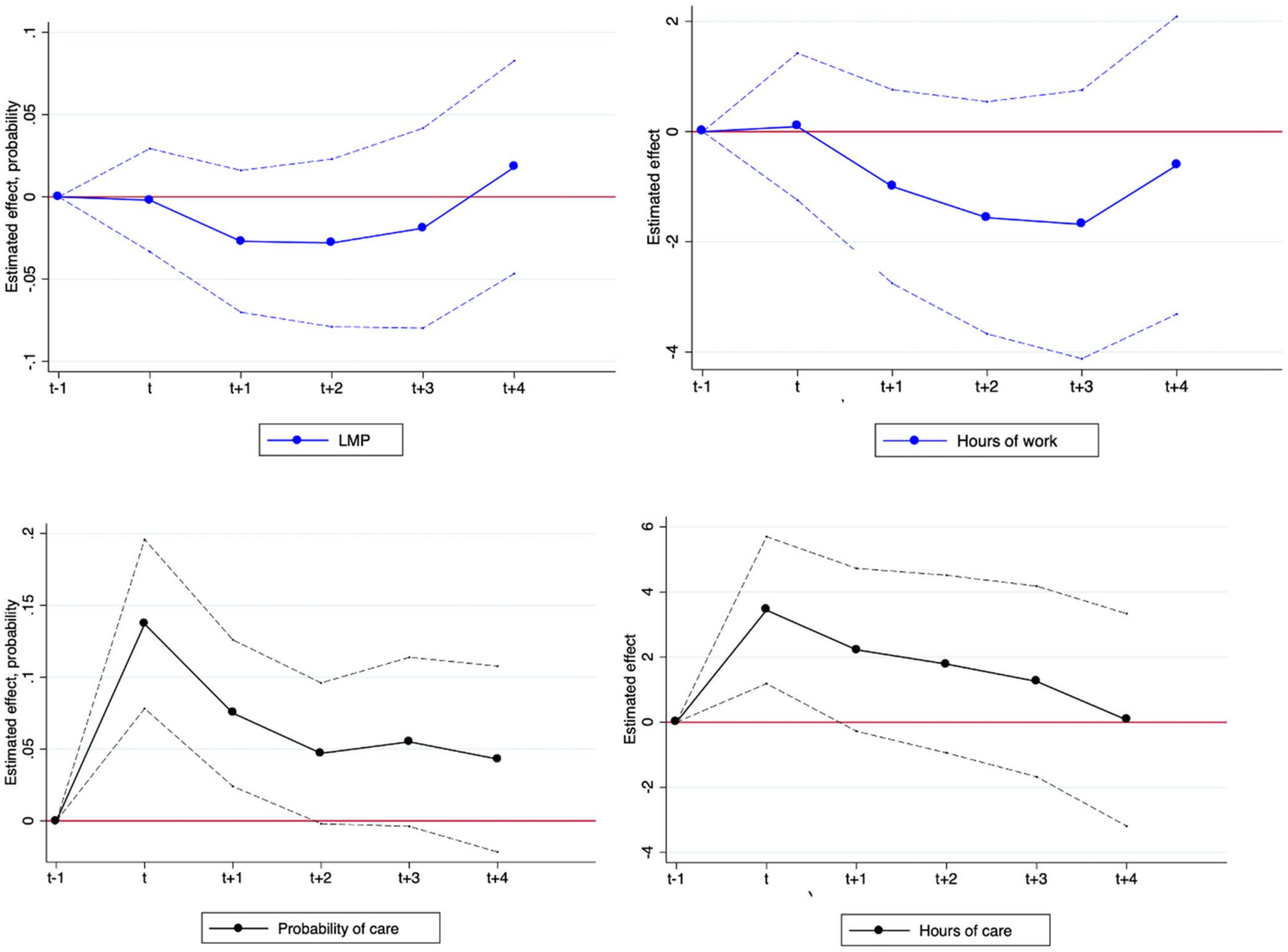

FIGURE 2 Behavioral response (ATT) to a partner's health shock [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 6 ATT in the short run, if shocked partner was labor market active as of $(t-1)$

	n (treated)	*n* (controls)	ATT	Std. Err.	*p* val	RSE
Potential AW's outcome, as of *t*						
Labor market participation	280	38,660	0.006	0.019	0.759	0.007
Hours, unconditional on LMP	277	37,484	0.417	0.951	0.661	0.014
Hours, conditional on LMP	224	31,931	0.244	0.839	0.772	0.007
Informal care provision to partner	280	37,836	**0.215**	0.054	0.000	7.414
Hours of care, unconditional on providing care	280	37,824	**2.263**	0.930	0.015	1.358
Hours of care, conditional on providing care	47	1373	10.841	10.466	0.309	0.414
Potential AW's outcome, as of $t+1$						
Labor market participation	236	31,606	−0.036	0.032	0.261	−0.046
Hours, unconditional on LMP	232	31,255	−1.332	1.245	0.285	−0.048
Hours, conditional on LMP	191	26,743	−1.340	1.341	0.318	−0.040
Informal care provision to partner	234	31,489	**0.083**	2.140	0.032	2.862
Hours of care, unconditional on providing care	234	31,471	2.049	1.167	0.080	1.298
Hours of care, conditional on providing care	39	1139	7.921	14.974	0.603	0.417

Note: ATT estimate in bold if significant at the conventional 5% level.

Source: UKHLS, waves 1–9.

TABLE 7 ATT in the short run, by potential AW's gender

	Male						Female					
	n (treat)	*n* (contr)	ATT	Std. Err.	*p* val	RSE	*n* (treat)	*n* (contr)	ATT	Std. Err.	*p* val	RSE
Potential AW's outcome as of t												
Labor market participation	233	24,533	0.0003	0.022	0.990	0.000	248	22,916	−0.009	0.022	0.650	−0.015
Hours, unconditional on LMP	232	24,325	0.206	1.135	0.856	0.008	246	22,710	−0.301	0.807	0.710	−0.016
Hours, conditional on LMP	155	20,750	0.308	1.106	0.781	0.008	145	17,052	−0.179	0.992	0.857	−0.006
Informal care provision to partner	232	24,540	**0.183**	0.049	0.000	1.578	248	22,920	**0.094**	0.035	0.008	0.610
Hours of care, unconditional on providing care	231	24,522	2.926	1.503	0.052	0.511	247	22,905	**3.516**	1.781	0.049	0.480
Hours of care, conditional on providing care	62	1281	8.383	7.360	0.259	0.221	70	1483	5.656	7.613	0.460	0.151
Potential AW's outcome as of $t + 1$												
Labor market participation	201	20,269	−0.019	0.031	0.543	−0.030	207	19,223	−0.030	0.031	0.324	−0.051
Hours, unconditional on LMP	197	20,075	−1.132	1.483	0.446	−0.045	207	19,005	−1.135	1.092	0.299	−0.067
Hours, conditional on LMP	138	17,167	−1.294	1.881	0.492	−0.035	121	14,384	−1.019	1.654	0.538	−0.036
Informal care provision to partner	197	20,178	0.042	0.034	0.220	0.356	200	19,160	**0.094**	0.039	0.015	0.657
Hours of care, unconditional on providing care	198	20,160	0.261	1.596	0.870	0.047	201	19,144	3.695	2.029	0.069	0.554
Hours of care, conditional on providing care	54	1011	0.380	8.282	0.964	0.012	58	1218	1.985	8.346	0.813	0.065

Note: ATT estimate in bold if significant at the conventional 5% level.

Source: UKHLS, waves 1–9.

for men and 15.7% for women). In the following year (i.e., $t + 1$), the increase in informal care provision persists for women in both statistical significance and magnitude, but loses statistical significance for men.

Table 8 and Figure 4, report results separately for individuals whose shocked partner does experience an increase in functional limitations (ADLs) when the health deterioration occurs, and for individuals whose partner does not. The remarkable gradient visible in the informal care adjustment, by shocked partner's increase in disability (number of functional limitations) documents the central role partners play as informal care providers, when that need arises. A lack of labor supply adjustment is common across the two subgroups of couples.[16] Such evidence suggests that beyond informal care needs other mechanisms (i.e., the Joint Leisure effect) act as counterweights to the income effect that would otherwise increase labor supply.

4.3 | Placebo checks

Balancing observed confounders does not guarantee against bias arising from additional unobserved confounders, such as risk and time preferences, potentially affecting both health and time use. In order to assess whether our strategy has successfully removed potential sources of bias, we estimate treatment effects for placebo outcomes, that is, outcomes for which the treatment is expected, a priori, to have no effect. This is, for example, the case for lagged outcomes observed at $t - 2$, 2 years before the health shock is reported, as the matching adjustment exploits only $t - 1$ outcomes as lagged outcomes. Significant ATTs estimated on outcomes at $t - 2$, would signal pre-existing differences in unobservables between treated couples and matched controls. However, results from this placebo test, reported in Table 9, reveal that, following preprocessing, no statistically significant difference in $t - 2$ outcomes is detected.

5 | CONCLUSION

We contribute to a limited literature on the existence of a health-related Added Worker Effect by providing novel direct evidence on the within household Caregiver Effect, that is, the informal care responses to a health shock of a partner as a mechanism that may counteract income effects that would otherwise increase a partner's labor supply.

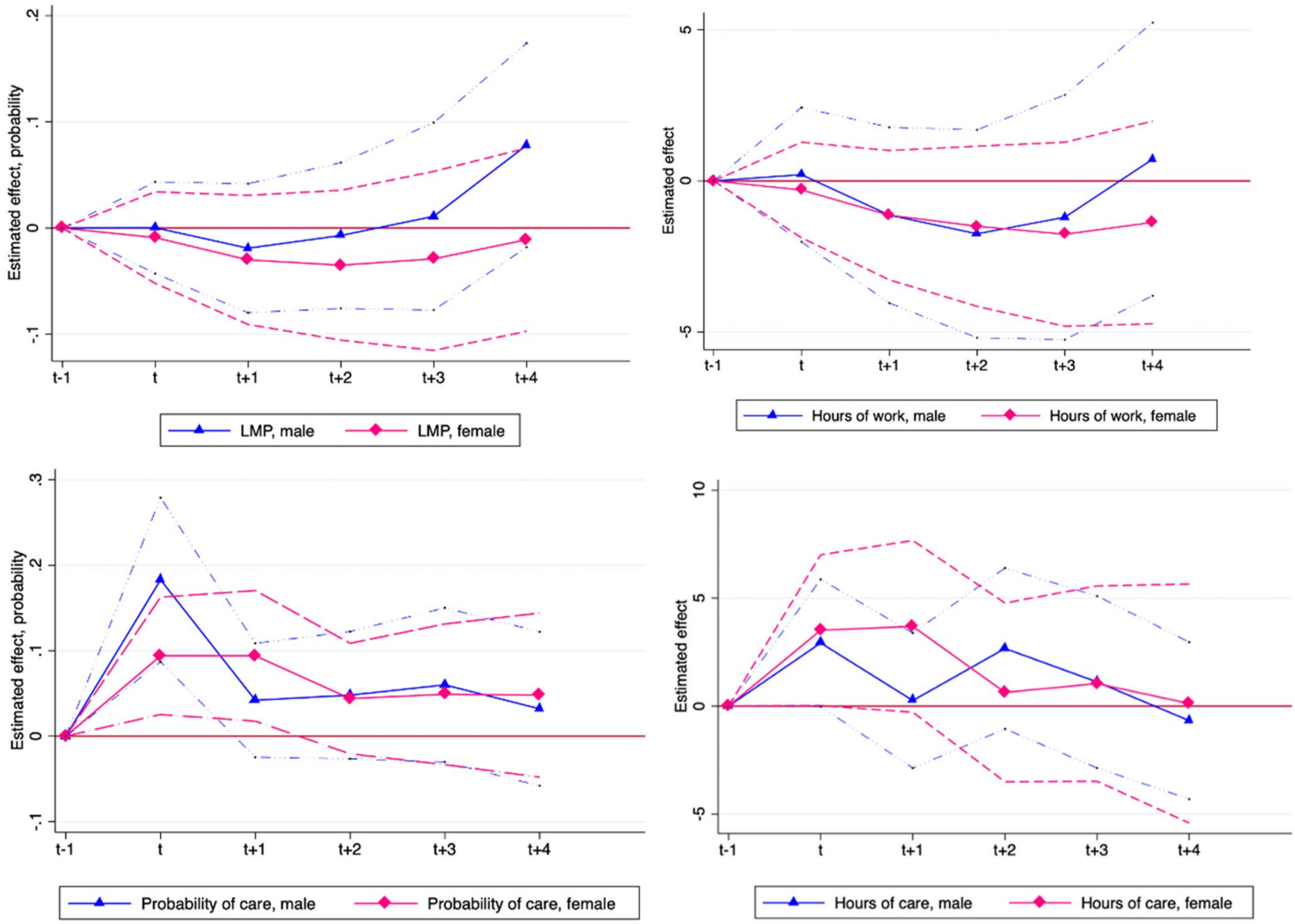

FIGURE 3 Behavioral response (ATT) to a partners' health shock, by potential AW's gender [Colour figure can be viewed at wileyonlinelibrary.com]

We do this by exploiting nine waves of panel data drawn from Understanding Society, where informal care provision is recorded. Major health events such as heart attacks, strokes and cancers, offer a source of unanticipated variation in the timing of health shocks. As the uniquely generous—in terms of variables and sample size - panel survey offers a rich set of observables including past health risk factors, we assume the chance that one partner experiences a major health shock at any particular point in time is conditionally random, and match couples where one partner experiences a health shock with observationally identical (in terms of labor, demographic, health, socioeconomic characteristics and lagged outcomes) controls. The matching algorithm combines Coarsened Exact Matching and Entropy Balancing, in a setting that offers a much larger number of control than treated units. ATTs are obtained through parametric modeling on the matched samples. Placebo tests on pre-shock outcomes fail to detect systematic differences between treated and matched control couples—which would have otherwise suggested a role for selection bias on unobservable characteristics.

Our work presents some limitations. While relying on survey data, as opposed to administrative records, allows the measurement of the informal care consequences of health shocks, it comes at the cost of a reduced sample size. Second, a caveat to identification under our approach is that a health shock might be proxying an underlying trend in health not observed in non-health shocked counterparts. This would lead to responses capturing, in part, the consequences of being on a potentially worse long-run health trajectory (see Ryan, 2018 for further discussion on the implications of matching on levels). However, even if the treated group was on a steeper declining health trajectory, this could also be regarded as part of the overall treatment effect (health deterioration) that we seek to measure. Finally, it is possible that a single health shock may be just the first of a series (e.g., multiple heart attacks or strokes) and in this respect, our selection of the first shock observed may introduce bias (Sandler & Sandler, 2014) by ignoring (or not observing) subsequent periods for people experiencing the most severe shocks.

Bearing these limitations in mind, results indicate that, in the case of UK couples where one partner experiences an acute health shock, there is no evidence that, on average, the labor supply of their partner increases. Our results hold whether or not the individual experiencing a health shock is active in the labor market prior to the shock. Our rejection of the AWE hypothesis

TABLE 8 ATT in the short run, by increase in shocked partner's number of limitations

	If no increase in reported ADLs						If increase in reported ADLs					
	n (treated)	*n* (controls)	ATT	Std. Err.	*p* Val	RSE	*n* (treated)	*n* (controls)	ATT	Std. Err.	*p* val	RSE
After 1 year (*t*)												
Labor market participation	321	42,862	0.001	0.019	0.956	0.002	159	3915	−0.000	0.028	0.992	0
Hours, unconditional on LMP	321	42,487	0.427	0.837	0.610	0.018	157	3879	−0.374	1.209	0.757	−0.017
Hours, conditional on LMP	210	34,656	0.604	0.856	0.481	0.017	89	2943	−1.009	1.506	0.504	−0.032
Informal care provision to partner	321	42,873	0.043	0.023	0.069	0.344	159	3916	**0.275**	0.061	0.000	2.254
Hours of care, unconditional on providing care	319	42,850	0.527	1.222	0.666	0.078	158	3908	**8.987**	2.465	0.000	1.537
Hours of care, conditional on providing care	62	1986	3.125	7.028	0.658	0.075	69	538	12.240	7.852	0.124	0.372
After 2 years (*t* + 1)												
Labor market participation	276	35,822	−0.022	0.027	0.407	−0.034	131	3136	−0.023	0.038	0.550	−0.042
Hours, unconditional on LMP	273	35,440	−1.118	1.086	0.304	−0.050	130	3107	−0.810	1.688	0.632	−0.042
Hours, conditional on LMP	180	29,015	−0.809	1.414	0.568	−0.024	78	2378	−2.237	2.659	0.402	−0.070
Informal care provision to partner	273	35,690	0.039	0.025	0.118	0.325	125	3116	**0.124**	0.057	0.029	0.743
Hours of care, unconditional on providing care	273	35,672	0.092	1.321	0.945	0.015	125	3103	**7.407**	2.849	0.010	1.311
Hours of care, conditional on providing care	54	1717	−3.306	7.617	0.666	−0.082	37	414	16.482	11.202	0.153	0.588

Note: ATT estimate in bold if significant at the conventional 5% level.

Source: UKHLS, waves 1–9.

is in line with the recent findings of Fadlon and Nielsen (2021) in Denmark and Dobkin et al. (2018) in the US. Instead, and although lacking in precision, our point estimates suggest a possible reduction in labor supply, at least in the short run, for both men and women, as found by Jeon and Pohl (2017) for Canada. In the UK context, the loss of labor income, which has been estimated to be around 7% of counterfactual individual earnings for shocked individuals (see Jones et al., 2020), does not result in a corresponding increase in their partners effort to earn labor income, at least in the short run. A plausible explanation for this is the presence of a national healthcare system in the UK, as opposed to an employment-contingent health insurance system, together with the availability of social security coverage in terms of disability-related benefits. Indeed, in related work Jones et al. (2020) detect a spike in disability benefit receipt after major income shocks, with an estimated ATT amounting to twice the baseline counterfactual value of disability benefit coverage.

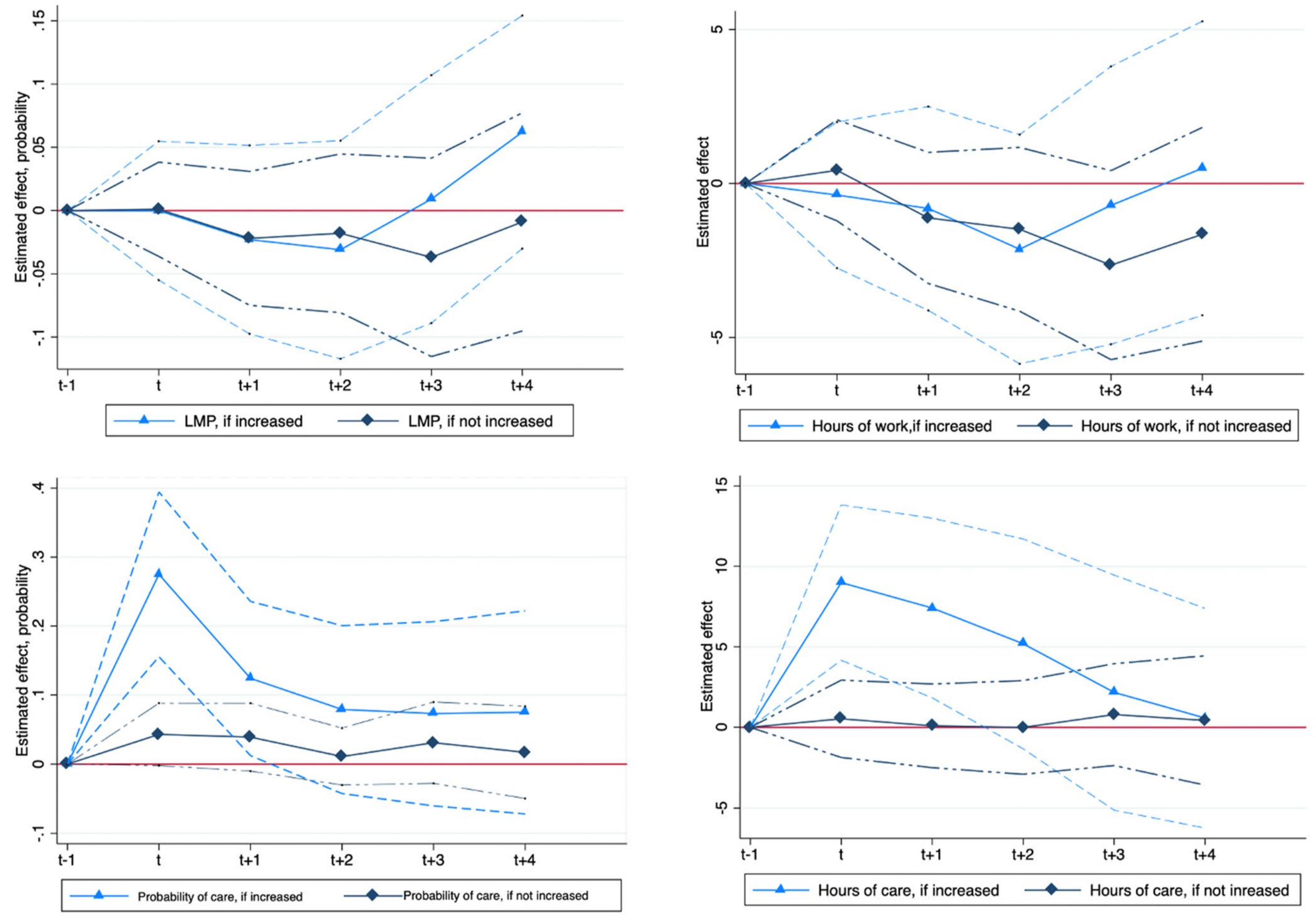

FIGURE 4 Behavioral response (ATT) to a partners' health shock, by increase in partner's number of limitations [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 9 Placebo checks: ATT on outcomes measured in $t-2$

	c (treated)	*n* (controls)	ATT	Std. Err.	*p* val
Outcomes as of $t-2$					
Labor market participation	356	38,514	−0.012	0.018	0.499
Hours worked	352	38,210	−0.034	0.832	0.967
Informal care provision to partner	356	38,491	0.004	0.015	0.781
Hours of care provided	355	38,467	1.170	1.112	0.293

Note: ATT estimate in bold if significant at the conventional 5% level.

Source: UKHLS, waves 1–9.

No evidence emerges for behavioral responses driven by gender specialization in labor income production versus home production (Riekhoff & Vaalavuo, 2021) which would have resulted in asymmetric responses by gender, with women increasing time devoted to paid work, and men increasing time devoted to informal care in the event of partners' health shock.

The novel contribution we offer is direct evidence on informal care provision, an outcome that administrative data sources used in recent studies fail to capture. We detect a significant informal care response to a partner's health shock. The increase is striking along the extensive margin, that is, in terms of increased likelihood of providing informal care, as opposed to the frequency of care conditional on being a carer. Such margin of response differs, interestingly, from that recently detected by Bergeot and Fontaine (2019) for the case of retirement in European countries. In their work, retirement does not impact the probability of providing care, but only its frequency, conditional on being a caregiver. Health shocks, instead, have emerged here as important triggers of care provision in the UK, where informal care plays a crucial role in meeting social care demands, even more so than the average of OECD countries (OECD, 2019).

Overall, our evidence confirms that the added worker effect can be rejected in favor of the joint caregiver and leisure complementarity hypotheses. But more than that, our results contribute to directly measuring the size of the caregiver effect, which turns out to be remarkable. The importance of measuring the caregiver effect separately is reinforced by the different implications that caregiving time and leisure time respectively display in terms of partners' mental health which is known to be substantively and persistently reduced by caregiving provision (as shown by Stockle & Bom, 2022, on the same Understanding Society data we use).

Population aging and the extension in working lives have profound implications for the design and reform of social protection and healthcare systems. As working life increases, so does the risk of experiencing a health shock while engaged in labor market activity. Health shocks represent a considerable source of economic risk. Indeed, informal care plays a crucial role in cushioning the adverse effect of such events within households, although the broader implications of such informal insurance mechanisms for household wellbeing is worthy of further research.

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CONFLICT OF INTEREST

Authors have no conflict of interest to declare.

DATA AVAILABILITY STATEMENT

Data can be requested to the UK Data Archive and obtained for non commercial usages.

ETHICS STATEMENT

We ensure the quality and integrity of our research and respect the confidentiality and anonymity of research respondents; no institutional or national ethical committee approval was required to conduct this research.

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ENDNOTES

[1] See also studies on labor market transitions away from full-time work, toward retirement or self-employment (Harris et al., 2021; Zhang et al., 2009; Zissimopoulos & Karoly, 2007).

[2] We are concerned with within household responses between partners. We use partners and spouses interchangeably, although we do not restrict analysis to married couples.

[3] Even for the unemployment related AWE, evidence on whether increases in labor supply happen or not, is mixed. According to Ashenfelter (1980), spousal labor supply acts as an insurance against partner's unemployment. Lundberg (1985), Juhn and Potter (2007), Ayhan (2018) and Giannakopoulos (2015) find a positive AWE, but only at the extensive margins. Analyzing different European countries, Bredtmann et al. (2017) relate the AWE variation registered along the extensive and intensive margins to welfare regimes and business cycles. However, Heckman and MaCurdy (1980) find no evidence of AWE and explain the result with lifecycle dynamics; Cullen and Gruber (2000) attribute the lack of AWE to the role of unemployment benefit programs. A further explanation is that women's low labor force attachment under a traditional division of labor could explain the lack of an AWE (Başlevent & Onaran, 2003; Bentolila & Ichino, 2008; Prieto-Rodriguez & Rodríguez-Gutiérrez, 2000). Relatedly, previous studies suggest that intra-household specialization plays a role in shaping spousal labor market adjustments.

[4] While the decline in earnings for the individual affected is estimated to be 19%, the corresponding reduction in household post-transfer income amounts to only 3%.

[5] For example, by considering how labor supply adjustments vary by income, and noting that the reduction in labor market participation is larger for higher income couples, Garcia-Gomez et al. (2013) hint at a preference for leisure as an explanatory mechanism, as higher income individuals can afford to purchase home production and informal services in the market. However, it might well be that partners prefer informal home production and care provision, despite market alternatives.

[6] In this study, we exploit heart attacks, strokes or cancers, for reasons explained in Section 3.1. The full list of conditions recorded in Understanding Society covers: asthma; arthritis; congestive heart failure; coronary heart disease; angina; heart attack or myocardial infarction; stroke;

emphysema; hyperthyroidism or an over-active thyroid; hypothyroidism or an under-active thyroid; chronic bronchitis; any kind of liver condition; cancer or malignancy; diabetes; epilepsy; high blood pressure; clinical depression.

[7] We use the combined the combined responses to two questions, firstly: "Is there anyone living with you who is sick, disabled or elderly whom you look after or give special help to (e.g., a sick, disabled or elderly relative, husband, wife or friend, etc)?" and secondly: "Now thinking about everyone who you look after or provide help for, both those living with you and not living with you—in total, how many hours do you spend each week looking after or helping them?". The response categories for the second question are bounded amounts, and we use the central value for each band (e.g., 7 where the response is the band "5–9") and 100 for the top band.

[8] Information on formal care received by (paid) providers is collected only in two waves.

[9] See Jones et al. (2020), and in particular Section 4, for further details on the matching techniques used here.

[10] In a further 6.3% of cases, two waves elapse since the previous interview. So, overall, in 97.5% of cases, either one or two waves elapse since the previous interview.

[11] Any previous diagnoses of high blood pressure, diabetes, congestive heart failure, coronary heart disease or angina.

[12] The ATT is expressed as a percentage of the contemporary average counterfactual outcome measured in the matched control sample.

[13] A similar increase occurs when including other household members, together with the shocked partner, suggesting that the bulk of additional informal care is devoted to the partner.

[14] The ATTs obtained for the labor market participation of the shocked partner, not reported here, are in line (3–4 per cent reduction in LMP in the first year past shock occurrence) with evidence from Jones e al. (2020) who, using the same data and methodological approach, report a 7 per cent reduction in the shocked individual's earnings.

[15] Descriptive statistics for gender-specific lagged outcomes are reported in the Appendix, Table A4.

[16] Sample size limitations hamper the possibility of studying couples where the shocked partner was working at baseline and then developing long term ADLs after the shock (a situation where the added worker effect might be most pronounced). However, results obtained on the small resulting subsample (84 observations) are reported in Table A5. These confirm the main results, that is, a lack of a significant labor supply response, but a significant increase in informal care provision (in terms of the probability of providing informal care).

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APPENDIX

TABLE A1 ATT in the short run, by type of condition experienced

	n (treat)	*n* (controls)	ATT	Std. Err.	*p* val
Potential AW outcome, as of *t*					
Heart attack or myocardial infarction					
Labor market participation	121	48,688	0.002	0.027	0.933
Informal care provision to partner	121	48,698	0.000	0.034	0.980
Stroke					
Labor market participation	67	48,686	0.015	0.046	0.750
Informal care provision to partner	67	48,696	0.150	0.079	0.056
Cancer or other malignancy					
Labor market participation	287	48,686	0.002	0.020	0.924
Informal care provision to partner	287	48,696	**0.215**	0.048	0.000

Note: ATT estimate in bold if significant at the conventional 5% level.

Source: UKHLS, waves 1–9.

TABLE A2 Descriptive statistics for AW's age and lagged outcomes, if shocked partner was labor market active as of ($t-1$)

	Mean	Std. Dev.
AW's age	51.81	7.82
Hours of work ($t-1$)	29.93	18.09
Hours of care ($t-1$)	2.05	10.62
Informal care provision ($t-1$)	0.05	0.23
Labor market participation ($t-1$)	0.83	0.38
Partner's age	52.97	7.85

Source: UKHLS, waves 1–9.

TABLE A3 ATT, if shocked partner's labor income ($t-1$) >50% of total household's income

	n (treated)	*n* (controls)	ATT	Std. Err.	*p* val	Relative effect
After 1 year (*t*)						
Labor market participation	250	35,487	0.005	0.019	0.791	0.006
Hours, unconditional on LMP	247	35,161	0.326	1.012	0.747	0.011
Informal care provision to partner	250	35,492	**0.201**	0.056	0.000	8.739
Hours of care	250	35,481	**2.847**	0.957	0.003	2.421
After 2 years ($t+1$)						
Labor market participation	213	29,665	−0.039	0.034	0.254	−0.048
Hours, unconditional on LMP	209	29,344	−1.466	1.334	0.272	−0.050

(Continues)

TABLE A3 (Continued)

	n (treated)	*n* (controls)	ATT	Std. Err.	*p* val	Relative effect
Informal care provision to partner	211	29,549	0.072	0.039	0.062	3.130
Hours of care	211	29,536	**2.463**	1.176	0.037	2.116

Note: ATT estimate in bold if significant at the conventional 5% level.

Source: UKHLS, waves 1–9.

TABLE A4 Descriptive statistics on potential AW's characteristics, by potential AW's gender

	Male		Female	
	Mean	Std. Dev.	Mean	Std. Dev.
AW's age	54.66	8.53	51.98	7.54
Hours of work ($t-1$)	27.56	21.16	19.49	18.44
Hours of care ($t-1$)	5.78	18.95	6.43	18.50
Informal care provision ($t-1$)	0.13	0.33	0.16	0.36
Labor market participation ($t-1$)	0.69	0.46	0.61	0.49
Partner's age	53.67	9.13	57.32	9.22

Source: UKHLS, waves 1–9

TABLE A5 ATT in the short run, if shocked partner was labor market active as of ($t-1$), by increase in shocked partner's number of limitations

	If no increase in reported ADLs						If increase in reported ADLs					
After 1 year (t)	*n* (treated)	*n* (controls)	ATT	Std. Err.	*p* Val	RSE	*n* (treated)	*n* (controls)	ATT	Std. Err.	*p* Val	RSE
Labor market participation	196	35,647	0.001	0.024	0.962	0.001	84	2989	0.035	0.029	0.227	0.045
Hours, unconditional on LMP	195	35,324	0.565	1.138	0.620	0.019	82	2955	−0.168	1.760	0.924	−0.006
Hours, conditional on LMP	158	29,977	0.877	0.967	0.365	0.024	66	2429	−1.728	1.720	0.317	−0.048
Informal care provision to partner	196	35,651	0.072	0.038	0.057	3.273	84	2989	**0.373**	0.105	0.000	5.738
Hours of care, unconditional on providing care	196	35,639	−0.349	0.765	0.648	−0.205	84	2987	**7.071**	2.629	0.008	2.530
Hours of care, conditional on providing care	19	1212	-	-	-	-	28	255	14.120	23.978	0.588	0.658

Note: ATT estimate in bold if significant at the conventional 5% level.

Source: UKHLS, waves 1–9.