The Short-Run Impact of Transitioning into Caregiving on Subjective Well-Being Using Evidence from the Understanding Society Survey

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Introduction

Informal caregiving plays a central role in the provision of long-term care in the United Kingdom, with a substantial proportion of support for individuals with health limitations provided by family members or friends. Understanding how transitions into caregiving affect subjective well-being is therefore crucial for assessing the welfare implications of existing care arrangements and for informing policies aimed at supporting carers.

Several empirical studies document a negative association between caregiving and psychological well-being. Identifying the causal effect of caregiving is empirically challenging, as caregiving entry is correlated with individual characteristics. Those who become caregivers may differ from non-carers in observable characteristics such as age and pre-treatment health, as well as in unobserved traits correlated with mental health. As a result, cross-sectional and pooled regression estimates may conflate the impact of caregiving with selection effects, limiting causal interpretation.

To address these concerns, several studies exploit longitudinal data and focus on transitions into caregiving rather than caregiving status at a single point in time. Using German panel data, Schmitz and Westphal (2015) apply propensity score matching (PSM) to estimate short- and medium-term health effects of caregiving entry, emphasising the importance of conditioning on pre-treatment characteristics and baseline outcomes. Using data from the UK Household Longitudinal Study, Xue et al. (2024) use PSM with longitudinal data to examine changes in subjective well-being around caregiving entry. These studies demonstrate that focusing on caregiving entry represents an important methodological improvement over purely cross-sectional analyses.

More recent research emphasises that adjustment to caregiving responsibilities evolves over time. Using a Difference-in-Differences (DiD) approach, Costi et al. (2023) examine short-run mental health responses to caregiving during the COVID-19 pandemic, exploiting variation in the timing of caregiving responsibilities. Similarly, Methi et al. (2024) document heterogeneous short-run changes across multiple dimensions of well-being following caregiving entry in Norway. These studies show that estimated caregiving effects depend on how caregiving entry and subsequent changes in well-being are modelled.

Taken together, this literature shows that estimated effects of caregiving entry are sensitive to the identifying assumptions underlying different empirical methods. Krämer and Bleidorn (2024) demonstrate that associations between caregiving transitions and well-being differ substantially depending on whether analyses rely on between-person regression models or within-person longitudinal specifications. This evidence underscores the importance of unobserved heterogeneity and emphasises the need to interpret empirical findings in relation to the identifying assumptions underlying each methodological approach. Regression and matching methods rely on selection-on-observables assumptions, whereas DiD designs exploit within-individual variation over time and account for time-invariant unobserved characteristics, conditional on the parallel trends assumption.

This paper examines the short-run relationship between entry into informal caregiving and subjective well-being using data from the Understanding Society Survey (UKHLS). The analysis focuses on individuals who are not caregivers prior to the treatment period and estimates the effect of caregiving entry on psychological well-being, measured using a reversed General Health Questionnaire (GHQ) Likert score. Empirical analysis applies and compares Ordinary Least Squares (OLS), PSM, and DiD within a unified framework. To support the DiD analysis, the sample period is extended to include multiple pre-treatment waves, allowing for an explicit assessment of the parallel trends assumption (Callaway and Sant'Anna, 2021). The feasibility of an instrumental variables strategy is also evaluated. Using English data, Eibich (2023) documents substantial limitations of commonly proposed instruments for caregiving, motivating the decision not to pursue an Instrumental variables estimation.

By comparing alternative empirical approaches within the UKHLS framework, this study contributes to the literature by demonstrating how estimated caregiving effects vary with underlying identifying assumptions.

Data and Methodology

2.1 Data

This study uses data from the UKHLS, a nationally representative longitudinal household survey of individuals resident in the United Kingdom. The analysis exploits the panel structure of the data to examine changes in subjective well-being around the transition into caregiving. The dataset contains UKHLS waves 2-9, which correspond to internal wave codes 1-8. All wave references use this internal coding.

The main empirical analysis focuses on waves 4 and 6 and is conducted using a balanced two-wave panel capturing subjective well-being immediately prior to and following caregiving entry. This design allows caregiving transitions to occur between observations while maintaining a clear comparison. To assess the parallel trends assumption underlying the DiD framework, the sample is extended to a balanced panel including waves 1, 2, 3, and 4 as the pre-treatment period and wave 6 as the treatment period.

Subjective well-being is measured using the GHQ Likert score. The measure is reversed so that higher values indicate higher levels of psychological well-being, facilitating interpretation of estimated coefficients.

The treatment of interest is entry into caregiving. An individual is classified as a carer if they report providing care either within the household or outside the household. Caregiving is measured using self-reported indicators and does not capture intensity or duration of care provision. The treatment group consists of individuals who do not report caregiving in the pre-treatment period and who enter caregiving between wave 4 and wave 6. Individuals who report caregiving in wave 4 or earlier are excluded from the analysis, ensuring that the comparison is between new carers and individuals who remain non-carers throughout the study period.

All control variables are measured in the pre-treatment wave. These include age, gender, educational attainment, marital or cohabiting status, number of children in the household, log of gross monthly personal income, long-standing illness or disability, British ethnicity, region of residence, and economic activity. Restricting covariates to the pre-treatment period avoids conditioning on post-treatment variables and ensures coherence across all empirical approaches.

2.2 Preliminary analysis

Table 1: Descriptive statistics for pre-treatment variables by caregiving entry status

Pre-treatment variables	Did not enter caregiving	Entered caregiving
Subjective well-being	25.29 (5.24)	24.68 (5.64)
Age	45.96 (16.31)	51.30 (15.38)
Male	0.46 (0.50)	0.39 (0.49)
Log gross income	7.17 (1.15)	7.06 (1.06)
Impairment	0.28 (0.45)	0.36 (0.48)
Married or cohabiting	0.80 (0.40)	0.81 (0.39)
Degree	0.43 (0.49)	0.36 (0.48)
Children	0.65 (0.98)	0.51 (0.91)
British	0.85 (0.36)	0.88 (0.33)

Table 1 reports descriptive statistics for pre-treatment variables measured in wave 4, separately for individuals who subsequently enter caregiving and those who do not. Means are reported with standard deviations in parentheses.

Table 2: Two-sample t-test with unequal variances for treatment-period subjective well-being

Group	Subjective well-being
Did not enter caregiving	25.48 (0.04)
Entered caregiving	24.57 (0.14)
Entered caregiving − Did not enter caregiving	−0.91 (0.14)

Table 2 reports the results of a two-sample t-test with unequal variances comparing treatment-period subjective well-being between individuals who enter caregiving and those who do not. Means are reported with standard errors in parentheses.

Full variable definitions are reported in appendix A.

2.3 Empirical Strategy

The empirical strategy compares alternative methods for estimating the effect of caregiving entry on subjective well-being, including OLS, PSM, and DiD. Each approach rests on distinct identifying assumptions, enabling an explicit assessment of how estimated effects vary with those assumptions.

2.4 Ordinary Least Squares

As a baseline specification, the effect of caregiving entry is estimated using OLS regression:

$$Y_{i6} = \beta_0 + \beta_1 \text{Treatment}_i + \beta_2 x_{i4} + \varepsilon_i,$$

where Y_{i6} denotes subjective well-being for individual i in wave 6, Treatment_i is an indicator for entry into caregiving, X_{i4} is a vector of control variables measured in wave 4, and ε_i captures unobserved determinants of well-being.

The coefficient β_1 measures the association between caregiving and subjective well-being conditional on observed characteristics. Identification requires that, conditional on X_{i4}, caregiving entry is independent of unobserved determinants of well-being. While this assumption is strong, the OLS estimates provide a useful benchmark against which more restrictive models can be assessed.

2.5 Propensity Score Matching

To address concerns regarding functional form and covariate imbalance, PSM is used to estimate the Average Treatment Effect on the Treated (ATT). Propensity scores are estimated using a binary response model conditioning on the same pre-treatment covariates included in the OLS specification.

Let $p(X_i) = P(\text{Carer}_{i6} = 1 \mid X_{i4})$ denote the estimated propensity score. Treated individuals are matched to non-treated individuals with similar propensity scores, and the ATT is computed as the average difference in outcomes between matched observations.

Propensity scores are estimated using both logit and probit specifications to assess sensitivity to functional form. Covariate balance and common support are assessed using standard post-matching diagnostics. As with OLS, PSM relies on a selection-on-observables assumption and therefore serves as a robustness exercise rather than a distinct identification strategy.

2.6 Difference-in-Differences

The primary causal estimates are obtained using a DiD design, which exploits within-individual changes in subjective well-being around the transition into caregiving. This approach controls for unobserved, time-invariant individual characteristics that may jointly influence caregiving and mental health.

The DiD specification is:

$$Y_{it} = \alpha + \delta \,\mathrm{Treatment}_i + \lambda \,\mathrm{Post}_t + \beta(\mathrm{Treatment}_i \times \mathrm{Post}_t) + u_{it},$$

where $\mathrm{Treatment}_i$ identifies individuals who enter caregiving by wave 6, Post_t is an indicator for the post-treatment period, and β is the DiD estimator of interest and captures the average change in subjective well-being associated with caregiving entry relative to individuals who do not enter caregiving over the same period. Additional specifications include pre-treatment covariates to improve precision. Standard errors are clustered at the individual level to account for serial correlation and heteroskedasticity.

The validity of the DiD estimator depends on the parallel trends assumption, which requires treated and control individuals to have followed similar trends in subjective well-being in the absence of caregiving. This assumption is assessed using pre-treatment data from waves 1 to 4.

2.7 Instrumental Variables Assessment

The feasibility of an instrumental variable strategy is also evaluated. A valid instrument must predict caregiving entry while affecting subjective well-being only through caregiving. Candidate instruments such as age and household composition are examined empirically for relevance and assessed theoretically for plausibility of the exclusion restriction.

Although some variables are correlated with caregiving entry, they are also plausibly related to subjective well-being through factors other than caregiving, including mental health, labour market outcomes, and life-cycle factors. As a result, the exclusion restriction cannot be credibly justified. Instrumental variables estimation is therefore not pursued, as the absence of a credible exclusion restriction would likely introduce more bias than it resolves.

2.8 Summary

This analysis outlines a coherent empirical framework for estimating the short-run effect of caregiving entry on subjective well-being. By comparing estimates across OLS, PSM, and DiD, the analysis evaluates the sensitivity of results to alternative identifying assumptions. Among these approaches, the DiD design provides the most credible identification strategy, conditional on the validity of the parallel trends assumption.

Results and Discussion

3.1 Results

Table 3: Estimated effect of caregiving entry on subjective well-being (reversed GHQ)

Method	Estimate	Std. Error	Observations
OLS (naive)	-0.907^{***}	0.143	17,147
OLS (controls)	-0.777^{***}	0.139	17,147
PSM ATET (logit, controls)	-0.889^{***}	0.192	3,330
PSM ATET (probit, controls)	-0.862^{***}	0.188	3,330
DiD (two-wave)	-0.339^{**}	0.140	36,496
DiD (two-wave, controls)	-0.304^{**}	0.142	34,294
DiD (extended pre-period)	-0.545^{***}	0.176	49,165

* p < 0.10, ** p < 0.05, *** p < 0.01.

All controlled specifications include the same set of pre-treatment covariates measured in wave 4. Heteroskedasticity-robust standard errors are reported for OLS and PSM estimates, and DiD specifications report individual-level clustered standard errors. A full list of control variables is reported in appendix A.

Table 3 reports estimated effects of caregiving entry on subjective well-being, measured using the reversed GHQ Likert score, across alternative empirical approaches. Each coefficient captures the estimated difference in subjective well-being between individuals who enter caregiving and those who do not over the same period.

OLS estimates indicate that individuals who enter caregiving experience a reduction of approximately 0.91 GHQ points in the treatment period relative to non-carers. Conditioning on pre-treatment covariates reduces the estimate to −0.78, though the effect remains highly statistically significant.

PSM yields estimates of similar magnitude. The Average Treatment Effect on the Treated is −0.89 when propensity scores are estimated using a logit specification and −0.86 under a probit specification. The close correspondence between PSM and controlled OLS estimates indicates limited sensitivity to functional form assumptions in the propensity score model.

DiD estimates are smaller in magnitude than those obtained using OLS and PSM but remain statistically significant. Using a two-wave regression-based specification, the estimated effect of caregiving entry is −0.34, declining to −0.30 when pre-treatment covariates are included. Extending the pre-treatment period to include waves 1 through 4 and applying a multi-period DiD estimator yields a larger estimate of −0.55. Although these specifications differ in implementation, both exploit within-individual variation over time to identify changes in subjective well-being associated with caregiving entry under the maintained DiD assumptions.

3.2 Parallel trends assessment

Figure 1: Parallel trends in subjective well-being before caregiving entry

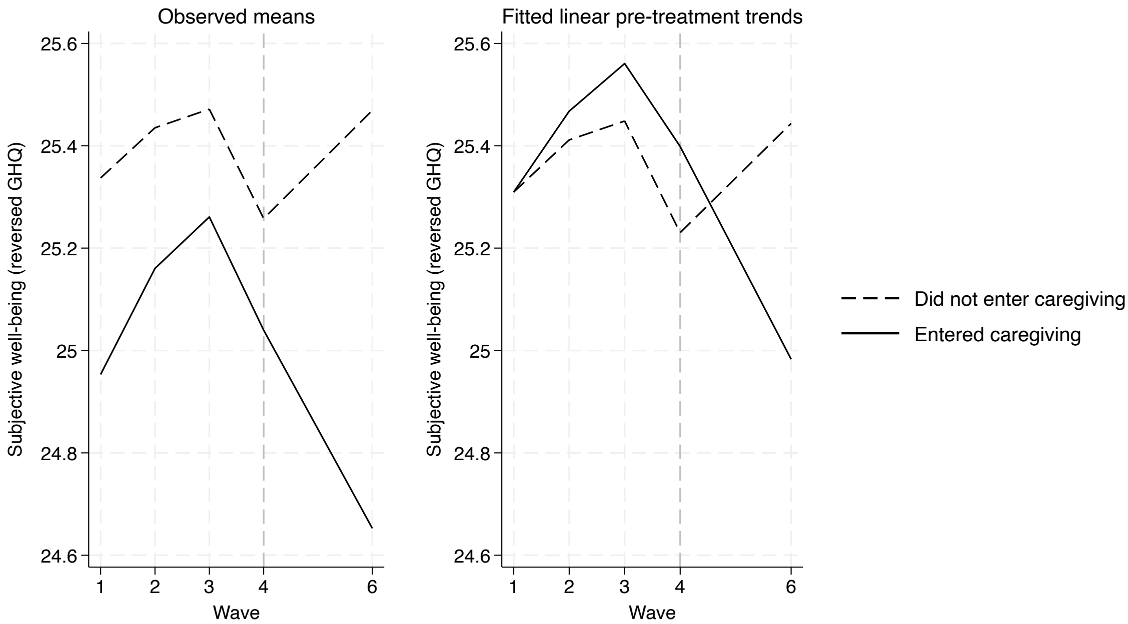


Figure 1 presents graphical evidence relevant to the parallel trends assumption underlying the DiD design. The left panel plots observed mean reversed GHQ scores for individuals who later enter caregiving and those who do not across the pre-treatment period. The right panel displays fitted linear trends estimated using pre-treatment observations only. Wave 4 denotes the final pre-treatment period.

A formal test of differential pre-treatment trends fails to reject the null hypothesis of equal trends between treated and control groups ($F = 0.63$, $p = 0.429$). While failure to reject the null does not constitute proof of parallel trends, the combination of graphical evidence and the formal test provides no indication of systematically different pre-treatment dynamics between future carers and non-carers. This supports the use of the DiD framework in the analysis, conditional on the maintained assumption of parallel trends.

3.3 Discussion

The results indicate that entry into informal caregiving is associated with a statistically significant short-run decline in subjective well-being. Although the estimated magnitude varies across empirical approaches, the negative sign is consistent across all specifications. This pattern suggests that caregiving entry is systematically associated with adverse psychological outcomes, while underscoring the importance of identifying assumptions in shaping estimated effects.

Estimates obtained using OLS and PSM are relatively large in magnitude. Both approaches rely on selection-on-observables assumptions and therefore may reflect not only the effect of caregiving entry, but also residual differences driven by unobserved characteristics correlated with both caregiving and mental health. The close correspondence between controlled OLS and PSM estimates indicates that adjusting for observed characteristics alone does not substantially alter the estimated association. This finding is consistent with matching-based evidence documenting sizeable, short-run declines in well-being around caregiving transitions (Schmitz and Westphal, 2015).

DiD estimates are smaller in magnitude but remain statistically significant. The attenuation observed when moving from OLS and PSM to DiD estimates is consistent with the DiD framework differencing out time-invariant unobserved characteristics that may jointly influence caregiving entry and subjective well-being. This pattern aligns with longitudinal evidence showing that between-person estimates tend to overstate within-individual changes following caregiving transitions (Krämer and Bleidorn, 2024). Nevertheless, DiD estimates may still be affected by time-varying unobserved factors correlated with caregiving entry, which cannot be fully excluded in observational data.

The extended pre-treatment DiD specification yields a larger estimate than the two-wave design, indicating some sensitivity to sample construction and the choice of comparison periods. Graphical analysis and formal tests however provide no evidence of differential pre-treatment trends between future carers and non-carers, supporting the plausibility of the parallel trends assumption. This emphasis on pre-treatment dynamics is consistent with methodological guidance for multi-period DiD designs (Callaway and Sant'Anna, 2021).

Overall, the comparison across empirical approaches illustrates that estimated caregiving effects are sensitive to identifying assumptions. While regression and matching methods yield larger estimates under selection-on-observables assumptions, DiD provides more conservative evidence by exploiting within-individual variation over time. Conditional on the maintained assumptions, the DiD results therefore offer the most credible evidence on the short-run association between caregiving entry and subjective well-being in the present analysis.

Conclusion

This study examines the short-run impact of transitioning into caregiving on subjective well-being using longitudinal data from the UKHLS. Across all empirical approaches, caregiving entry is associated with a statistically significant decline in psychological well-being. Estimates from OLS and PSM are larger in magnitude, while DiD estimates are smaller but remain statistically significant, consistent with between-person estimates overstating effects due to unobserved heterogeneity. Evidence from extended pre-treatment periods supports the parallel trends assumption, strengthening the credibility of the DiD results.

The findings suggest that entry into caregiving is associated with immediate well-being costs, which is relevant for the assessment of policies that rely on informal care provision. The analysis is limited to short-run effects and cannot account for longer-term adaptation or time-varying unobserved factors. While instrumental variables strategies have been proposed in related work, the absence of a credible instrument in this setting constrains their applicability. Future research could extend this framework by examining longer horizons, heterogeneity by caregiving intensity or relationship to the care recipient, and by exploiting settings where more compelling sources of exogenous variation in caregiving entry are available.

Appendix

Appendix A: Variable Definitions

Core variables

Variable	Definition
Subjective well-being	Reversed GHQ Likert score ($36 - GHQ\ Likert$)
Carer	Indicator equal to 1 if individual reports providing care within or outside the household
Treatment	Indicator equal to 1 if individual enters caregiving between waves 4 and 6
Post	Indicator equal to 1 for post-treatment period
$Treatment \times post$	Interaction identifying caregiving entry in the post-treatment period

Pre-treatment control variables

Variable	Definition
Age	Age in years
Age squared	Age in years squared
Male	Indicator equal to 1 if male
Log gross income	Log of monthly gross personal income
Impairment	Indicator equal to 1 if long-standing illness or disability
Married or cohabiting	Indicator equal to 1 if married or cohabiting
Degree	Indicator equal to 1 if degree or higher degree is highest level of qualification
A Level	Indicator equal to 1 if A-level is highest level of qualification
GCSE	Indicator equal to 1 if GCSE is highest level of qualification
Children	Number of children in household
British	Indicator equal to 1 if British ethnicity
Region	Government Office Region
Economic activity	Labour market status

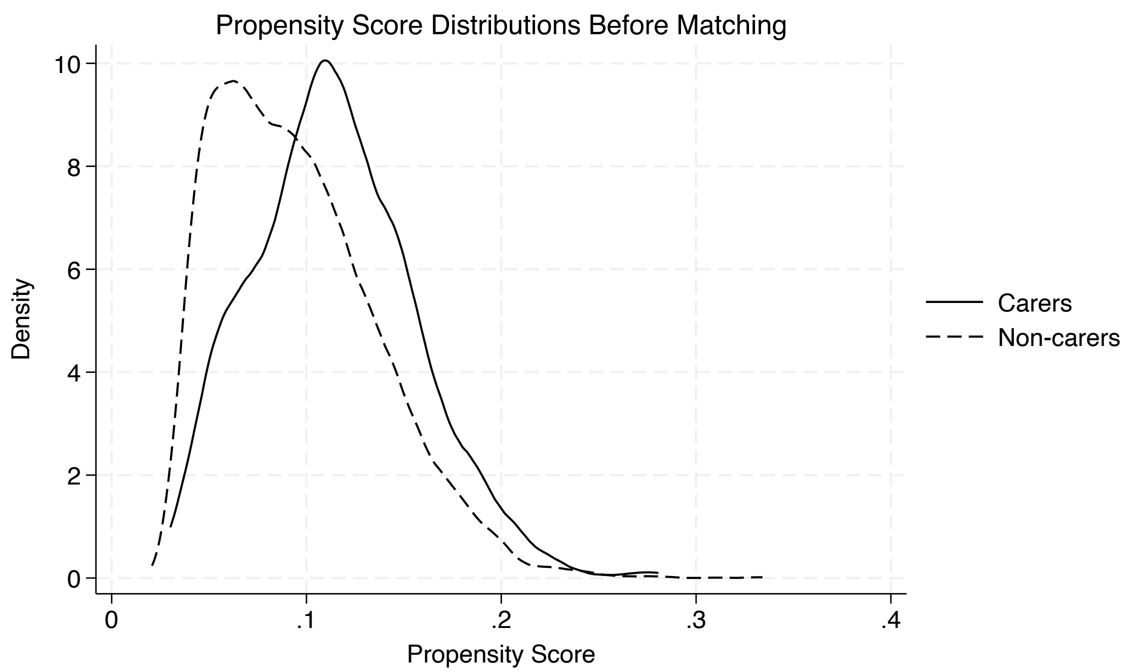
Appendix B: Propensity Score Matching Diagnostics

Table B1: Covariate balance before and after propensity score matching

Variable	Raw standardised difference	Matched standardised difference
Age	0.337	−0.029
Age squared	0.312	−0.025
Male	−0.146	−0.029
Log gross income	−0.102	0.001
Impairment	0.174	−0.014
Married or cohabiting	0.018	−0.042
Degree	−0.130	−0.010
A Level	−0.029	−0.013
GCSE	0.037	−0.003
Children	−0.145	−0.001
British	0.082	0.002

Standardised differences are reported before and after matching. Region and economic activity indicators are included in the propensity score model but are omitted from Table B1.

Figure B1: Propensity score distributions before matching



Appendix C: Full Regression Results

Table C1: Naive Ordinary Least Squares Estimates

Dependent variable: Reversed GHQ Likert score (wave 6)

Variable	Coefficient
Treatment (caregiving entry)	-0.907***
	(0.143)
Constant	25.48***
	(0.0409)
R-squared	0.003
Observations	17147

Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C2: Ordinary Least Squares Estimates with Pre-Treatment controls

Dependent variable: Reversed GHQ Likert score (wave 6)

Variable	Coefficient
Treatment (caregiving entry)	-0.777***
	(0.139)
Male	0.869***
	(0.0802)
Age	-0.105***
	(0.0168)
Age squared	0.00151***
	(0.000176)
Log gross income	-0.00917
	(0.0394)
Impairment	-2.114***
	(0.0970)
Married or cohabiting	0.412***
	(0.128)
Degree	0.477***
	(0.124)
A Level	0.298**
	(0.138)
GCSE	0.200
	(0.136)
Children	-0.151***
	(0.0486)
British	0.140
	(0.125)
Constant	26.65***
	(0.482)
Region	included
Economic activity	included
R-squared	0.063
Observations	17147

Robust standard errors in parentheses. All covariates measured in wave 4.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C3: Two-wave Difference-in-Differences Estimates with pre-treatment controls

Dependent variable: Reversed GHQ Likert score

Variables	Coefficient
Treatment (caregiving entry)	-0.424***
	(0.139)
Post	0.192***
	(0.0425)
$Treatment \times post$	-0.304**
	(0.142)
Male	0.850***
	(0.0691)
Age	-0.142***
	(0.0147)
Age squared	0.00185***
	(0.000156)
Log gross income	0.0427
	(0.0350)
Impairment	-2.234***
	(0.0840)
Married or cohabiting	0.619***
	(0.111)
Degree	0.503***
	(0.108)
A Level	0.334***
	(0.120)
GCSE	0.262**
	(0.119)
Children	-0.162***
	(0.0419)
British	0.175
	(0.107)
Constant	26.98***
	(0.423)
Region	Included
Economic activity	Included
R-squared	0.069
Observations	34294

Standard errors clustered at the individual level in parentheses. All covariates measured in wave 4.

The $\text{Treatment} \times \text{post}$ coefficient identifies the Difference-in-Differences estimator.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C4: Two-wave Difference-in-Differences Estimates

Dependent variable: Reversed GHQ Likert score

Variable	Coefficient
Treatment (caregiving entry)	-0.566***
	(0.141)
Post	0.218***
	(0.0418)
$Treatment \times post$	-0.339**
	(0.140)
Constant	25.22***
	(0.0414)
R-squared	0.002
Observations	36496

Standard errors clustered at the individual level in parentheses.

The $\mathrm{Treatment} \times \mathrm{post}$ coefficient identifies the Difference-in-Differences estimator.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C5: Difference-in-Differences with extended pre-treatment period

Dependent variable: Reversed GHQ Likert score

Variable	Coefficient
ATET (caregiving entry)	-0.545***
	(0.176)
Wave 2	0.106**
	(0.0491)
Wave 3	0.147***
	(0.0522)
Wave 4	-0.0673
	(0.0530)
Wave 6	0.140**
	(0.0560)
Constant	25.31***
	(0.0332)
Observations	49165

Standard errors clustered at the individual level in parentheses.

Wave coefficients represent time fixed effects relative to the omitted base period (Wave 1).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

AI Declaration

I confirm that artificial intelligence tools were used in the preparation of this assignment.

Tool used: ChatGPT
Purpose: Clarification of econometric concepts, assistance with structuring academic arguments, and proofreading for clarity and grammar.
Extent of use: Moderate.

AI-generated content was adapted to suit my preferred academic style and was not used to generate original empirical analysis. Any factual content was independently verified using academic sources.

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