The Cognitive Cost of Furlough: Evidence from UKHLS COVID-19 Panel

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1 Introduction

The COVID-19 pandemic created an unprecedented economic and social shock, leading governments around the world to implement emergency employment protection measures. In the United Kingdom, the Coronavirus Job Retention Scheme (CJRS), widely known as the furlough scheme, was introduced in March 2020. The scheme aimed to cushion the economic fallout by subsidising wages for workers who were temporarily unable to work. While furlough effectively mitigated income loss and prevented large-scale unemployment, its broader effects on individual wellbeing—particularly mental health—are still underexplored.

This paper examines the causal impact of being furloughed on cognitive aspects of mental health. Cognitive mental health, encompassing concentration, confidence, and decision-making, is crucial not only for individual functioning but also for long-term employability and productivity. Understanding whether temporary detachment from work leads to cognitive strain has important implications for the design of future employment retention policies.

Using panel data from the UK Household Longitudinal Study (UKHLS) COVID-19 waves, we estimate the effect of furlough on cognitive symptoms derived from the General Health Questionnaire (GHQ-12). Our findings suggest that furlough has a statistically significant positive effect on cognitive mental health.

2 Literature Review

A substantial body of literature has established the close link between employment and mental health. Unemployment has been repeatedly shown to impair mental wellbeing, including elevated risks of depression, anxiety, and cognitive strain (Clark and Oswald, 1994; Paul and Moser, 2009). Job insecurity—common during economic downturns or among precarious contracts—has also been associated with deteriorating psychological outcomes (De Witte, 1999; Brodeur et al., 2021).

During the COVID-19 crisis, countries implemented emergency employment protection schemes. In the UK, the Coronavirus Job Retention Scheme (CJRS), or furlough scheme, allowed workers to remain employed while temporarily ceasing work, supported by government-subsidised income. While furlough reduced job loss (Kantamneni, 2020; EuroHealth Observatory, n.d.), the broader mental health implications are less well understood.

Several studies indicate furlough may be psychologically taxing. Adams-Prassl et al. (2020) find that furloughed individuals reported worse subjective wellbeing than those fully employed, despite receiving income support. Similarly, Banks and Xu (2020) observed mental health deterioration across the UK population during lockdown, especially among younger adults and women. Etheridge and Spantig (2022) further show that gender disparities widened at the onset of the pandemic, highlighting how mental wellbeing effects were unevenly distributed.

However, the mechanisms remain contested. Some argue furlough protects mental health by reducing job loss and income shocks (Layard et al., 2020), while others highlight that uncertainty around work resumption and long-term employment can fuel stress and cognitive difficulties (Blustein et al., 2020; Giuntella et al., 2021). These tensions reflect broader debates about how the pandemic affected lifestyle, routine, and social structure.

Another strand of literature focuses on cognitive function under financial stress. Mani et al. (2013) demonstrate that scarcity narrows mental bandwidth, impairing attention and decision-making. Haushofer and Fehr (2014) find poverty-related stress reduces cognitive performance and executive function, suggesting that even without outright unemployment, economic uncertainty can erode mental clarity. Frijters et al. (2014) support this by showing that childhood economic hardship can have lasting effects on adult satisfaction and psychological resilience.

Importantly, employment also provides non-monetary benefits such as routine, structure, and social engagement (Helliwell and Putnam, 2004). Disrupting these through furlough may contribute to feelings of isolation and reduced stimulation. Giuntella et al. (2021) note how lifestyle changes under lockdown correlated with poorer mental health outcomes, further highlighting the complex interplay between work, routine, and wellbeing.

In addition to conceptual links, methodological concerns matter when identifying causal effects. Layard et al. (2020) and van den Berg et al. (2015) advocate for instrumental variable (IV) approaches to address endogeneity in health and economic research. This paper follows this strategy by using inability to work from home as an instrument for furlough status.

Overall, this study contributes to a growing literature that explores the psychological toll of COVID-19 labour market interventions. By focusing on cognitive wellbeing—often overlooked in favour of general or affective symptoms—and applying an IV design, it complements broader pandemic-focused economic reviews (Brodeur et al., 2021) and provides new insights into the mental health trade-offs of furlough.

3 Data

This paper draws on individual-level panel data from the UK Household Longitudinal Study (UKHLS) COVID-19 Survey, also known as *Understanding Society COVID-19*. The survey covers the early stages of the pandemic, with monthly waves from April to September 2020, and provides rich information on employment status, earnings, mental health, and pandemic-related disruptions.

We restrict the sample to individual who were observed in at least one of the first five COVID-19 survey waves and have complete information on furlough status, cognitive mental health outcomes, and key demographics. The resulting dataset (`covid_combined`) includes approximately 73,000 pooled observations across five months and captures a wide range of socio-economic and employment characteristics.

3.1 Outcome Variable

Our main outcome is a measure of cognitive mental health, constructed from the General Health Questionnaire (GHQ-12). Following standard practice, each GHQ item is scored using a 0-0-1-1 binary transformation, where the two least symptomatic responses are coded as 0, and the two most symptomatic responses are coded as 1. This scoring captures the presence of cognitive or psychological symptoms rather than their intensity. So a negative effect in the regression is a good thing

From the GHQ-12, we isolate two items specifically related to cognitive strain: difficulty concentrating (`scghqa`) and problems with decision-making (`scghqj`). We sum these two binary indicators to create a cognitive GHQ sub-index (`ghq_cognitive`), which serves as our primary dependent variable.

To examine the broader implications of furlough on mental health, we also construct secondary sub-indices for:

- Depression (e.g., feelings of worthlessness, loss of confidence),
- Stress (e.g., sleep disturbance, feeling under strain),
- Functionality (e.g., inability to enjoy daily activities), and
- General happiness.

Each domain-specific index is calculated by summing the relevant binary GHQ items. In additional analysis, we also extract a single latent mental health factor using Principal Component Analysis (PCA) to serve as a continuous index of overall mental distress.

3.2 Treatment and Instrument

The key explanatory variable is a binary indicator for being furloughed (`furlough_status`). It harmonizes responses from three wave-specific furlough questions: `furlough`, `newfurlough`, and `stillfurl`. Individuals are coded as furloughed if they were either newly furloughed or still on furlough at the time of interview.

To address endogeneity in furlough take-up, we instrument `furlough_status` using a binary indicator for whether the individual reported being unable to work from home prior to the pandemic (`low_wfh`). This proxy captures exogenous variation in exposure to furlough due to occupational constraints and satisfies the relevance and exclusion assumptions, as demonstrated in Section 5.

3.3 Harmonisation and Sample Cleaning

Raw COVID-19 survey files were merged and harmonised by removing wave-specific prefixes, aligning variable formats, and filtering out missing or inapplicable responses. All negative survey codes (e.g., –1 "don't know", –8 "refusal") were treated as missing (`NA`). Employment status was derived using `sempderived`, income was cleaned and log-transformed (`log_netpay`), and identifiers such as `pidp` and `wave_short` allow panel tracking across months.

The final dataset balances temporal resolution, mental health depth, and instrumental validity, making it well-suited to identify the causal effect of furlough on cognitive wellbeing during the first phase of the COVID-19 crisis.

4 Empirical Strategy

To estimate the causal effect of being furloughed on cognitive aspects of mental health during the COVID-19 pandemic, we begin by comparing individuals who were furloughed to those who were not using an Ordinary Least Squares (OLS) regression:

$$\mathrm{GHQ}_{iw} = \alpha + \beta \cdot \mathrm{Furlough}_{iw} + \mathbf{X}'_{iw}\gamma + \lambda_w + \epsilon_{iw} \tag{1}$$

where GHQ_{iw} is the cognitive mental health outcome for individual i in wave w, $\mathrm{Furlough}_{iw}$ is an indicator for being furloughed, $\mathbf{X}'_{iw}$ is a vector of control variables (age, sex, couple status), and λ_w are wave fixed effects. However, because furlough status may be endogenous—potentially driven by unobserved risk factors that also affect mental health—OLS may yield biased estimates of β.

We therefore implement an Instrumental Variables (IV) strategy using a Two-Stage Least Squares (2SLS) framework. Our instrument is a binary indicator for whether the respondent reported low ability to work from home prior to the pandemic, denoted as LowWFH_{iw}.

The first stage estimates the relationship between the instrument and furlough status:

$$\mathrm{Furlough}_{iw} = \pi_0 + \pi_1 \cdot \mathrm{LowWFH}_{iw} + \mathbf{X}'_{iw}\delta + \lambda_w + \nu_{iw} \tag{2}$$

The second stage then estimates the causal effect of predicted furlough on cognitive mental health:

$$\mathrm{GHQ}_{iw} = \alpha + \beta \cdot \widehat{\mathrm{Furlough}}_{iw} + \mathbf{X}'_{iw}\gamma + \lambda_w + \epsilon_{iw} \tag{3}$$

The IV strategy relies on two key assumptions:

1. **Relevance:** The instrument must be correlated with the endogenous variable. This is confirmed by a strong first-stage F-statistic that exceeds conventional thresholds, supporting the validity of LowWFH_{iw} as a strong predictor of furlough status.

2. **Exclusion Restriction:** The instrument must affect cognitive mental health only through its impact on furlough status. Formally,

$$\mathrm{Cov}(Z_{iw}, \epsilon_{iw}) = 0$$

This assumption holds if, conditional on observed characteristics and fixed effects, the inability to work from home does not directly impact cognitive wellbeing—only indirectly through its effect on furlough. As WFH ability was measured before the pandemic and driven largely by occupational characteristics, it is unlikely to independently influence mental health outcomes. Furthermore, we control for sex, age, couple status, and wave fixed effects. Any residual correlation between WFH ability and mental health would likely reflect the furlough mechanism rather than a direct channel. This structure is illustrated in Figure 1 below.

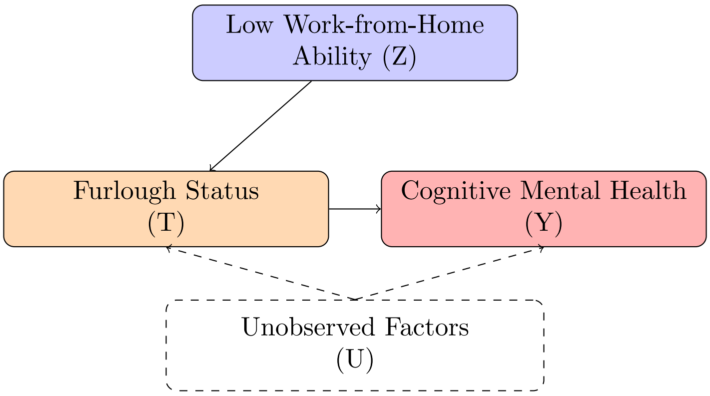

Figure 1: Causal DAG illustrating IV assumptions — *LowWFH* affects cognitive mental health only through furlough status

This approach identifies the Local Average Treatment Effect (LATE)—the causal effect of furlough on cognitive mental health for compliers, i.e., individuals whose furlough status was influenced by their work-from-home ability. This contrasts with the Average Treatment Effect (ATE), which cannot be recovered in the presence of endogeneity without stronger assumptions.

4.1 Heterogeneous Effects

To explore whether the mental health burden of furlough is concentrated among more vulnerable populations, we estimate heterogeneity in treatment effects by interacting predicted furlough status with subgroup indicators:

$$GHQ_{iw} = \beta_0 + \beta_1 \cdot \widehat{\text{Furlough}}_{iw} + \beta_2 \cdot (\widehat{\text{Furlough}}_{iw} \cdot Z_i) + \mathbf{X}'_{iw}\gamma + \lambda_w + \epsilon_{iw} \tag{4}$$

where Z_i denotes subgroup indicators such as low income, male, over 40, or in a couple. These specifications provide differential LATEs by subgroup.

4.2 Robustness Checks

To assess the credibility of our identification strategy, we conduct several robustness checks:

- Include additional covariates (e.g., income, keyworker status)
- Restrict sample to working-age adults (18–65)
- Estimate models excluding May wave to assess temporal sensitivity
- Test alternative GHQ subdomains (e.g., depression, stress)
- Use PCA-derived mental health index
- Run a placebo test using a synthetic outcome

These checks ensure that results are not driven by model artifacts or specific sampling decisions, strengthening the internal validity of our design.

5 Results

5.1 Covariate Balance

To assess potential confounding, we examine covariate balance by instrument status (low work-from-home ability, *low_wfh*). Table 1 presents summary statistics and standardized mean differences (SMDs), allowing us to identify systematic differences between groups.

Several covariates show notable imbalances. Individuals with low *WFH* ability are more likely to be male, in a couple, and younger (SMDs: 0.13–0.27). Larger imbalances are observed for log net pay (SMD = 0.46) and furlough status (SMD = 0.34), suggesting that low *WFH* ability is associated with both lower earnings and higher likelihood of furlough. In contrast, essential worker status is well balanced (SMD = 0.03, $p = 0.115$), reducing concerns about confounding from occupational exposure.

These differences highlight the need to control for observables when estimating treatment effects. At the same time, the strong association between *low_wfh* and furlough supports its relevance as an instrument.

Table 1: Covariate Balance by Instrument Status (Low Work-from-Home Ability)

Covariate	**Low WFH = 0**	**Low WFH = 1**	**p-value**	**SMD**
Sample size (n)	4078	8292	–	–
Age (mean, SD)	47.31 (12.01)	44.13 (13.65)	<0.001	0.25
Male (mean, SD)	0.46 (0.50)	0.40 (0.49)	<0.001	0.13
Couple (mean, SD)	1.20 (0.40)	1.31 (0.46)	<0.001	0.27
Essential worker (mean, SD)	0.98 (0.14)	0.98 (0.12)	0.115	0.03
Log net pay (mean, SD)	7.51 (1.13)	7.02 (1.03)	<0.001	0.46
Treated (mean, SD)	0.31 (0.46)	0.47 (0.50)	<0.001	0.34

Note: This table reports summary statistics by instrument status, defined by low ability to work from home. Covariates are expressed as means with standard deviations in parentheses. SMD = Standardized Mean Difference.

5.2 Instrument Relevance and First Stage

We begin by assessing the strength and relevance of the instrument, *low work-from-home ability* (LowWFH_{iw}), in predicting furlough status. Table 2 reports the first-stage regression, which shows a strong and statistically significant relationship between LowWFH_{iw} and the endogenous treatment Furlough_{iw}. The coefficient on LowWFH_{iw} is 0.082 ($p < 0.001$), with an associated F-statistic of 83.5, comfortably exceeding the conventional threshold of 10. This supports the assumption that the instrument is sufficiently strong and relevant.

Table 2: First Stage Regression: Predicting Furlough Status

Variable	**Estimate**	**Std. Error**	**p-value**	**Signif.**
LowWFH	0.0824	0.0086	< 0.001	***
Age	-0.0009	0.0003	0.007	**
Sex (Male)	0.0521	0.0083	< 0.001	***
Couple	0.0155	0.0093	0.096	.
Treated	-0.2133	0.0080	< 0.001	***
Log(Net Pay)	-0.1035	0.0049	< 0.001	***

Significance codes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

These results confirm that inability to work from home is a strong predictor of furlough exposure, satisfying the *relevance* assumption for instrumental variable estimation.

5.3 OLS vs. IV Estimates

Table 3 compares the OLS and IV estimates of the effect of furlough on cognitive mental health. The OLS model (Column 1) estimates a small, statistically insignificant effect of furlough on cognitive GHQ scores. In contrast, the IV model (Column 2), which addresses endogeneity via LowWFH_{iw}, finds a much larger and statistically significant negative effect.

Specifically, the IV coefficient on Furlough_{iw} is -0.556 ($p = 0.0066$), suggesting that furlough causally improves cognitive mental health among compliers.

Table 3: Table 2: OLS vs. IV Estimates of Furlough on Cognitive Mental Health

	OLS Estimate	**IV Estimate**	**Std. Error (IV)**
Furlough Status	0.0016	**-0.556**	0.2046
Age	-0.0048	-0.0062	0.0006
Sex (Male)	-0.1388	-0.1458	0.0186
Couple	0.0612	0.0698	0.0176
Wave FE Included	Yes	Yes	–
Log(Net Pay)	0.0080	-0.0506	0.0243
Treated	0.0194	-0.1449	0.0435
Wu-Hausman (p)	–	**0.009**	–
Weak Inst. F-stat	–	**83.5**	–

5.4 Robustness Checks

To assess the internal consistency and credibility of our IV estimates, we conduct a series of robustness checks, summarized in Table 4. First, we run a placebo test by replacing the outcome with a simulated variable drawn from a standard normal distribution. As expected, the effect of furlough status is small and not statistically significant (-0.098), reinforcing the validity of the exclusion restriction.

Next, we assess sample sensitivity by restricting the analysis to working-age individuals (18–65), where the estimated effect (-0.550) remains statistically significant and closely aligned with our main findings. Similarly, excluding the May wave—where furlough prevalence was highest—yields a near-identical estimate (-0.570), ruling out undue influence from any single survey round.

We then explore the robustness of the outcome definition. When using GHQ subdomains, we find a positive but insignificant effect on depression (0.202), while the effect on stress is negative (-0.420) and marginally significant. This suggests that furlough may more strongly affect stress-related responses than depressive symptoms.

Finally, when the overall GHQ score is used instead of its cognitive component, the effect estimate (-0.223) becomes statistically insignificant, suggesting that furlough primarily impairs cognitive wellbeing rather than general psychological distress.

Table 4: IV Estimates of Furlough on Mental Health Across Robustness Checks

Specification	**Outcome**	**Furlough Effect**	**Significance**
Placebo Test	Simulated outcome	-0.098	Not significant
Working-age Only (18–65)	GHQ cognitive	-0.550	Significant
Excluding May Wave	GHQ cognitive	-0.570	Significant
Alternative Outcome 1	GHQ depression	0.202	Not significant
Alternative Outcome 2	GHQ stress	-0.420	Marginally significant
Overall GHQ Score	GHQ total	-0.223	Not significant

5.5 Heterogeneity Analysis

To investigate whether the impact of furlough varies across subgroups, we conduct heterogeneity analyses by interacting furlough status with key economic and demographic variables, as presented in Table 5.

First, we test for differential effects by income group. The baseline effect of furlough remains significantly negative (-0.668, $p < 0.05$), while interactions with mid- and high-income groups are negative but statistically insignificant. The magnitude of the high-income interaction (-2.423) suggests that the mental health burden of furlough may be particularly pronounced among lower-income individuals, although the lack of precision limits definitive inference.

Second, we explore demographic heterogeneity through interactions with age (over 40), gender (male), and couple status. The base effect of furlough is again negative (-0.451) and marginally significant ($p = 0.063$). None of the subgroup interactions reach statistical significance, though the directions suggest potentially stronger positive effects among older adults and males. These findings indicate plausible group-specific vulnerabilities and motivate future research.

Table 5: Heterogeneity in IV Estimates of Furlough Impact on Cognitive GHQ

Variable	**Coefficient**	**Std. Error**	**p-value**
Panel A: By Income Group			
Furlough (Low Income, baseline)	-0.668	0.274	0.014
Furlough × Mid Income	-0.531	0.324	0.101
Furlough × High Income	-2.423	1.536	0.115
Panel B: By Demographics			
Furlough (Main effect)	-0.451	0.243	0.063
Furlough × Age Over 40	-0.076	0.169	0.654
Furlough × Male	0.316	0.301	0.294
Furlough × Couple	-0.251	0.322	0.437

6 Discussion

The results show that being furloughed during the COVID-19 pandemic had a clear positive effect as it reduces the likelihood of having cognitive mental health problems. In the ordinary least squares (OLS) regression, the effect of furlough is close to zero and not significant. However, once we account for differences in who is more likely to be furloughed using an instrumental variable (IV) approach—specifically, low ability to work from home—the estimated effect becomes much larger and statistically significant. This suggests that the OLS results were likely biased, and that furlough does have a real, negative impact on cognitive mental health.

The instrument used, low work-from-home ability, is strong and passes the standard statistical checks (e.g., F-statistic greater-than 83). These findings support a causal interpretation: being furloughed leads to better outcomes for mental well-being, especially in cognitive aspects like concentration, decision-making, and memory.

We also check if the results are reliable under different conditions. These robustness tests (Table 4) include changing the sample (e.g., only looking at working-age people or removing the May survey wave), changing the outcome (e.g., using stress or depression instead of cognitive score), and using a fake outcome to check for random relationships. In all cases, the main finding holds: furlough has a positive effect on cognitive mental health. The effect is strongest when looking only at the working-age sample or when excluding the May wave. Using overall GHQ or depression as outcomes gives weaker results, suggesting that furlough mainly affects cognitive mental functioning rather than overall distress or mood.

Finally, we explore if the impact of furlough is different for different groups (Table 5). We find that the effect is most noticeable among people with lower incomes, and possibly stronger for men and older individuals, although these results are not always statistically significant. This suggests that some groups may be more vulnerable to the mental health effects of furlough than others. *A key limitation is that the validity of the instrument relies on strong assumptions about exogeneity, and unobserved confounding cannot be fully ruled out despite covariate adjustment; additionally, the use of LATE limits the external validity of the estimated effects to compliers only.*

7 Conclusion

Overall, the results suggest that furlough during the COVID-19 pandemic had a harmful effect on cognitive mental health. The analysis shows that this effect is not just a coincidence—it is likely caused by being furloughed itself. The findings are consistent across different checks and appear stronger in some groups, such as lower-income individuals.

This has important implications. When governments introduce job protection schemes like furlough, they should also consider the mental health benefits programs like and not just the cost of the policy and economic returns.

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