

1 Heavy drinking days and mental health: an exploration of the dynamic ten year longitudinal
2 relationship in a prospective cohort of untreated heavy drinkers

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1 **Abstract (Word count: 297/300)**

2 **Background:** Identifying dominant processes which underlie the development of other
3 processes is important when evaluating the temporal sequence between disorders. Such
4 information not only improves our understanding of aetiology but also allows for effective
5 intervention strategies to be tailored. The temporal relationship between alcohol intake and
6 mental health remains poorly understood, particularly in non-clinical samples. The purpose of
7 this study was to disentangle the dominant temporal sequence between mental health and
8 frequency of heavy drinking days.

9 **Methods:** A ten year (1997-2007) prospective cohort study of 500 respondents (74% male)
10 from the Birmingham Untreated Heavy Drinkers project. Participants were aged 25-55 years
11 at baseline, drinking a *minimum* of 50/35 UK units of alcohol for men/women on a weekly
12 basis and were not seeking treatment for their alcohol use upon recruitment into the study.
13 Heavy drinking days were defined as consuming 10/7+ UK units of alcohol in a single day
14 for men/women. Mental health was assessed using the mental health component score of the
15 SF-36 questionnaire. Dynamic longitudinal structural equation models were used to test
16 competing theoretical models (frequency of heavy drinking days leading to changes in mental
17 health scores; and vice versa) and a reciprocal relationship (both mental health scores and the
18 frequency of heavy drinking days influencing changes in each other).

19 **Results:** A model whereby mental health scores were predictors of change in the frequency
20 of heavy drinking days was of best fit. In this model, mental health scores were negatively
21 related to change in heavy drinking days (β -0.80, SE 0.28) indicating that those with higher
22 mental health scores (i.e. better functioning) made larger reductions in the number of heavy
23 drinking days over time.

- 1 **Conclusions:** Mental health appears to be the stronger underlying process in the relationship
- 2 between mental health and frequency of heavy drinking days.
- 3 **Keywords:** alcohol, mental health, longitudinal, reciprocal, self-medication, temporality

1 **Introduction**

2 While most theories relating to the effect of alcohol consumption and physical and mental
3 health are dynamic – involving multiple related components to describe changes occurring
4 over time, the methods typically employed to study such phenomena often fail to adequately
5 capture the hypothesised interrelated evolution between processes (Ferrer and McArdle,
6 2010). It is a crucial goal of public health research to identify dominant processes which
7 underlie the development of other processes and specify models which allow for the temporal
8 sequence between them to be evaluated. Consider the relationship between alcohol use and
9 depression – two processes which have long been thought to be intertwined. That is, harmful
10 alcohol use can be seen as a risk factor for depression (Boden and Fergusson, 2011; Boschloo
11 et al., 2012; Fergusson et al., 2009), whilst depression is also believed to be associated with
12 increased alcohol consumption (Bolton et al., 2009; Kuo et al., 2006). Furthermore it is often
13 postulated that a feedback cycle exists between alcohol use and depression whereby, for
14 example, high levels of alcohol consumption lead to greater severity of depression, which in
15 turn fuels further alcohol consumption. While these type of feedback relationships are
16 typically theorised, more often than not, empirical research has failed to adequately capture
17 these dynamic processes.

18 Recently members of the author panel demonstrated that when considering changes in both
19 weekly volume of alcohol consumed and mental health, that mental health symptoms
20 appeared to be the driving force – finding no evidence in favour of drinking increasing
21 psychological distress or for a reciprocal relationship existing (Bell and Britton, 2014).
22 However, this study was not able to capture drinking pattern and was limited to a largely
23 moderate drinking cohort. Previous work on the association between alcohol consumption
24 and mental health has found that drinking pattern is a stronger predictor of poor mental health

1 than total volume consumed (Graham et al., 2007). Furthermore, as previously proposed there
2 may be differences in the dynamics between alcohol intake and mental health at different
3 points in the alcohol consumption distribution (Bell and Britton, 2014). It is therefore
4 important to determine whether a consistent association exists across different drinking
5 measures as well as drinking groups to strengthen causal inference.

6 The purpose of this paper is to explore the dynamic longitudinal association between mental
7 health and the frequency of heavy drinking days using repeat measures of both in a heavy
8 drinking cohort – comparing competing theoretical models (mental health leading to changes
9 in the frequency of heavy drinking; and, frequency of heavy drinking leading to changes in
10 mental health) as well as examine whether a reciprocal relationship exists between processes.

11 **Materials and Methods**

12 **Study sample**

13 Data from the Birmingham Untreated Heavy Drinkers (BUHD) project (Rolfe et al., 2009)
14 were used to explore the dynamic relationship between mental health and frequency of heavy
15 drinking days. The BUHD project is a prospective cohort study of 500 participants (375
16 men, 125 women) recruited from the West Midlands community in the UK who were aged
17 between 25-55 years at baseline in 1997. Participants had to be drinking a minimum of 50/35
18 (men/women) UK units of alcohol on a weekly basis (where 1 unit is equivalent to 8 g or 10
19 ml of ethanol) and not be seeking treatment for their alcohol use (nor had sought treatment in
20 the previous 10 years) upon recruitment into the study. Participants were re-interviewed
21 every two years for a decade (until 2007) with 259 (52%) of the original sample taking part in
22 the final wave.

1 **Measurements**

2 **Heavy drinking days**

3 Participants were asked to report the number of heavy drinking days they had in the past year
4 – using cut-off values of 10+ UK units for men and 7+ UK units for women in a single day
5 to define a heavy drinking day (where one UK unit is equivalent to 8 g or 10 ml of ethanol).

6 This was done with a trained interviewer who had, prior to this, discussed in detail a
7 participant's past week drinking using the Time Line Follow Back form (Sobell and Sobell,
8 1992) as well as changes in the participant's drinking habits over the previous 2 years.

9 Interviewers had a detailed conversion chart for calculating UK units and the number of UK
10 units in different drink types was explained to the participants throughout. Interviewers were
11 given a week of training and closely supervised throughout data-collection, including on-
12 going discussion/clarification of issues related to these measurements. Interviews were taped
13 and monitored for quality. These yearly values were then divided by 12 to calculate an
14 average number of heavy drinking days per month.

15 **Mental health**

16 Mental health (broadly defined as psychological distress, combining symptoms of depression
17 and anxiety) was assessed using the SF-36 questionnaire, which covers physical,
18 psychological and social health in the last four weeks. The mental health component (MCS)
19 was used in analyses (Ware et al. 1994; Ware et al. 1995). The MCS has been demonstrated
20 to be reliable (Ware et al. 1994) and valid using UK data sources (Jenkinson et al., 1997).
21 The MCS uses a scale of 0 to 100 with higher scores reflecting better functioning.

1 **Covariates**

2 Models were adjusted for a variety of baseline covariates including: age (centred on the
3 sample mean), gender (Bell and Britton, 2011; male reference group; Van de Velde et al.,
4 2010) and ethnicity (white (referent) or non-white) (Chartier et al., 2014; Weich et al., 2004).
5 Socioeconomic position (Batty et al., 2012; Lorant et al., 2003) was divided into three
6 categories on the basis of occupation type: high (consisting of professional/managerial
7 occupations), intermediate (reference; made up of skilled manual and skilled non-manual
8 roles) and low (partly skilled, unskilled or inadequately described). Marital status was
9 collapsed to a binary variable with a married/cohabiting (reference) category and a not in a
10 relationship category (Temple et al., 1991; Van de Velde et al., 2010) – which included those
11 divorced, separated, single or widowed. Educational attainment (Bjelland et al., 2008;
12 Grittner et al., 2013) was reduced to three categories, as follows: post-secondary (university
13 degree, teaching/nursing qualifications, A-levels, City and Guilds [professional manual
14 qualifications], and ‘other’), secondary (reference; passed GCSE/O-levels), and no
15 qualifications obtained. Employment status (Flint et al., 2013; Temple et al., 1991) was
16 defined as active (reference) or inactive (including the unemployed, students and those who
17 had retired). Smoking status (Boden et al., 2010) was categorised as being a non-smoker
18 (reference) or current smoker. A binary indicator of poor physical health (Geerlings et al.,
19 2000; Stockwell et al., 2012) was created using the physical health component of the SF36
20 instrument - defined as belonging to the lowest sex-specific quartile. Body mass index (BMI;
21 centred on the mean value) was entered into the final model (de Wit et al., 2010), and an
22 indicator of illicit drug use (Brook et al., 2002) in the year before baseline was also included
23 (no [reference] vs yes).

1 **Statistical analysis**

2 We used bivariate latent change score (LCS) modelling, which unites measurement of
3 growth/decline with reciprocity between related processes, to explore the relationship
4 between frequency of heavy drinking days and mental health. A comprehensive outline of the
5 mathematical and statistical properties of LCS models can be found elsewhere (Hamagami
6 and McArdle, 2001; McArdle and Hamagami, 2001).

7 Briefly, change in a variable (Δ) is considered as a function of three main components: (1) a
8 constant amount (α) which is the additive sum of change scores over time, (2) a quantity
9 proportional to the previous state of itself (β) – in many ways representing a self-feedback
10 loop, and (3) an amount proportional to the previous value of the alternative variable (γ).

11 Placing certain constraints on parts of the model allow for specific hypotheses to be tested.

12 For example, constraining the coupling parameter (γ) from x to y to be zero, while estimating
13 the parameter from y to x , would model a leading effect of y to changes in x . Alternatively,
14 one is able to free both coupling parameters to explore whether there is a reciprocal dynamic
15 relationship between both variables over time.

16 Both the intercepts (estimated values for heavy drinking days and mental health scores at
17 baseline) and slopes (α terms) were fitted as random effects, allowing for variation between
18 individuals. Intercepts and slopes were correlated within single processes (for example, the
19 mental health intercept with the mental health slope) and between processes (for example, the
20 alcohol intercept with the mental health slope). Intercepts and slopes were estimated
21 conditional on baseline covariates described above.

22 To achieve our aims of testing lag-leading and reciprocal relationship hypotheses four models
23 were used. Firstly we estimated a model whereby heavy drinking days and mental health
24 were unable to influence changes in each other (but their intercepts and slopes were

1 correlated) – this was used as the baseline model to which other models would be compared.
2 We then estimated a model whereby previous occasion frequency of heavy drinking days was
3 allowed to affect upcoming change in mental health scores, but mental health scores exerted
4 no effect on changes in heavy drinking days – this model was used to test for heavy drinking
5 days as a leading indicator of change. Our third model was one whereby mental health scores
6 were specified as the dominant process being able to affect changes in heavy drinking days
7 while heavy drinking days were unable to affect changes in mental health. Our final model
8 was one whereby both mental health scores and frequency of heavy drinking days were able
9 to affect upcoming change in the alternate process – reflecting a dynamic, reciprocal
10 relationship between both processes. For ease of presentation only the parameter estimates
11 from the best fitting model are included within this paper (estimates from other models
12 specified are available upon request from the corresponding author).

13 Models were estimated in Mplus version 6.12 (Muthén and Muthén, 1998) using Full
14 Information Maximum Likelihood (FIML) which means that all available data were used
15 when estimating model parameters (Raykov, 2005).

16 Model fit was examined using the Tucker–Lewis index (TLI), the comparative fit index
17 (CFI), and the root mean squared error of approximation (RMSEA). Cut-off values
18 approaching 0.95 were used to determine a good fit for TLI and CFI, while a threshold close
19 to 0.06 was used for RMSEA (Hu and Bentler, 1999). Nested models were compared using a
20 χ^2 difference test to determine the best-fitting model.

1 **Results**

2 **Descriptive statistics**

3 Outlined in Table 1 are the basic descriptive statistics of the BUHD project sample. At
4 baseline the mean age of participants was 37.4 years, approximately three quarters of the
5 sample were male, around 90% of participants were of white ethnicity, socioeconomic
6 position was roughly equally spread, a little over a third of the sample were married or
7 cohabiting, the majority of the sample had secondary or post-secondary education, 57% of
8 participants were currently in employment, almost 60% of the sample were current smokers
9 at baseline, mean BMI was 25.6, and over 55% of participants had taken illicit drugs in the
10 year before baseline.

11 In terms of the main variables of interest (presented in Table 2), at baseline the average
12 number of heavy drinking days per month was 16, this figure decreased to 11 by the end of
13 follow-up. Mental health scores started at 45 at baseline, increasing to 48 at follow-up (both
14 of which fall below the population average score of 50).

15 **Model comparison**

16 One can see that the fit statistics for all four models (Table 3) indicate well specified models
17 according to common indices (such as the RMSEA, TLI and CFI). In both age and sex
18 adjusted models, as well as models adjusted for a full range of confounding factors, the
19 model whereby mental health influences changes in heavy drinking days but not vice versa
20 was found to be of best fit to our data ($P < 0.01$ in both instances). As such, we will proceed
21 by providing estimates relating to this model below.

1 **Regression estimates**

2 As findings were robust to adjustment for confounding factors only the estimates from the
3 fully-adjusted models will be described (although age and sex adjusted models are also
4 presented in Table 4). The estimates relating to covariates are presented in *supplemental*
5 *digital content 1*.

6 Reported in Table 4 are coefficients from the model whereby mental health influences
7 changes in the frequency of heavy drinking days but heavy drinking days have no effect on
8 changes in mental health. A significant autoproportional effect was observed for number of
9 heavy drinking days per month (β -0.61, SE 0.10) but not for mental health (β -0.20, SE
10 0.18). The coupling parameter from mental health scores to change in heavy drinking days
11 was also significant and negative (β -0.80, SE 0.28) indicating that those with higher mental
12 health scores (i.e. better functioning) made larger reductions in the number of heavy drinking
13 days they engaged with over time.

14 The dynamics of the system are brought about by jointly estimating as well as interpreting the
15 parameter estimates (as they are highly dependent upon each other as well as scales of
16 measurement). One of the best ways to do so is to plot the expected direction and magnitude
17 of change in both mental health scores and the frequency of heavy drinking on a monthly
18 basis between measurement occasions within a vector field (Boker and McArdle, 1995) as
19 done so in Figure 1. The ellipsoid reflects 95% of the data. These plots also showcase the
20 significant correlations observed between intercept and slopes within and between processes
21 as one can clearly see that those who engaged in fewer heavy drinking days at baseline who
22 also had poorer mental health scores significantly increased in the frequency of heavy
23 drinking, while those who had more heavy drinking days but were in better mental health
24 significantly reduced in the frequency of doing so between occasions.

1 **Discussion**

2 **Interpretation**

3 The purpose of this paper was to explore the dynamic relationship between the frequency of
4 heavy drinking days and mental health. We tested hypotheses of heavy drinking frequency as
5 a leading indicator of change in the system, as well as mental health scores as leading
6 indicators of change, and finally we tested a reciprocal relationship – it was found that a
7 model whereby mental health scores influenced upcoming change in the frequency of heavy
8 drinking was of best fit. This indicates that mental health is likely to be the dominant
9 underlying process in the dynamic system.

10 **Comparison to other studies**

11 This work is an extension of other work undertaken by two of the co-authors (Bell and
12 Britton, 2014) which also found that mental health was a better leading indicator of change in
13 the dynamic system between total weekly alcohol consumption and mental health. This
14 convergence of evidence in two different datasets (with very different sample compositions)
15 using two different alcohol measures further strengthens the notion that mental health is the
16 leading indicator of change at a population level.

17 Other studies focussing on clinical disorders have found that alcohol use disorders appear to
18 predict major depressive disorder (Boden and Fergusson, 2011); however, these studies are
19 generally focussed on the transition or maintenance of a clinical state or binary “heavy
20 drinker” or “symptoms of mental health problems” status. It is unlikely that the
21 developmental trajectory underlying the progression to a clinical disorder is as simple as
22 moving from one state to another (e.g. no mental illness to having a mental illness); it is
23 much more likely that it characterised by an escalation of symptoms and behaviours over

1 time which our models using continuous measures over repeat occasions were better able to
2 capture.

3 Nevertheless, it may be that there are two separate dynamic systems at play pre- and post-
4 clinical disorder (Bell and Britton, 2014) as multiple studies have shown that symptoms of
5 problematic alcohol consumption are associated with mental health disorders (Fergusson et
6 al., 2009) independent of the amount of alcohol consumed (Bulloch et al., 2012). Individuals
7 who self-medicate symptoms of anxiety (Rosa M. Crum et al., 2013) or depression (R.M. Crum
8 et al., 2013) with alcohol have also been demonstrated to have an increased risk of developing
9 alcohol dependence. Mental health symptoms may therefore impact changes in alcohol intake
10 until symptoms of dependence begin to emerge, at which point the dynamics shift and these
11 symptoms of alcohol dependence start to drive changes in mental health. It is also
12 conceivable that the association between mental health and heavy drinking days may have
13 been different at the onset of drinking (i.e. before participants became heavy drinkers).
14 However, given that similar associations between alcohol intake and mental health have been
15 observed in non-heavy drinking samples (Bell and Britton, 2014) this hypothesis is less
16 likely. Nevertheless, examining discontinuities in these dynamics may shed further light on
17 the aetiology of co-morbid common mental health syndromes and alcohol use disorders.

18 **Strengths and limitations**

19 Our study has several strengths; firstly, we used analytic methods that were able to
20 appropriately capture our hypotheses of lag-leading and reciprocal relationships between
21 frequency of heavy drinking days and mental health scores in a manner that previous studies
22 on the topic have failed to. Furthermore we utilised multiple measurement occasions to
23 model change in both heavy drinking and mental health scores over time. Previous work has
24 shown that variability in alcohol consumption is important to consider (Britton et al., 2010)

1 and our approach directly incorporated individual change in both the frequency of heavy
2 drinking days as well as mental health scores.

3 We also used a cohort of participants who were non-clinical heavy drinkers at baseline – such
4 participants are often under-represented in existing longitudinal studies and the majority of
5 research specifically exploring alcohol use and mental health tends to focus on clinical
6 samples and treatment outcomes.

7 Furthermore, often the relationship between alcohol use and mental health (as well as other
8 health outcomes) is complicated by including non-drinkers who can be a mix of lifelong non-
9 drinkers and former drinkers (with different reasons for quitting) (Rehm et al., 2008) in
10 samples at baseline. Our study avoids this pitfall as participants had to be drinking alcohol at
11 baseline, we therefore know that none of the sample were lifelong abstainers, and reductions
12 in alcohol consumption to abstinence throughout follow-up were captured in our models.

13 Of course our study also has a number of limitations; these include a relatively small sample
14 size and the fact that participants were recruited from a single geographical area in England.
15 However, with respect to the latter point, our findings are consistent with those we observed
16 in another longitudinal cohort (the Whitehall II study of British civil servants (Marmot and
17 Brunner, 2005)) suggesting that this bias may not be quite as detrimental as one might first
18 believe – but we encourage replication of such analyses in nationally representative cohorts
19 not only within the UK but world-wide to examine the consistency of effect across cultures
20 which is important in terms of making wider inferences.

21 Furthermore, while participants were not seeking treatment for their alcohol consumption at
22 baseline no limitations were put on them seeking treatment for mental health problems,
23 therefore we cannot guarantee that participants were not currently undergoing chemical or
24 psychological therapy for existing mental health disorders. However, given that undergoing

1 treatment for mental health problems is likely to result in improvements in mental health
2 scores (Uher et al., 2010), not being able to control for this at baseline may actually mean that
3 our parameter estimates are slight underestimates of the true effect.

4 While we set out the fact that all participants were drinkers at baseline and reduction to non-
5 drinking over time was captured in our models as a strength above, we must also
6 acknowledge that we did not explicitly model the transition to abstinence as either a risk
7 factor for or consequence of mental health scores. This was not the purpose of the present
8 study which was concerned with exploring how the frequency of heavy drinking days and
9 mental health were inter-related – but we agree that non-drinking is an important feature to
10 explore in the relationship between mental health and alcohol consumption (Bell et al., 2014;
11 Skogen et al., 2011).

12 An additional cause for concern was the relatively large attrition rate over time (52% of the
13 original sample took part in the final measurement occasion) – however, we accounted for
14 attrition over time by using FIML to estimate our model parameters and there was no
15 evidence of selective attrition on the basis of the number of heavy drinking days a participant
16 reported at baseline nor their (mental) health (Rolfe et al., 2009). Further methodological
17 shortcomings include that we only adjusted for baseline values of covariates and our mental
18 health variable was a composite variable reflecting general mental health related quality of
19 life and not solely psychiatric symptoms. On the other hand, there is some debate that is
20 challenging to effectively disentangle symptoms of specific characteristics of anxiety from
21 those of depression using self-report questionnaires due to the substantial overlap of
22 symptoms between disorders. It is likely that self-reported symptoms measure a combination
23 of depressive as well as other mood and stress-related disorders (Goldberg, 1972; Prince et

1 al., 2007) and as such methods of measuring them at a population level are likely to be
2 measuring a single latent construct (Clark and Watson, 1991; Watson, 2005).

3 Another issue relates to differences in the time metric of the main measures used in this
4 study. Information on heavy drinking days relates to the previous 12 months (though
5 expressed in approximately a 30 day metric) while the SF-36 based mental health measure is
6 a 4 week measure. The mismatch may not greatly matter in the wave to wave framework but
7 could conceivably introduce bias in the baseline covariance terms.

8 The competing models we specified also 1) assumed a constant relationship between mental
9 health and heavy drinking measures over time, and 2) only allowed for the previous occasion
10 heavy drinking days and/or mental health score to influence change in the alternative variable
11 at the next occasion. However, in terms of the former, even though the relationship is
12 specified as static over time, because the proportional and coupling parameters are multiplied
13 by values which change over measurement occasions nonlinear trajectories can be captured.
14 In terms of the latter, it is possible that the best fitting model may have been different if we
15 allowed for longer lag specifications.

16 We also used statistical information to select the most parsimonious model (Kline, 2010) but
17 acknowledge that the statistical difference between some models is very minor (specifically
18 the contrast between the model whereby mental health is specified as the dominant process
19 and the dynamic model when only adjusting for age and sex). One might argue that the two
20 are essentially equivalent; however, the estimated effect of MCS scores on upcoming change
21 in heavy drinking days in the dynamic model was 0.267 in the model adjusted for only age
22 and sex ($p=0.16$) and 0.002 in the fully adjusted model ($p=0.98$) (data not shown) –
23 suggesting that after controlling for confounding factors the impact of heavy drinking days on
24 mental health is essentially zero (hence the equivalence between models).

1 **Implications and directions for future work**

2 Our findings indicate that the dominant process underlying the dynamic relationship between
3 frequency of heavy drinking and mental health is likely to be mental health. This provides
4 further support for existing campaigns that ensuring good mental health at a population level
5 is essential to public health (Centre for Mental Health, Department of Health et al., 2012) and
6 may, in part, help reduce hazardous drinking. The fact that those with poor mental health
7 were more likely to increase their alcohol consumption is concerning as it indicates that
8 people may be using poor coping techniques to deal with psychological distress. Tackling the
9 stigma surrounding mental health issues (Evans-Lacko et al., 2014) is a central goal of such
10 campaigns – if people feel comfortable discussing their mental health issues or seeking
11 treatment then they may not resort to drinking as a means of self-medicating their symptoms.
12 Future work should seek to examine discontinuities in dynamic processes concerning alcohol
13 intake and symptoms of alcohol use disorders alongside subsyndromal symptoms of poor
14 mental health and major common mental health outcomes to determine whether there is a
15 critical value at which point symptoms of mental health and drinking interact to lead to the
16 manifestation of clinical disorders.

17 **Conclusions**

18 We found that mental health appears to be the stronger underlying process in the relationship
19 between mental health and frequency of heavy drinking days in this sample of heavy drinkers
20 from England. Those with poor mental health are more likely to increase the number of heavy
21 drinking days, while those with good mental health are more likely to reduce their number of
22 heavy drinking days over time. Efforts to improve mental health at a population level may
23 also serve to reduce heavy drinking.

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11 necessarily those of the Department of Health.

12 **Conflict of interests**

13 No authors have any conflict of interests to declare.

14 **Author contributions**

15 SB devised the research question, analysed the data and wrote the first draft of the
16 manuscript. JO and AB provided important intellectual content and contributed to the revised
17 manuscript. SB had full access to all of the data in the study and takes responsibility for the
18 integrity of the data and the accuracy of the data analysis. All authors read and approved the
19 final manuscript.

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Figures

Figure 1- Vector field plotting expected changes in both heavy drinking days and mental health as a function of the mental health $\rightarrow \Delta$ heavy drinking days system. Ellipsoid reflects 95% of the data.

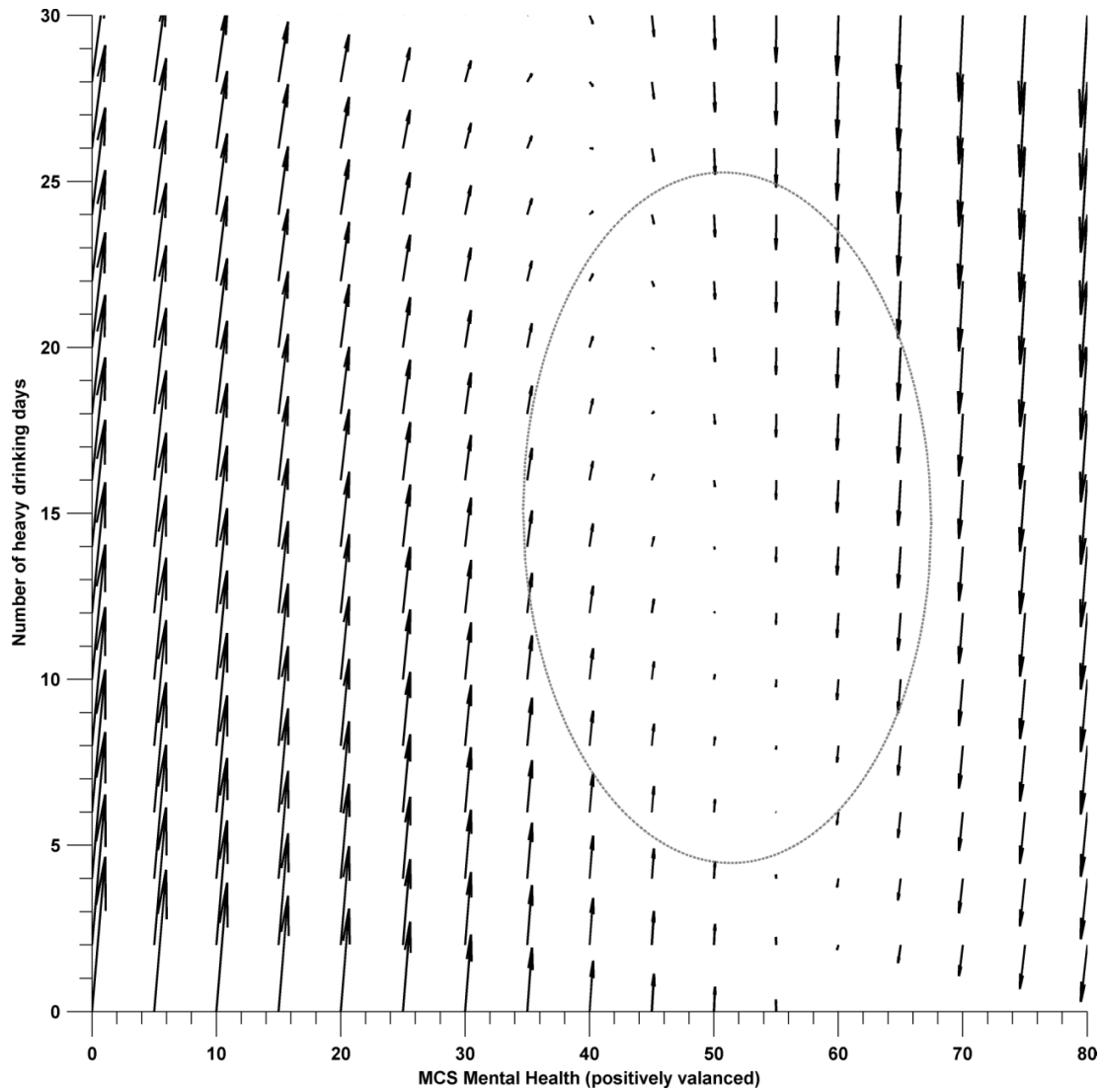


Table 1 – Descriptive information for the Birmingham Untreated Heavy Drinkers cohort at baseline

	Total	
	N	% or Mean (S.D.)
Age	500	37.6 (8.6)
Gender	500	
Men	372	74.4
Women	128	25.6
Ethnic group	500	
White	454	90.8
Other	46	9.2
Socioeconomic position	500	
High	144	28.8
Intermediate	186	37.2
Low	170	34.0
Marital status	500	
Married/cohabiting	170	34.0
Not in a relationship	330	66.0
Education level	499	
Post-secondary	188	37.7
Secondary	201	40.3
No qualifications	110	22.0
Economic activity	500	

Active	287	57.4
Inactive	213	42.6
Smoking status	500	
Non-smoker	210	42.0
Smoker	290	58.0
Poor physical health	493	
No	365	74.0
Yes	128	26.0
Body mass index	475	25.7 (4.7)
Illicit drug use	500	
No	213	42.6
Yes	287	57.4

Table 2 - Means (standard deviations) of heavy drinking days and mental health scores over time

	Heavy drinking days		Mental health score	
	N	Mean (S.D.)	N	Mean (S.D.)
Wave 1	495	16.3 (8.6)	493	44.8 (12.3)
Wave 2	403	13.2 (9.8)	403	44.8 (12.2)
Wave 3	350	13.8 (10.3)	349	46.8 (11.6)
Wave 4	321	12.1 (10.2)	321	46.7 (11.8)
Wave 5	280	11.6 (10.5)	280	46.1 (12.2)
Wave 6	259	10.8 (10.5)	259	48.0 (11.8)

Table 3 - Model fit indices and comparison of LCS models for frequency of heavy drinking days (HDD) and mental health in the Birmingham Untreated Heavy Drinkers project

	Baseline	HDD → ΔMCS	MCS → ΔHDD	Reciprocal
Age and sex adjusted				
Fit statistics				
Log likelihood	-17337.154	-17337.086	-17332.492	-17330.881
χ^2 (df)	166.442 (87)	166.306 (86)	157.118 (86)	153.897 (85)
RMSEA	0.043	0.043	0.041	0.04
AIC	34738.308	34740.172	34730.984	34729.762
SSA BIC	34771.605	34774.51	34765.322	34765.141
CFI	0.95	0.95	0.955	0.957

TLI	0.949	0.947	0.953	0.954
Model comparison (difference in χ^2 fit (df))				
Versus baseline	–	0.136 (1), P = 0.71	9.324 (1), P < 0.01	12.545 (2), P < 0.01
Versus previous best	–	–	–	3.221 (1), P = 0.07
Fully adjusted				
Fit statistics				
Log likelihood	-22831.569	-22830.758	-22823.357	-22823.357
χ^2 (df)	252.887 (159)	251.266 (158)	236.464 (158)	236.464 (157)
RMSEA	0.034	0.034	0.032	0.032
AIC	45943.138	45943.517	45928.714	45930.714
SSA BIC	46088.814	46090.234	46075.431	46078.472
CFI	0.945	0.946	0.954	0.954
TLI	0.932	0.932	0.943	0.942
Model comparison (difference in χ^2 fit (df))				
Versus baseline	–	1.621 (1), P = 0.20	16.423 (1), P < 0.001	16.423 (2), P < 0.001
Versus previous best	–	–	–	0 (1), P = 1.00

AIC, Akaike information criterion; CFI, comparative fit index; df, degrees of freedom; LCS, latent change score; MCS, mental health component score; RMSEA, root mean square error of approximation; SSA BIC, sample size adjusted Bayesian information criterion; TLI, Tucker-Lewis index.

Table 4 – Coefficients (standard error) estimated for mental health leading to changes in the frequency of heavy drinking days

MCS → Δ HDD	Age and sex adjusted		Fully adjusted	
<i>Fixed effects</i>				
	Alcohol	MCS	Alcohol	MCS
Intercept	16.44*** (0.45)	45.67*** (0.58)	14.87*** (0.87)	51.06*** (1.11)
Slope (α)	41.18** (15.06)	4.25 (9.05)	47.71** (14.99)	10.81 (9.41)
Autoproportional (β)	-0.59*** (0.11)	-0.08 (0.19)	-0.61*** (0.10)	-0.20 (0.18)
Coupling (γ)	-0.73* (0.30)	--	-0.80** (0.28)	--
<i>Random effects</i>				
Intercept/slope correlation	0.37**	0.32	0.48***	0.72**
Intercept correlation	-0.09		-0.02	
Slope correlation	0.43		0.69***	
HDD intercept, MCS slope correlation	0.31		0.33	
MCS intercept, HDD slope correlation	0.75***		0.76***	

*** p < 0.001; ** p < 0.01; * p < 0.05

N=500

Fully adjusted = age, sex, ethnicity, socioeconomic position, marital status, educational attainment, economic activity, smoking status, poor physical health, body mass index, and use of illicit drugs in past 12 months.

Supplemental Digital Content: 1

File name: Bell et al - Supplemental Digital Content 1.pdf

File title: Bell et al. Supplemental Digital Content 1 – covariate effects

Description: An additional table including the effect of covariates on the intercepts and slopes.

Table e5 - Covariate coefficients (standard errors) for mental health affecting change in frequency of heavy drinking day models

*** p < 0.001; ** p < 0.01; * p < 0.05

	HDD intercept	HDD slope	MCS intercept	MCS slope
Age and sex adjusted				
Age	0.11* (0.05)	0.11* (0.05)	0.01 (0.06)	0.01 (0.01)
Gender	-1.49 (0.88)	-2.62 (1.36)	-3.56** (1.15)	0.05 (0.61)
Fully adjusted				
Age	0.06 (0.05)	0.07 (0.06)	-0.07 (0.06)	0 (0.02)
Gender	-1.05 (0.84)	-2.64* (1.29)	-3.36** (1.11)	-0.34 (0.55)
Ethnicity	-2.10 (1.28)	-2.40 (1.60)	-2.07 (1.65)	0.27 (0.49)
Socioeconomic position	0.95 (0.53)	0.23 (0.64)	-0.42 (0.68)	-0.03 (0.19)
Marital status	-0.25 (0.79)	-1.47 (1.14)	-2.30* (1.02)	-0.46 (0.49)
Education level	1.03 (0.53)	1.10 (0.67)	0.35 (0.69)	0.17 (0.22)
Economic activity	1.68* (0.81)	-3.33* (1.59)	-4.94*** (1.04)	-0.83 (0.88)
Smoking status	2.54** (0.82)	0.31 (1.00)	-0.49 (1.05)	-0.39 (0.35)
Poor physical health	-0.16*** (0.05)	0.03 (0.05)	-0.04 (0.06)	0.01 (0.02)
Body mass index	0.12 (0.08)	-0.08 (0.10)	0.11 (0.11)	-0.05 (0.03)
Illicit drug use	-0.47 (0.81)	-1.41 (1.10)	-2.24* (1.03)	-0.25 (0.45)

N=500

Models were adjusted for: age (centred on the sample mean), gender (male referent group) and ethnicity (white (referent) or non-white). Socioeconomic position was divided into three categories on the basis of occupation type: high (consisting of professional/managerial occupations), intermediate (reference; made up of skilled manual and skilled non-manual roles) and low (partly skilled, unskilled or inadequately described). Marital status was collapsed to a binary variable with a married/cohabiting (reference) category and a not in a relationship category – which included those divorced, separated, single or widowed. Educational attainment was reduced to three categories, as follows: post-secondary (university degree, teaching/nursing qualifications, A-levels, City and Guilds [professional manual qualifications], and ‘other’), secondary (reference; passed GCSE/O-levels), and no qualifications obtained. Employment status was defined as active (reference) or inactive (including the unemployed, students and those who had retired). Smoking status was categorised as being a non-smoker (reference) or current smoker. A binary indicator of poor physical health was created using the physical health component of the SF36 instrument - defined as belonging to the lowest sex-specific quartile. Body mass index (BMI; centred on the mean value) was entered into the final model, and an indicator of illicit drug use in the year before baseline was also included (no [reference] vs yes).