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

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Abstract (Word count: 297/300)

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

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

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

Conclusions: Mental health appears to be the stronger underlying process in the relationship between mental health and frequency of heavy drinking days.

Keywords: alcohol, mental health, longitudinal, reciprocal, self-medication, temporality

Introduction

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

Recently members of the author panel demonstrated that when considering changes in both weekly volume of alcohol consumed and mental health, that mental health symptoms appeared to be the driving force – finding no evidence in favour of drinking increasing psychological distress or for a reciprocal relationship existing (Bell and Britton, 2014). However, this study was not able to capture drinking pattern and was limited to a largely moderate drinking cohort. Previous work on the association between alcohol consumption and mental health has found that drinking pattern is a stronger predictor of poor mental health than total volume consumed (Graham et al., 2007). Furthermore, as previously proposed there may be differences in the dynamics between alcohol intake and mental health at different points in the alcohol consumption distribution (Bell and Britton, 2014). It is therefore important to determine whether a consistent association exists across different drinking measures as well as drinking groups to strengthen causal inference.

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

Materials and Methods

Study sample

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

Measurements

Heavy drinking days

Participants were asked to report the number of heavy drinking days they had in the past year – using cut-off values of 10+ UK units for men and 7+ UK units for women in a single day to define a heavy drinking day (where one UK unit is equivalent to 8 g or 10 ml of ethanol). This was done with a trained interviewer who had, prior to this, discussed in detail a participant's past week drinking using the Time Line Follow Back form (Sobell and Sobell, 1992) as well as changes in the participant's drinking habits over the previous 2 years. Interviewers had a detailed conversion chart for calculating UK units and the number of UK units in different drink types was explained to the participants throughout. Interviewers were given a week of training and closely supervised throughout data-collection, including on-going discussion/clarification of issues related to these measurements. Interviews were taped and monitored for quality. These yearly values were then divided by 12 to calculate an average number of heavy drinking days per month.

Mental health

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

Covariates

Models were adjusted for a variety of baseline covariates including: age (centred on the sample mean), gender (Bell and Britton, 2011; male reference group; Van de Velde et al., 2010) and ethnicity (white (referent) or non-white) (Chartier et al., 2014; Weich et al., 2004). Socioeconomic position (Batty et al., 2012; Lorant et al., 2003) 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 (Temple et al., 1991; Van de Velde et al., 2010) – which included those divorced, separated, single or widowed. Educational attainment (Bjelland et al., 2008; Grittner et al., 2013) 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 (Flint et al., 2013; Temple et al., 1991) was defined as active (reference) or inactive (including the unemployed, students and those who had retired). Smoking status (Boden et al., 2010) was categorised as being a non-smoker (reference) or current smoker. A binary indicator of poor physical health (Geerlings et al., 2000; Stockwell et al., 2012) 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 (de Wit et al., 2010), and an indicator of illicit drug use (Brook et al., 2002) in the year before baseline was also included (no [reference] vs yes).

Statistical analysis

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

Briefly, change in a variable (Δ) is considered as a function of three main components: (1) a constant amount (α) which is the additive sum of change scores over time, (2) a quantity proportional to the previous state of itself (β) – in many ways representing a self-feedback loop, and (3) an amount proportional to the previous value of the alternative variable (γ). Placing certain constraints on parts of the model allow for specific hypotheses to be tested. For example, constraining the coupling parameter (γ) from *x* to *y* to be zero, while estimating the parameter from *y* to *x*, would model a leading effect of *y* to changes in *x*. Alternatively, one is able to free both coupling parameters to explore whether there is a reciprocal dynamic relationship between both variables over time.

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

To achieve our aims of testing lag-leading and reciprocal relationship hypotheses four models were used. Firstly we estimated a model whereby heavy drinking days and mental health were unable to influence changes in each other (but their intercepts and slopes were correlated) – this was used as the baseline model to which other models would be compared. We then estimated a model whereby previous occasion frequency of heavy drinking days was allowed to affect upcoming change in mental health scores, but mental health scores exerted no effect on changes in heavy drinking days – this model was used to test for heavy drinking days as a leading indicator of change. Our third model was one whereby mental health scores were specified as the dominant process being able to affect changes in heavy drinking days while heavy drinking days were unable to affect changes in mental health. Our final model was one whereby both mental health scores and frequency of heavy drinking days were able to affect upcoming change in the alternate process – reflecting a dynamic, reciprocal relationship between both processes. For ease of presentation only the parameter estimates from the best fitting model are included within this paper (estimates from other models specified are available upon request from the corresponding author).

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

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

Results

Descriptive statistics

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

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

Model comparison

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

Regression estimates

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

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

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

Discussion

Interpretation

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

Comparison to other studies

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

Other studies focussing on clinical disorders have found that alcohol use disorders appear to predict major depressive disorder (Boden and Fergusson, 2011); however, these studies are generally focussed on the transition or maintenance of a clinical state or binary "heavy drinker" or "symptoms of mental health problems" status. It is unlikely that the developmental trajectory underlying the progression to a clinical disorder is as simple as moving from one state to another (e.g. no mental illness to having a mental illness); it is much more likely that it characterised by an escalation of symptoms and behaviours over time which our models using continuous measures over repeat occasions were better able to capture.

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

Strengths and limitations

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

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

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

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

Furthermore, while participants were not seeking treatment for their alcohol consumption at baseline no limitations were put on them seeking treatment for mental health problems, therefore we cannot guarantee that participants were not currently undergoing chemical or psychological therapy for existing mental health disorders. However, given that undergoing treatment for mental health problems is likely to result in improvements in mental health scores (Uher et al., 2010), not being able to control for this at baseline may actually mean that our parameter estimates are slight underestimates of the true effect.

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

An additional cause for concern was the relatively large attrition rate over time (52% of the original sample took part in the final measurement occasion) – however, we accounted for attrition over time by using FIML to estimate our model parameters and there was no evidence of selective attrition on the basis of the number of heavy drinking days a participant reported at baseline nor their (mental) health (Rolfe et al., 2009). Further methodological shortcomings include that we only adjusted for baseline values of covariates and our mental health variable was a composite variable reflecting general mental health related quality of life and not solely psychiatric symptoms. On the other hand, there is some debate that is challenging to effectively disentangle symptoms of specific characteristics of anxiety from those of depression using self-report questionnaires due to the substantial overlap of symptoms between disorders. It is likely that self-reported symptoms measure a combination of depressive as well as other mood and stress-related disorders (Goldberg, 1972; Prince et al., 2007) and as such methods of measuring them at a population level are likely to be measuring a single latent construct (Clark and Watson, 1991; Watson, 2005).

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

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

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

Implications and directions for future work

Our findings indicate that the dominant process underlying the dynamic relationship between frequency of heavy drinking and mental health is likely to be mental health. This provides further support for existing campaigns that ensuring good mental health at a population level is essential to public health (Centre for Mental Health, Department of Health et al., 2012) and may, in part, help reduce hazardous drinking. The fact that those with poor mental health were more likely to increase their alcohol consumption is concerning as it indicates that people may be using poor coping techniques to deal with psychological distress. Tackling the stigma surrounding mental health issues (Evans-Lacko et al., 2014) is a central goal of such campaigns – if people feel comfortable discussing their mental health issues or seeking treatment then they may not resort to drinking as a means of self-medicating their symptoms.

Future work should seek to examine discontinuities in dynamic processes concerning alcohol intake and symptoms of alcohol use disorders alongside subsyndromal symptoms of poor mental health and major common mental health outcomes to determine whether there is a critical value at which point symptoms of mental health and drinking interact to lead to the manifestation of clinical disorders.

Conclusions

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

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Conflict of interests

No authors have any conflict of interests to declare.

Author contributions

SB devised the research question, analysed the data and wrote the first draft of the manuscript. JO and AB provided important intellectual content and contributed to the revised manuscript. SB had full access to all of the data in the study and takes responsibility for the integrity of the data and the accuracy of the data analysis. All authors read and approved the 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 → Δ heavy drinking days system. Ellipsoid reflects 95% of the data.

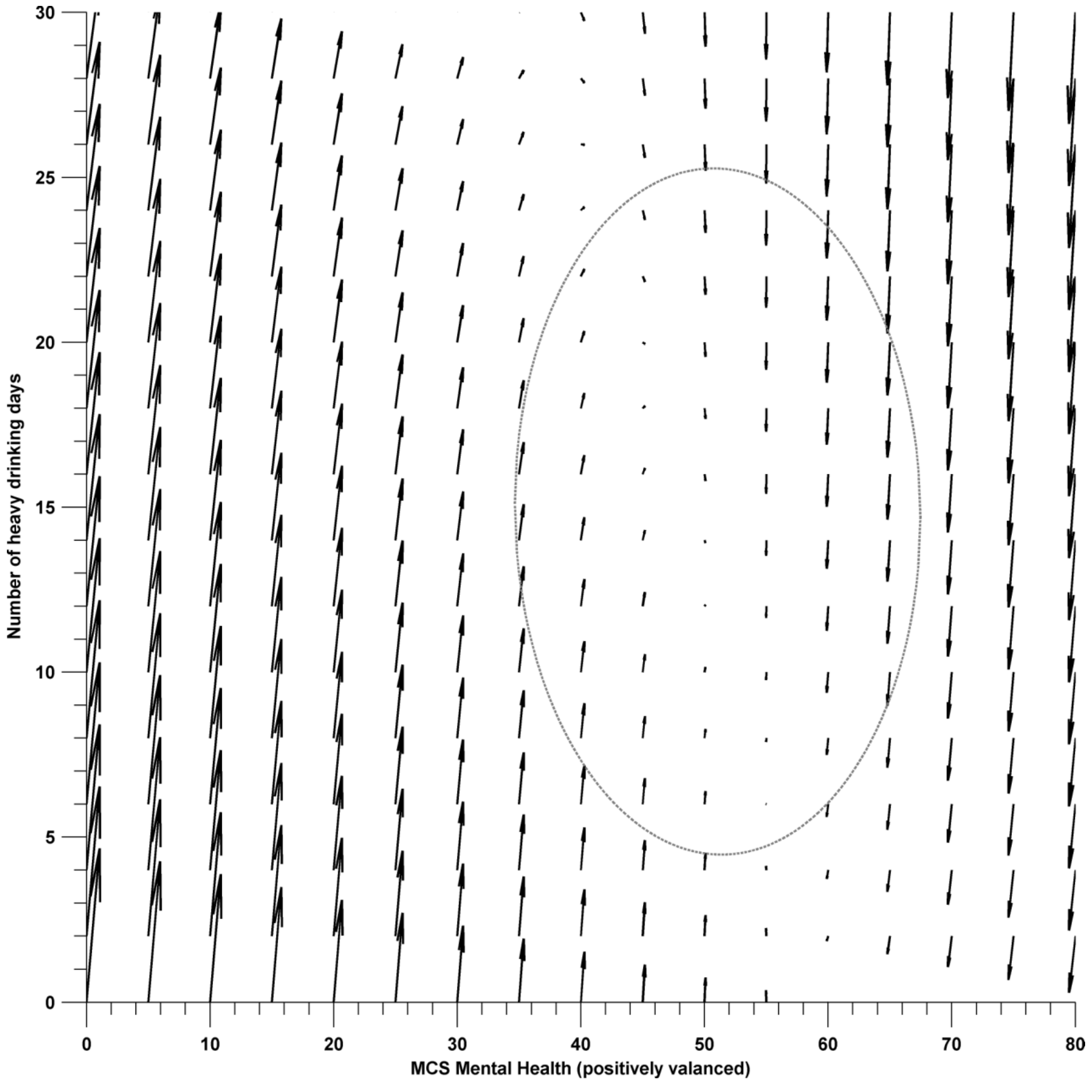

Table 1 – Descriptive information for the Birmingham Untreated Heavy Drinkers cohort at baseline

	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	
Fixed effects				
	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)	--
Random effects				
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).