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

3 **Authors and affiliations:**

4 Steven Bell, PhD*[1]

5 Jim Orford, PhD[2]

6 Annie Britton, PhD[1]

7

8 [1] Research Department of Epidemiology and Public Health, University College London, 1-19

9 Torrington Place, London, WC1E 6BT, United Kingdom.

10 [2] School of Psychology, University of Birmingham, Edgbaston, Birmingham, B15 2TT,

11 United Kingdom.

12 * Corresponding author: Email: steven.bell@ucl.ac.uk Tel: +44(0) 207 679 5627 Fax: +44(0)

13 207 679 1831

14 **Word count:** 4,090 (exclusive of abstract, acknowledgements/conflict of interests, reference

15 list and tables/captions)

16 **Number of tables:** 4

17 **Number of figures:** 1

18 **Number of references:** 50

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

3

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.

Materials and Methods

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.

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

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).

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.

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.

Reference list

Batty, G.D., Bhaskar, A., Emslie, C., Benzeval, M., Der, G., Lewars, H., Hunt, K., 2012. Association of life course socioeconomic disadvantage with future problem drinking and heavy drinking: gender differentials in the west of Scotland. Int. J. Public Health 57, 119–126.

Bell, S., Britton, A., 2011. Alcohol and men's health. Trends Urol. Mens Health 2, 9–12.

Bell, S., Britton, A., 2014. An exploration of the dynamic longitudinal relationship between mental health and alcohol consumption: a prospective cohort study. BMC Med. 12, 91.

Bell, S., Britton, A., Kubinova, R., Malyutina, S., Pajak, A., Nikitin, Y., Bobak, M., 2014. Drinking Pattern, Abstention and Problem Drinking as Risk Factors for Depressive Symptoms: Evidence from Three Urban Eastern European Populations. PLoS ONE 9, e104384.

Bjelland, I., Krokstad, S., Mykletun, A., Dahl, A.A., Tell, G.S., Tambs, K., 2008. Does a higher educational level protect against anxiety and depression? The HUNT study. Soc. Sci. Med. 66, 1334–1345.

Boden, J.M., Fergusson, D.M., 2011. Alcohol and depression. Addiction 106, 906–914.

Boden, J.M., Fergusson, D.M., Horwood, L.J., 2010. Cigarette smoking and depression: tests of causal linkages using a longitudinal birth cohort. Br. J. Psychiatry 196, 440–446.

Boker, S.M., McArdle, J.J., 1995. Statistical Vector Field Analysis Applied to Mixed Cross-Sectional and Longitudinal Data. Exp. Aging Res. 21, 77–93.

Bolton, J.M., Robinson, J., Sareen, J., 2009. Self-medication of mood disorders with alcohol and drugs in the National Epidemiologic Survey on Alcohol and Related Conditions. J. Affect. Disord. 115, 367–375.

Boschloo, L., van den Brink, W., Penninx, B.W.J.H., Wall, M.M., Hasin, D.S., 2012. Alcohol-use disorder severity predicts first-incidence of depressive disorders. Psychol. Med. 42, 695–703.

Britton, A., Marmot, M.G., Shipley, M.J., 2010. How does variability in alcohol consumption over time affect the relationship with mortality and coronary heart disease? Addiction 105, 639–645.

Brook, D.W., Brook, J.S., Zhang, C., Cohen, P., Whiteman, M., 2002. Drug Use and the Risk of Major Depressive Disorder, Alcohol Dependence, and Substance Use Disorders. Arch. Gen. Psychiatry 59, 1039–1044.

Bulloch, A., Lavorato, D., Williams, J., Patten, S., 2012. Alcohol Consumption and Major Depression In The General Population: The Critical Importance of Dependence. Depress. Anxiety 29, 1058–1064.

Centre for Mental Health, Department of Health, Mind, NHS Confederation Mental Health Network, Rethink Mental Illness, Turning Point, 2012. No Health Without Mental Health: Implementation Framework (No. 17688).

Chartier, K.G., Vaeth, P.A., Caetano, R., 2014. Focus on: ethnicity and the social and health harms from drinking. Alcohol Res. Curr. Rev. 35, 229.

Clark, L.A., Watson, D., 1991. Tripartite model of anxiety and depression: Psychometric evidence and taxonomic implications. J. Abnorm. Psychol. 100, 316–336.

Crum, R.M., La Flair, L., Storr, C.L., Green, K.M., Stuart, E.A., Alvanzo, A.A.H., Lazareck, S., Bolton, J.M., Robinson, J., Sareen, J., Mojtabai, R., 2013. Reports of Drinking to Self-Medicate Anxiety Symptoms: Longitudinal Assessment for Subgroups of Individuals with Alcohol Dependence. Depress. Anxiety 30, 174–183.

Crum, R.M., Mojtabai, R., Lazareck, S., Bolton, J.M., Robinson, J., Sareen, J., Green, K.M., Stuart, E.A., La Flair, L., Alvanzo, A.A.H., Storr, C.L., 2013. A prospective assessment of reports of drinking to self-medicate mood symptoms with the incidence and persistence of alcohol dependence. JAMA Psychiatry 70, 718–726.

De Wit, L., Luppino, F., van Straten, A., Penninx, B., Zitman, F., Cuijpers, P., 2010. Depression and obesity: A meta-analysis of community-based studies. Psychiatry Res. 178, 230–235.

Evans-Lacko, S., Corker, E., Williams, P., Henderson, C., Thornicroft, G., 2014. Effect of the Time to Change anti-stigma campaign on trends in mental-illness-related public stigma among the English population in 2003–13: an analysis of survey data. Lancet Psychiatry 1, 121–128.

Fergusson, D.M., Boden, J.M., Horwood, L.J., 2009. Tests of Causal Links Between Alcohol Abuse or Dependence and Major Depression. Arch. Gen. Psychiatry 66, 260–266.

Ferrer, E., McArdle, J.J., 2010. Longitudinal Modeling of Developmental Changes in Psychological Research. Curr. Dir. Psychol. Sci. 19, 149–154.

Flint, E., Bartley, M., Shelton, N., Sacker, A., 2013. Do labour market status transitions predict changes in psychological well-being? J. Epidemiol. Community Health 67, 796–802.

Geerlings, S.W., Beekman, A.T.F., Deeg, D.J.H., Van Tilburg, W., 2000. Physical health and the onset and persistence of depression in older adults: an eight-wave prospective community-based study. Psychol. Med. 30, 369–380.

Goldberg, D.P., 1972. The Detection of Psychiatric Illness by Questionnaire (No. 21), Maudsley Monograph. Oxford University Press, London.

Graham, K., Massak, A., Demers, A., Rehm, J., 2007. Does the Association Between Alcohol Consumption and Depression Depend on How They Are Measured? Alcohol. Clin. Exp. Res. 31, 78–88.

Grittner, U., Kuntsche, S., Gmel, G., Bloomfield, K., 2013. Alcohol consumption and social inequality at the individual and country levels—results from an international study. Eur. J. Public Health 23, 332–339.

Hamagami, F., McArdle, J.J., 2001. Advanced Studies of Individual Differences Linear Dynamic Models for Longitudinal Data Analysis. In: New Developments and Techniques in Structural Equation Modeling. Lawrence Erlbaum Associates, Inc, Mahwah, New Jersey, pp. 203–246.

Hu, L., Bentler, P.M., 1999. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Struct. Equ. Model. Multidiscip. J. 6, 1–55.

Jenkinson, C., Layte, R., Lawrence, K., 1997. Development and Testing of the Medical Outcomes Study 36-Item Short Form Health Survey Summary Scale Scores in the United Kingdom: Results from a Large-Scale Survey and a Clinical Trial. Med. Care 35, 410–416.

Kline, R.B., 2010. Principles and Practice of Structural Equation Modeling, 3rd ed. The Guildford Press, New York, USA.

Kuo, P., Gardner, C.O., Kendler, K.S., Prescott, C.A., 2006. The temporal relationship of the onsets of alcohol dependence and major depression: using a genetically informative study design. Psychol. Med. 36, 1153–1162.

Lorant, V., Deliège, D., Eaton, W., Robert, A., Philippot, P., Ansseau, M., 2003. Socioeconomic Inequalities in Depression: A Meta-Analysis. Am. J. Epidemiol. 157, 98–112.

Marmot, M., Brunner, E., 2005. Cohort Profile: The Whitehall II study. Int. J. Epidemiol. 34, 251–256.

McArdle, J.J., Hamagami, F., 2001. Latent Difference Score Structural Models for Linear Dynamic Analyses With Incomplete Longitudinal Data. In: New Methods for the Analysis of Change. American Psychological Association, Washington, DC, pp. 137–176.

Muthén, L.K., Muthén, B.O., 1998. Mplus User's Guide. Sixth Edition. Muthén & Muthén, Los Angeles, CA.

Prince, M., Patel, V., Saxena, S., Maj, M., Maselko, J., Phillips, M.R., Rahman, A., 2007. No health without mental health. The Lancet 370, 859–877.

Raykov, T., 2005. Analysis of Longitudinal Studies With Missing Data Using Covariance Structure Modeling With Full-Information Maximum Likelihood. Struct. Equ. Model. Multidiscip. J. 12, 493–505.

Rehm, J., Irving, H., Ye, Y., Kerr, W.C., Bond, J., Greenfield, T.K., 2008. Are Lifetime Abstainers the Best Control Group in Alcohol Epidemiology? On the Stability and Validity of Reported Lifetime Abstention. Am. J. Epidemiol. 168, 866–871.

Rolfe, A., Orford, J., Martin, O., 2009. Birmingham Alcohol, Drugs, Gambling and Addiction Research. Department of Health.

Skogen, J.C., Mykletun, A., Ferri, C.P., Bebbington, P., Brugha, T., Coid, J., Meltzer, H., Stewart, R., 2011. Mental and personality disorders and abstinence from alcohol: results from a national household survey. Psychol. Med. 41, 809–818.

Sobell, L.C., Sobell, M.B., 1992. Timeline follow-back: A technique for assessing self-reported alcohol consumption. In: Measuring Alcohol Consumption: Psychosocial and Biochemical Methods. The Humana Press Inc, Totowa, New Jersey, pp. 41–72.

Stockwell, T., Greer, A., Fillmore, K., Chikritzhs, T., Zeisser, C., 2012. How good is the science? BMJ 344, e2276.

Temple, M.T., Fillmore, K.M., Hartka, E., Johnstone, B., Leino, E.V., Motoyoshf, M., 1991. A meta-analysis of change in marital and employment status as predictors of alcohol consumption on a typical occasion. Br. J. Addict. 86, 1269–1281.

Uher, R., Muthén, B., Souery, D., Mors, O., Jaracz, J., Placentino, A., Petrovic, A., Zobel, A., Henigsberg, N., Rietschel, M., Aitchison, K.J., Farmer, A., McGuffin, P., 2010. Trajectories of change in depression severity during treatment with antidepressants. Psychol. Med. 40, 1367–1377.

Van de Velde, S., Bracke, P., Levecque, K., 2010. Gender differences in depression in 23 European countries. Cross-national variation in the gender gap in depression. Soc. Sci. Med. 71, 305–313.

Ware, J., Kosinski, M., Keller, S., 1994. SF-36® Physical and Mental Health Summary Scales: A User's Manual. The Health Institute, Boston, MA.

Ware, J.E., Kosinski, M., Bayliss, M.S., McHorney, C.A., Rogers, W.H., Raczek, A., 1995. Comparison of Methods for the Scoring and Statistical Analysis of SF-36 Health Profile and Summary Measures: Summary of Results from the Medical Outcomes Study. Med. Care 33, AS264–AS279.

Watson, D., 2005. Rethinking the mood and anxiety disorders: A quantitative hierarchical model for DSM-V. J. Abnorm. Psychol. 114, 522–536.

Weich, S., Nazroo, J., Sproston, K., McManus, S., Blanchard, M., Erens, B., Karlsen, S., King, M., Lloyd, K., Stansfeld, S., Tyrer, P., 2004. Common mental disorders and ethnicity in England: the EMPIRIC study. Psychol. Med. 34, 1543–1551.

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.
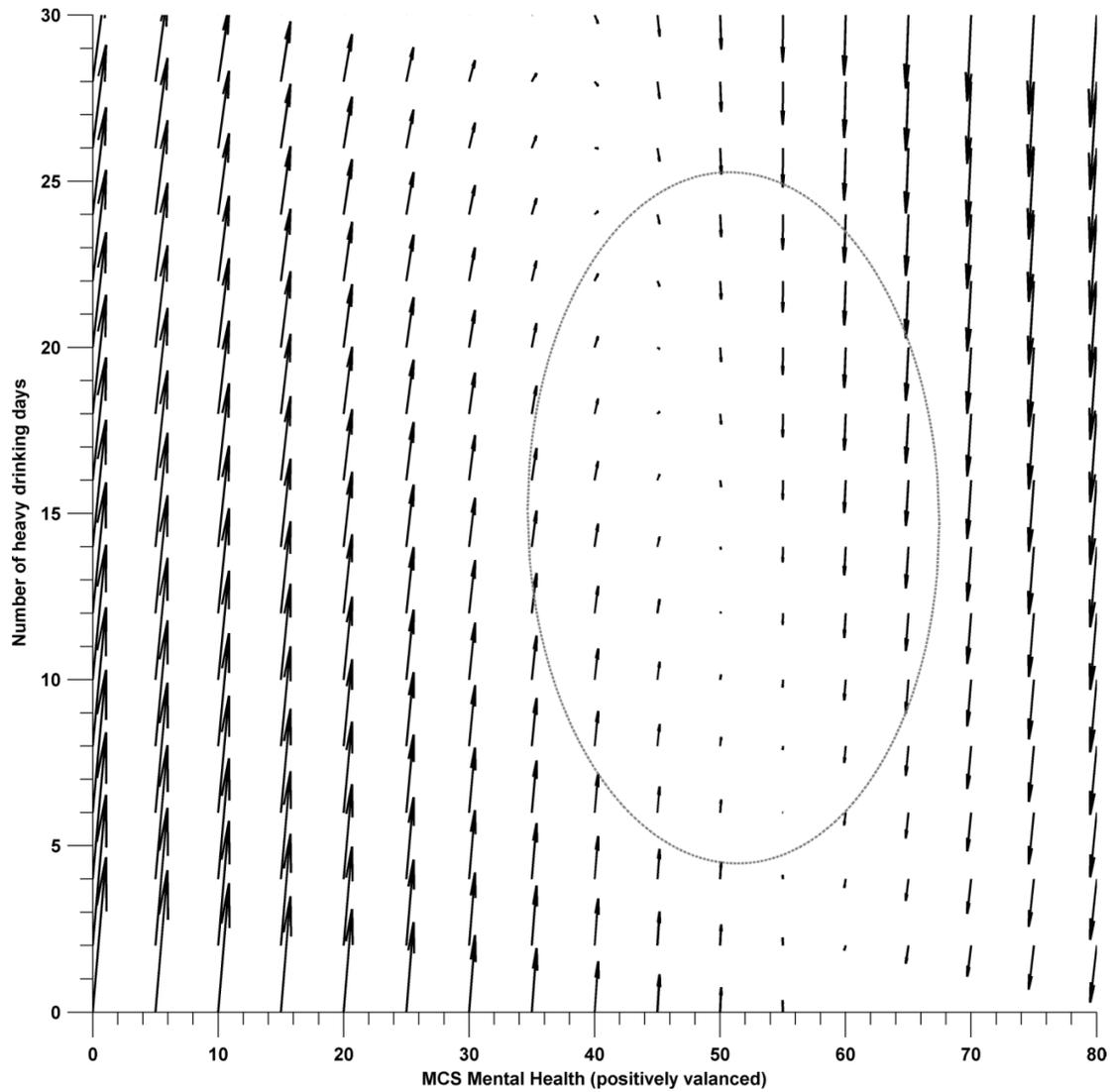
Table 1 – Descriptive information for the Birmingham Untreated Heavy Drinkers

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).