

Supplementary S1 – covariates*Better Access Scheme services*

To be eligible for this study women had to have claimed at least one of the following Medicare items that were related to the Better Access Scheme: initial GP consultation (Item 2710, 2702) or any item in relation to the Treatment Therapy mental health services which included all Psychological Therapy Services (Item 80000-80020), Focussed Psychology Strategies which includes registered psychologists, occupational therapists and social workers (Item 80100-80170) and GP mental health treatment (2713, 2721-2731) [1] between 1 January 2007 and 31 December 2013. The study aimed to capture those women who had made a claim for any mental health service, including those women that only had an initial GP mental health consultation with no further treatment. Eligibility of this sample is reflective of women that may have attended a GP's surgery to seek help.

Supplementary S2.***Method of Latent Growth Mixture Model Analysis***

To evaluate the goodness of fit, the model fit statistics used included the Bentler Comparative Fit Index (CFI/TLI) which indicates the proportion in the improvement of the overall fit of the model compared to the null model, root mean square error of approximation (RMSEA) and standardized root mean square residual (SRMR) which provides a standardised summary of the average covariance residuals calculated as the difference between the observed and expected covariances, and the relative chi-square of less than 2 or 3 [2, 3]. Models with CFI \geq 0.85, RMSEA $<$ 0.5 and SRMR $<$ 0.05 were deemed to fit the data well[4].

Information criteria BIC, AIC, and Adjusted BIC, were used to compare the relative fit for each model as the number of latent classes increased. Once model building was complete, the optimal model was assessed based on the lowest information criteria.

We also used the entropy score which ranged from 0.0 to 1.0 with scores closer to 1.0 indicating the best classification rate for class membership [5]. As well as, the Lo-Mendell-Rubin (LMR) test which was used to check the improvement between neighbouring class models. The test compared the two-class with the three-class model, the three-class with the four-class model and so on, and provided a p-value indicating whether there was any statistically significant improvement in the model when including the additional class. P-values greater than 0.05 indicate that the model with the extra class had not improved the model when comparing to the previous model [6].

Statistical Analysis strategy

In the first analytic step in this study, we identified the most appropriate model type to represent the data. Initial models were subjected to a variety of exploratory analyses in order to assess the best single-group model to serve as the base model. The initial models included the intercept, linear, quadratic and latent basic models. For the intercept model, two scenarios were considered; a latent factor representing service use as a binary variable, the number of services represented as a continuous and count variable. Growth models were initially developed using a traditional approach with intercept and slope variances initially fixed then permitted to vary. The

growth parameters had variation in both intercept and slope parameters and models assigning random effects were also analysed.

Further, once the base model was selected, growth curve models with baseline covariates “educational qualifications”, “living in an urban area” and “mental health measures” were assessed prior to performing latent class analysis.

Due to the administrative collection of the data, there is not missing data.

Supplementary S3

Latent class classification

Our LGMM were used to identify mental health services use latent classes based on linked medical claims to the ALSWH. The main objective of the analysis was to discern meaningful patterns of service use and determine how many useful latent classes the women could be profiled into. In Supplementary S3, we explored the solution to the 4-class, 5-class and 6-class model. Using the repeated measure data allowed for statistical power to improve and therefore increased the ability to detect smaller latent classes.

The best model was found to be the six-class model shown in Table S3.2. This model resulted in the lowest AIC, BIC and sample Adjusted BIC and the LMR-test comparing improvement between the four and six-class models concluding in statistically significant outcomes (log likelihood test 68.77, $p=0.0058$). The six-class model resulted in a low entropy score of 0.56 which was not as reasonable as the four-class model entropy classification (0.628).

In general, an entropy of 0.8 or higher is more advisable to clearly identify individuals following different trajectory types but lower entropies can still produce good parameter estimates [6, 7]. The 6-class model was based on the best AIC/BIC/Adjusted BIC and a significant Lo-Mendall-Rubin test, but it is possible that a clear distinction of trajectory types is not evident in the data. Whilst, a larger entropy is recommended, we chose to use the six-class model where a substantial drop in the fit statistics AIC (71129.8), BIC fit statistic (71321.85) compared to the four-class model, suggested that the 6-class model solution was more desirable. However, the lower entropy score of 0.556 may therefore suggest large variations in individual patterns across the six time-periods. The six class model entropy score suggests that higher entropy might be achieved by adding key covariates or key distal outcomes to the model[7]. The average diagonal values in Table S3.1 (in bold) however, suggest that class six (predicted probability = 0.529) may not be distinguished from the other classes.

Table S3.1 shows the average latent class probabilities for the most likely latent class membership (represented by each row) by the classified latent class (represented by the column). Each participant has a probability of being in each class, with the largest probability on the diagonal. Those women in Class 1 have an average probability of being in class one of 0.67. The mean estimated probability of women in Class 1 being in class 2 is 0.015, in class 3 is 0.031, in class 4 is 0.036, in class 5 is 0.248 and in class 6 is 0.00. The highest predicted probabilities were returned for Classes 3 and 5 with scores greater than 0.7. Classes 1, 2 and 4 had probabilities between 0.6 and 0.7. Class 6 had the lowest predicted probability of 0.516 indicating that this group may have

substantial variation within individuals in the group. By observation, this group was more likely to have women who had not accessed any mental health services or, at most, in the latter period of the study.

Latent class membership	Classified latent Class					
	1	2	3	4	5	6
1	0.669	0.015	0.031	0.036	0.248	0.000
2	0.045	0.632	0.024	0.135	0.110	0.054
3	0.017	0.001	0.899	0.069	0.014	0.000
4	0.030	0.034	0.190	0.675	0.006	0.065
5	0.090	0.015	0.089	0.029	0.778	0.000
6	0.202	0.100	0.011	0.119	0.040	0.529

Table S3.1 Average predicted probabilities for the 6-class model

As a comparison, the four class and the six class models showed that while the four-class model did present with the best entropy score of 0.628, the six-class model (Figure S3.1) described the patterns of mental health service use with more clarity. The model with six classes was also considered the best model based on the AIC, BIC and LMR tests.

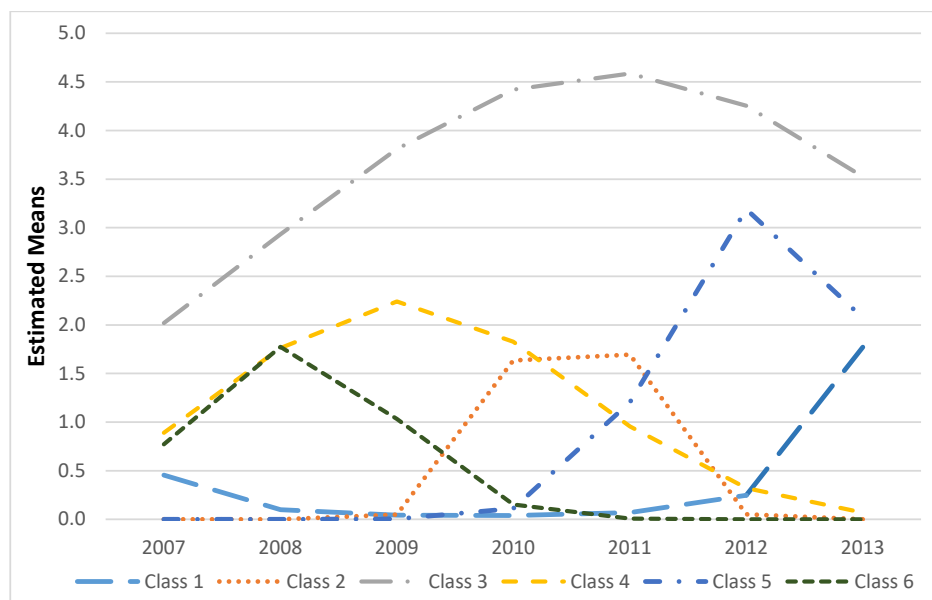


Figure S3.1. Latent Class membership (posterior probabilities) for the six-class model for women from the 1973-78 Cohort

Classification of classes:

Class 1 defined “most recent”

Class 2 defined “late/low”

Class 3 defined “consistently high”

Class 4 defined “consistent-reduced”

Class 5 defined “late-high”

Class 6 defined “early”

	1 Class	2 Classes	3 Classes	4 Classes	5 Classes	6 Classes	7 Classes
Free Parameters	10	14	18	22	26	30	34
AIC	73127.88	72486.72	71615.41	71345.70	71240.85	71129.78	71042.35
BIC	73191.90	72576.35	<i>71730.65</i>	71486.55	71371.32	71321.85	71260.04
Sample Adjusted BIC	73160.13	72531.87	71673.46	71416.64	71288.70	71238.79	71152.00
Entropy		0.515	0.595	0.628	0.558	0.556	0.595
Lo, Mendell, Rubin LRT test	<i>na</i>	2 v 1 Value =630.40 <i>p</i> =0.000	3 v 2 Value = 853.9 <i>p</i> < .0000	4 v 3 Value = 269.68 <i>P</i> < .0.000	5 v 4 Value = 172.19 <i>P</i> = 0.000	6 v 5 Value = 80.68 <i>P</i> = 0.0016	7 v 6 Value = 95.67 <i>P</i> = 0.2296
<i>N</i> for each class	<i>C1 = 4458</i> <i>100%</i>	<i>C1=1605 36.0%</i> <i>C2=2853 64.0%</i>	<i>C1=1429 32.1%</i> <i>C2=954 21.4%</i> <i>C3=2075 46.5%</i>	<i>C1=875 (19.6%)</i> <i>C2=713 (16.0%)</i> <i>C3=947 (21.2%)</i> <i>C4=1923 (43.1%)</i>	<i>C1= 822 (15.4%)</i> <i>C2 = 839 (18.8%)</i> <i>C3 = 839 (18.8%)</i> <i>C4 = 764 (17.1%)</i> <i>C5 =119 (26.8%)</i>	<i>C1 = 652 (14.6%)</i> <i>C2 = 643 (14.4%)</i> <i>C3 = 662 (14.9%)</i> <i>C4 = 432 (9.7%)</i> <i>C5 = 587 (13.2%)</i> <i>C6 = 1482 (33.2%)</i>	<i>C1 = 309 (6.9%)</i> <i>C2 = 626 (14.0%)</i> <i>C3 = 578 (13.0%)</i> <i>C4 = 375 (8.4%)</i> <i>C5 = 531 (11.9%)</i> <i>C6 = 1514 (34.0 %)</i> <i>C7 = 525 (11.8%)</i>

Table S3.2 Latent class definitions for the 1973-78 cohort

Latent class growth models with covariates

We modelled the growth mixture models adding baseline covariates educational qualifications, urban living and mental health score, prior to determining the latent class variables. The analysis showed women with higher educational qualifications (0.404 $p < 0.001$) and those living in an urban area (0.379, $p < 0.001$) were more likely to have increased use of the mental health services compared to women with only school level educational qualifications and those in non-urban area, respectively. Meanwhile, women having a higher baseline mental health score (-0.009, $p < 0.001$) were more likely to have decreased use of services compared to women with lower baseline mental health scores. Area of residence, qualifications, and baseline mental health score also had a significant effect on the slope, suggesting there was a difference in uptake of the BAS mental health services over time ($p = 0.015$) based on baseline covariates.

Based on the LGMM, an estimate of service use for women in the 1973-78 Cohort based on baseline covariates area of residence, educational level and baseline mental health score was made. In 2007, women living in an urban area, with post school qualifications and with a baseline mental health score of 52, had 1.21 sessions per individual (1210 sessions per 1000 individuals). By 2013, mental health service use had increased to 1.962 sessions. In comparison, women living in a non-urban area with similar baseline characteristics had 0.826 sessions per individual (826 sessions per 1000 individuals) in 2007 and by 2013 had 1.496 sessions, suggesting that services to non-urban areas were reaching women in need but geographic differences in receiving care existed.

Likewise, women living in an urban area with Year 12 or less schooling and with a baseline mental health score of 52, were receiving 0.806 sessions per individual in 2007 and 1.675 by 2013. In comparison, women living in a non-urban area with Year 12 or less schooling and a baseline mental health score of 52 were receiving 0.552 sessions per individual in 2007 and 1.278 by 2013. These results show that women living in urban areas, regardless of their educational qualifications, were receiving more mental health services than women living in non-urban areas.

References

- [1] A. G. D. o. H. a. Ageing. "Better Access to Psychiatrists, Psychologists and General Practitioners through the Medicare Benefits Schedule (Better Access) initiative." Department of Health and Ageing. <http://www.health.gov.au/mentalhealth-betteraccess>
<https://www.humanservices.gov.au/organisations/health-professionals/enablers/education-guide-better-access-mental-health-care-general-practitioners-and-allied-health> (accessed 16 November 2017).
- [2] Kline Rex B., *Principles and Practice of Structural Equation Modeling (Methodology In The Social Sciences)-Third Edition*. The Guilford Press, p. 427.
- [3] J. B. Ullman, "A first course in structural equation modeling," *Applied Psychological Measurement*, vol. 25, no. 1, pp. 101-102, Mar 2001, doi: 10.1177/01466216010251008.
- [4] L. M. Muthén, B. , Ed. *Mplus Statistical Analysis With Latent Variables. User's Guide. (Sixth Edition)*. Los Angeles, 1998-2007. [Online]. Available: http://www.statmodel.com/download/usersguide/Mplus%20user%20guide%20Ver_7_r6_web.pdf.
- [5] L. S. Collins Linda M, *Latent Class and Latent Transition Analysis: With Applications in the Social, Behavioral, and Health Sciences* (Series in Probability and Statistics). Hoboken, New Jersey: Wiley, 2010, p. 285.
- [6] K. L. Nylund, T. Asparouhov, and B. O. Muthen, "Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study (vol 14, pg 535, 2007)," (in English), *Structural Equation Modeling-a Multidisciplinary Journal*, Correction vol. 15, no. 1, pp. 182-182, Jan-Mar 2008, doi: 10.1080/10705510701793320.
- [7] B. Muthén, "Latent variable analysis: Growth mixture modeling and related techniques for longitudinal data.," in *Handbook of quantitative methodology for the social sciences.*, K. D., Ed. Newbury Park: Sage, 2004, ch. 19.