**Online Appendix D**

We considered two alternative procedures for sparse principal components analysis (SPCA) as well as conventional principal components analysis (PCA) and exploratory factor analysis techniques.

The two SPCA estimators may be preferred as alternatives to the TT as they have the same objective of identifying a minimal set of factors each with relatively few variables with non-zero loadings. Instead of the iterative approach used in the TT, these procedures seek to identify factors by using regularisation. The first, referred to here as Sparse PCA (EN) uses the elasticnet procedure introduced by Zou, H., Hastie, T. and Tibshirani, R. (2006). Broadly, this procedure restates the conventional PCA estimator as a regression problem and then applies the elasticnet regularisation procedure. The second, Sparse PCA (SPCA), introduced by Erichson et al. (2020) , builds on the approach of Zou et al. (2006) but uses an alternative variable-projection procedure which potentially deals better with outliers. In our case the results are similar, although EN seems to do a better job of delivering sparse factors.

Alongside conventional PCA we also employed three exploratory factor analysis rotations that are designed to produce a simple/sparse factor structure: the orthogonal varimax (which maximizes the squared loadings of each factor, and thus limits the number of variables per factor) and quartimax (minimizing the number of factors explaining each variable) well as the oblique oblimin rotation (akin to quartimax but doesn’t require factors to be orthogonal.)

Figure D1 reports the factor loading structure for each of these methods. Whilst there are differences across methods, as should be expected, in each case the overall conclusion is similar. In every case standard diagnostics suggest retaining three factors, and these results are reported in the first column in plots A,C,E, etc. The length of each bar reflects the absolute value of that trait’s loading on that factor, and the colour the sign with blue positive and red negative. For clarity, the intensity of the colour also reflects the absolute value of the loading.

Each of Varimax (plot A), Quartimax (C), Oblimin (E) produces results in line with those of the TT. A first factor containing with large loadings for traits associated with ‘attractiveness’, a second with *criminal*, *physicallydominant*, and *financiallygreedy.* The third factor then contains *competent* and *organised*. However, unlike the TT these results factors are not sparse and we see that each factor often includes other traits with a small loading. For example, in plot A, inter alia, *organised* has a small positive weight on the first ‘attractiveness’ factor, and *criminal* a small negative weight.

This is more pronounced in plot G which reports the results of a conventional PCA analysis. Here, the same overall pattern can be easily discerned. But, *physicallyattractive* seems to load on both the ‘attractiveness’ and ‘criminality’ factors. However, the results of the EN sparse-PCA in plot I more clearly place *physicallyattractive*  on the `attractiveness’ factor, as does the SPCA sparse-PCA in plot J.

The second column, containing plots B,D, etc. makes clear that when, ignoring the diagnostics, we entertain the possibility of a fourth factor it seems to have little direct interpretation with small loadings on a large number of traits. The exception is potentially the fourth principal component reported in plot H, where the fourth factor component might be interpretable as appealing facial traits that are not related to physical attractiveness.

Table D1 reports results analogous to column 6 of Table 3 but replacing Attractiveness, Criminality, and Competence with those derived from the alternative procedures described above. The results are consistent with those in Table 3. Attractiveness is always negative, although not always significant. Criminality is also always negative, and precisely estimated in almost every column. Competence is always positive and again almost always significant. The Fourth Factor is inconsistent in sign, and never significant. The results for the four-factor oblimin rotation in column 11 are an outlier in that no factor is significant, although the estimates are similar to those in other columns they are less precise. However, given there is no statistical reason to prefer the four factor model over the three factor model, we do not pursue this further. The overall conclusion is that factor structure and the relationships between these factors and overclaiming are robust to alternative dimension reduction procedures.

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**Figure D1. Plots showing the loading of each measured trait for a selection of Sparse Principal Components and Factor Analysis estimators.**

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**Additional References:**

Zou, H., Hastie, T. and Tibshirani, R. (2006). [Sparse Principal Component Analysis.](http://users.stat.umn.edu/~zouxx019/Papers/spca.pdf) Journal of Computational and Graphical Statistics, 15(2), 265-286.

Erichson, N. Benjamin Zheng, Peng,  Manohar, Krithika, Brunton, Steven L.,  Kutz, J. Nathan, and  Aravkin, Aleksandr Y. (2020) [Sparse Principal Component Analysis via Variable Projection](https://epubs.siam.org/doi/abs/10.1137/18M1211350), *Siam Journal on Applied Mathematics,80(2), 977-1002.*