Replicable and Coupled Changes in Innate and Adaptive Immune Gene Expression in Two Case-Control Studies of Blood Microarrays in Major Depressive Disorder

Supplemental Information

Contents

List of MRC Immunopsychiatry Consortium Members

Supplementary Text

Samples

Microarray data

Differential gene expression in each case-control study separately

Combining P-values for differential gene expression from two studies

Weighted gene correlation network analysis

Effects of controlling for comorbid anxiety

Supplementary Tables

Table S1. Summary of case-control studies of whole genome expression in peripheral blood cells from patients with major depressive disorder compared to healthy controls.

Table S2. Patient demographics in Janssen-BRC and GSK-HiTDiP data sets.

Table S3. List of differentially expressed genes in the GSK-HiTDiP data set.

Table S4. List of differentially expressed genes in the Janssen-BRC data set.

Table S5. List of 165 genes that are significantly differentially expressed with consistent sign of fold change in both the GSK-HiTDiP and Janssen-BRC studies.

Table S6. List of 393 genes that are significantly differentially expressed across both studies using Fisher's chi squared test with FDR=10%.

Table S7. Enrichment analysis of genes differentially expressed in both GSK-HiTDiP and Janssen-BRC studies.

Table S8. List of 150 genes that overlap with the NESDA study.

Table S9. List of 21 genes that are significantly differentially expressed with consistent sign of fold change in both the GSK-HiTDIP and Janssen-BRC studies when not correcting for anxiety.

Table S10. Enrichment analysis of the MDD-21 consensus set of genes that were differentially over-expressed or under-expressed in MDD patients compared to healthy controls in both GSK-HiTDiP and Janssen-BRC studies when not correcting for anxiety.

Table S11. Gene transcriptional network modules were tested for case-control differences in eigengene expression.

Supplementary Figures

Figure S1. Schematic of statistical analysis

Figure S2. Bayesian analysis of genes differentially expressed in patients with MDD compared to healthy controls in both GSK-HiTDiP and Janssen-BRC studies**.**

Figure S3. Statistical correction for effects of body mass index on significance and effect size of case-control differences in the MDD-165 consensus gene set.

Supplementary References

List of MRC Immunopsychiatry Consortium Members

University of Cambridge

Edward Bullmore Petra E. Vértes Rudolf Cardinal *Department of Psychiatry, Behavioural and Clinical Neuroscience Institute, University of Cambridge, Cambridge CB2 0SZ*

MRC Biostatistics Unit (Cambridge)

Sylvia Richardson Gwenaél G.R. Leday *MRC Biostatistics Unit, Cambridge Institute of Public Health, Forvie Site, Robinson Way, Cambridge Biomedical Campus, Cambridge CB2 0SR*

University of Edinburgh

Tom Freeman David Hume Tim Regan Zhaozong Wu *System Immunology Group, Division of Genetics and Genomics, The Roslin Institute and Royal (Dick) School of Veterinary Studies, University of Edinburgh, Easter Bush, Midlothian EH25 9RG*

King's College London

Carmine Pariante Annamaria Cattaneo Patricia Zuszain Alessandra Borsini *Psychiatry and Immunology Lab & Perinatal Psychiatry, Institute of Psychiatry, Psychology and Neuroscience, King's College London G.32.01, The Maurice Wohl Clinical Neuroscience Institute, Cutcombe Road, London SE5 8AF*

Robert Stewart David Chandran *Institute of Psychiatry, Psychology and Neuroscience, King's College London, The Maurice Wohl Clinical Neuroscience Institute, Cutcombe Road, London SE5 9RT*

University College London

Livia Carvalho Joshua Bell Luis Henrique Souza-Teodoro *Department of Epidemiology and Public Health, UCL, 1-19 Torrington Place, London WC1E 7HB*

University of Southampton

Hugh Perry *Centre for Biological Sciences, University of Southampton, Mail Point 840 LD80B, South Lab and Path Block, Southampton General Hospital, SO16 6YD*

University of Sussex

Neil Harrison *Brighton & Sussex Medical School, University of Sussex, Brighton BN1 9RR, United Kingdom*

Peripheral immune transcripts and depression Leday, Vertés *et al.* Supplement **Contract Contract Contrac**

Janssen

Wayne Drevets Gayle M Wittenberg Yu Sun *Janssen Research & Development, 1125 Trenton-Harbourton Road, Titusville, NJ 08560*

Declan Jones *J&J Innovation Centre, One Chapel Place London W1G 0BG*

GlaxoSmithKline

Edward Bullmore Robert B Henderson *ImmunoInflammation Therapeutic Area Unit, GSK R&D, Gunnels Wood Road, Stevenage SG1 2NY*

Shahid Khan Annie Stylianou *GSK R&D, Gunnels Wood Road, Stevenage SG1 2NY*

Supplementary Text

Samples

We analysed data from two case-control studies of depression: the GSK-HiTDiP study and the Janssen-BRC study. Other aspects of these studies have been previously reported (1-5) but the microarray data on peripheral gene expression has not been previously reported for the HiTDIP study.

GSK-HiTDiP: This study was designed primarily as a case-control study to identify genetic sequence (DNA) variations associated with a diagnosis of major depressive disorder (MDD). In total, N=1022 Caucasian patients with recurrent MDD were recruited at the Max-Planck Institute of Psychiatry in Munich, Germany, and at two other hospitals in the Munich area (BKH Augsburg and Klinikum Ingolstadt). Patients were evaluated using the semi-structured Schedule for Clinical Assessment in Neuropsychiatry (SCAN; (6)), administered by trained staff. Patients were included if they had a diagnosis of recurrent MDD, i.e., at least two episodes of depression satisfying DSM-IV or ICD10 criteria. Exclusion criteria included: i) experience of mood-incongruent psychotic symptoms or lifetime history of schizophrenia, schizoaffective disorder or other axis 1 disorders; ii) lifetime history of intravenous drug use or diagnosis of drug dependency; iii) lifetime history of depression secondary to alcohol, substance abuse, medical disorders or use of prescribed medication; iv) lifetime history of obsessive compulsive disorder (OCD) or post-traumatic stress disorder (PTSD). Note that history of anxiety symptoms or disorders (apart from OCD and PTSD) was not an exclusion criterion.

The control group comprised 968 Caucasian healthy controls recruited from a Munich-based community sample at the Max-Planck Institute of Psychiatry. All participants were screened for schizophrenia, anxiety and mood disorders using the Composite International Diagnostic Screener (7) and were included if there was no evidence for these disorders.

Micro-array data were available from whole blood on a subset of this sample, comprising patients with MDD (N=128, 64 with generalised anxiety disorder, diagnosed by the MINI questionnaire, and 64 without anxiety disorder) and healthy controls (N=64). RNA was isolated from all samples using the standard PAXgene protocol on the Qiagen Biorobot 8000. All samples gave good quality RNA, as assessed by Agilent Bioanalyser. The yield range was 0.86-15.05ug with an average of 6.25ug. Samples were then randomised into batches, with each batch containing a representative number of controls, depression with anxiety and depression without anxiety, and the same ratio of females to males (3:1). 50ng of RNA from each sample was converted to a biotin labeled cDNA probe using NuGEN SPIA amplification. The probes were then hybridized to Affymetrix U133_Plus2.0 Genechips.

All participants provided informed consent in writing. The study was approved by an independent ethics review board.

Janssen-BRC: This study was designed to study molecular profiles (gene expression, proteomics and metabolomics) of depressed patients in conjunction with data being captured as part of the BRC International Database to seek the best biomarker profiles for depression including personal and medical history, cognition, and EEG. One hundred (100) participants (66% females) with MDD were recruited from Sydney, New South Wales and Adelaide, South Australia. Participants were referred from general practitioners and psychiatrists. In addition to the 100 clinical subjects, 100 healthy controls matched by age, gender, education, and recruitment site were included. Patients were required to be drug naïve or exceed a compound-specific washout period based on time required for the amount of drug in the patient's system to be less than 3% of the minimum daily therapeutic dose. Depressed patients had a HAM-D17 total score >= 18. Patients with a history of substance abuse in the last year, or with a history of a mental disorder not related to depression were excluded. Anxiety symptoms were reported on the MINI, and symptoms of melancholia were reported by the CORE score (8).

Gene expression was profiled on RNA isolated from whole blood using the Ovation™ Whole Blood Solution. Amplified and labeled RNA were hybridized to the Affymetrix Human Genome U133 Plus 2.0 Array interrogating over 47,000 transcripts. Samples were stored at BRC at -20°C prior to shipping for molecular profiling. Micro-array data were included for patients whose samples were stored for less than 1 year. This comprised patients with MDD (N=94, 40 with generalised anxiety disorder indicated on the MINI) and healthy controls (N=100). All participants provided informed consent in writing. The study was approved by an independent ethics review board.

Patient demographics for patients whose expression data is included in each study are shown in **Supplementary Table S2**.

Microarray data

Whole blood samples from the GSK-HiTDIP and from the Janssen-BRC studies were both analysed using the Affymetrix Human Genome U133 Plus 2.0 Array. Affymetrix CEL files were read and RNA normalized using the R package *affy* (version 1.46.1; (9)). Data were quality controlled using the R package *arrayQualityMetrics* (10) resulting in the exclusion of 22 GSK-HiTDIP samples that failed one or more of the outlier tests. At this stage, the microarray data consisted of 54,675 probes measured on 113 cases versus 57 controls for GSK-HiTDIP, and on 94 cases versus 100 controls for Janssen-BRC. These matching samples were quantile normalized using the R package *limma* (11). Probes were annotated with the Bioconductor Annotation package hgu133plus2.db (version 3.1.3) and 13,124 unannotated probes were removed. From the remaining 41,551 annotated probes, we selected a unique and optimal probeset per gene using the scoring method (12) implemented in the R package *jetset* (version 3.1.3). This resulted in identification of 18,949 probes from the GSK-HiTDiP study and 18,889 probes from the Janssen-BRC study, which were used for the differential expression analysis in each dataset. For all further analysis we used the data from 18,863 unique probes measured in both studies.

Differential gene expression in each case-control study separately

We first conducted differential expression analysis in each of the two studies, separately; see **Supplementary Figure S1** for schematic overview of data analysis strategy. Each list of *P*-values was thresholded to control the false discovery rate (FDR) at 10%. In doing so we found 133 genes differentially expressed in the GSK-HiTDiP study and 12 genes in the Janssen-BRC study, with no overlapping genes between the two (**Supplementary Tables S1 and S2**). We here remark that the significance level is 10% for each study, but that the significance level for discoveries lying within the intersection between the two thresholded lists of P-values is controlled at a level much lower than 10%. Therefore, to improve the power of our statistical analysis we employed the Bayesian approach of Blangiardo & Richardson (13) that allows the determination of a more lenient *P*-value threshold to yield higher specificity while maintaining good sensitivity.

Combining P-values for differential gene expression from two studies

To identify MDD-related genes that replicate in both GSK-HiTDiP and Janssen-BRC datasets, we statistically assessed the intersection between the probability measures (*P*values) provided by the differential expression analyses of the two studies. We remark that to do this, it is tempting to use a pre-specified threshold *q* on the *P*-values in each experiment and carry out a chi-square test of independence between the two sets of significant genes to evaluate whether the degree of overlap is greater than expected by chance. However, this approach relies heavily on the arbitrary choice of *q* and ignores the levels of evidence for differential expression represented by the *P*-values. For these reasons, we instead adopted the Bayesian method of Blangiardo & Richardson (13), implemented in the R package *sdef* (14). Briefly, this means mapping the *P*-value threshold

 q to a ratio $R(q)$ which is proportional to the number of genes differentially expressed in both studies divided by the number expected by chance. By tuning *q* threshold selection to optimise the ratio between observed and expected numbers of genes differentially expressed in both studies, this method confers greater power than more conventional approaches such as simply identifying the genes in common between two lists each thresholded conservatively to control type 1 error. We chose to use the threshold q_2 , which represents the largest (most lenient) threshold for which there are at least twice as many significant case-control differences in common between the two studies as expected by chance (**Supplementary Figure S2**). To cross-validate the results of this analysis we also used Fisher's chi square test to combine *P*-values from the GSK-HiTDIP and Janssen-BRC datasets.

The method identifies the *P*-value threshold associated with optimal value of the ratio between the number of significant case-control differences observed at the same genes in both studies *versus* the number of coincidental differences expected by chance. More formally, assuming a fixed (common) *P*-value threshold $0 < q < 1$ for both lists of p *P*-values (corresponding to p genes or probes), we are interested in the following ratio:

$$
T(q) = \frac{O_{HB}(q)}{p^{-1}O_B(q)O_H(q)},
$$
\n(1)

where $O_H(q)$ and $O_B(q)$ are the number of differentially expressed genes in the GSK-HiTDIP and Janssen-BRC data sets, respectively, and $O_{HR}(q)$ is the number of differentially expressed genes in common. $T(q)$ represents the ratio between the observed and expected number of genes in common between the two experiments. Note that marginal frequencies are assumed fixed given *q*. Ideally, the threshold *q* is chosen so as to maximize $T(q)$. However, $T(q)$ may have high variance, in particular when q is small and only a handful of genes are differentially expressed in each experiment. To improve inference about $T(q)$ and the determination of an appropriate threshold, we used a Bayesian approach (13) that fully accounts for the uncertainty in the marginal frequencies. The model assumes that the data *O* (observed frequencies) arise from a multinomial distribution:

$$
Multi(O | q, p) \mu q_1(q)^{O_{HB}(q)} q_2(q)^{O_H(q)-O_{HB}(q)} q_3(q)^{O_B(q)-O_{HB}(q)} q_4(q)^{p-O_H(q)-O_B(q)+O_{HB}(q)} \qquad (2)
$$

with a conjugate Dirichlet prior placed on the vector of parameters $q(q) \Box Dir(a,a,a,a)$, where $a = 0.5$. The value $a = 0.5$ reflects a high prior variance on frequencies and, hence, will have a relatively small influence on inference. Conjugacy facilitates efficient sampling from the joint posterior distribution. Our interest is in

$$
R(q) = \frac{q_1(q)}{(q_1(q) + q_2(q))(q_1(q) + q_3(q))},
$$
\n(3)

which represents the ratio of the number of differentially expressed genes in common for both experiments divided by the number of genes in common that are expected under the null hypothesis of a multinomial distribution. By sampling from the posterior distribution it is possible to obtain standard summary statistics of the distribution of $R(q)$, including mean, median and credible intervals (CIs). These can then be used to determine an appropriate threshold q. Following Blangiardo and Richardson (13) we used

$$
q_2 = \arg \max \{ Median(R(q) | O, p)^3 \ 2:1 \mid Cl_{95} \},\tag{4}
$$

to threshold P-values from the GSK-HiTDIP and Janssen-BRC datasets. q_2 represents the largest threshold for which *Median* $(R(q) | 0, p)$ ³ 2, i.e., there are at least twice as many case-control differences in common between the two studies as expected by chance, and the 95% credible interval CI_{95} does not include 1 (which would indicate that the observed number of common differences was the same as expected by chance). In simulations, Blangiardo and Richardson (13) demonstrated that thresholding P-value lists based on q_2 yields high specificity while maintaining good sensitivity.

Note that this Bayesian method of threshold setting does not exercise such strong type 1 error (false positive) control as the more established false discovery rate procedures for genome-wide frequentist testing of each gene separately.

To cross-validate the results of this analysis we also used Fisher's statistic, F, to combine *P*values from the GSK-HiTDIP and Janssen-BRC datasets:

$$
F = -2\hat{\mathbf{q}}_{s=1}^{s} \log(p_{is}) \Box \mathbf{c}_{2s}^{2}
$$
 (5)

where $S = 2$ denotes the number of experiments and p_{is} denotes the *P*-value for the casecontrol difference of the i-th gene in the s-th study. For each gene, Fisher's statistic is distributed as chi-square on 2S degrees of freedom and the corresponding list of *P*-values was thresholded by FDR = 10% to define a set of genes significantly expressed in common between both studies, controlling for multiple comparisons (15).

Weighted Gene Correlation Network Analysis (WGCNA; 14, 15)

From the WGCNA software package in R (16), we used the "signed" network option, with the minimum module size set to 50 and options softPower=6 and deepSplit=2. This yielded a normative gene co-expression network with 17 modules, which was visualised using *BioLayout Express3D* software (17, 18). For clarity, we only included links with positive or negative correlation strength greater than 0.7 and nodes connected to the largest component of the graph.

Effects of controlling for comorbid anxiety

In this work, gene expression was primarily adjusted for batch, age, gender and anxiety. When differential expression (within each study) was estimated by a model that did not code for presence or absence of comorbid anxiety, we found 24 differentially expressed genes in the GSK-HiTDIP study and 29 in the Janssen-BRC study, both at 10% FDR. The Bayesian analysis, combining *P*-values from both studies, reported 24 genes that were differentially expressed (without controlling for anxiety) in both studies, of which 21 were fold-change concordant (**Supplementary Table S9**). Although the set of replicable and concordant differentially expressed genes was reduced by not statistically controlling for comorbid anxiety, we still observe some overlap with our previous results and the NESDA study. Among the 21 concordant genes, 15 belong to the list of 165 genes identified by the primary analysis (controlling for anxiety): *MMP8, HP, NRG1, RNASE1, SLPI, CAMP, S100A12, PGLYRP1* and *MGST1*. Two genes (*PGLYRP1* and *NFATC2*) were also differentially expressed in the NESDA study at $FDR = 5%$. When the FDR threshold for the NESDA study was relaxed to 10% and 20%, 5 and 11 of the 20 genes differentially expressed in both GSK-HiTDiP and Janssen-BRC studies (respectively) were also differentially expressed in the NESDA study (**Supplementary Table S9**). By comparison, we expect to find 0.26, 1.11 and 4.05 genes in common by chance with the NESDA study at FDR thresholds of 5%, 10% and 20%, respectively.

Table S1. Summary of case-control studies of whole genome expression in peripheral blood cells from patients with major depressive disorder (MDD) compared to healthy controls.

Table S2. Demographic and clinical sample characteristics for both GSK-HiTDiP and Janssen-BRC case-control studies.

Note: Only limited socio-demographic and clinical data were available on these samples. In particular, for the GSK-HiTDiP study, which was designed primarily as a genetic association study, clinical phenotyping data were not available on participants. Neither study collected data on drug or alcohol consumption, ethnicity, or exposure to immuno-modulatory medication. In BRC, CORE score, BMI and substance abuse were missing for some subjects, as indicated above. Melancholia was defined as CORE >=8. P-values were chi-squared for gender, anxiety, melancholia, and substance abuse, two-tailed t-test for age, HAMD-17, and BMI.

Table S3. List of differentially expressed genes in the GSK-HiTDIP data set. Genes are ranked according to their FDR $<$ 0.1, estimated parametrically by the limma software package. *P*-values and FDR are also reported by permutation tests. FC = fold change of gene expression in MDD compared to healthy controls; FC CI = FC 95% confidence interval.

Table S4. List of differentially expressed genes in the Janssen-BRC data set. Genes are ranked according to their FDR < 0.1, estimated parametrically by the *limma* software package. *P*-values and FDR are also reported by permutation tests. FC = fold change of gene expression in MDD compared to healthy controls; FC CI = FC 95% confidence interval.

Table S5. List of 165 genes that are significantly differentially expressed (q_2 = 0.02) **with consistent sign of fold change in both the GSK-HiTDIP and Janssen-BRC studies.** This list was defined using a Bayesian rule for finding the largest *P*-value threshold associated with twice as many differentially expressed genes in both studies as would be expected by random coincidence (implemented in sdef software; Blangiardo et al [14]). Genes are ranked according to the HiTDIP fold-change (FC). The last four columns indicate genes that are "in NESDA", i.e., that were measured by the microarrays used in the NESDA study, and those among them that were replicated in the NESDA study at FDR thresholds of 5% (7 genes), 10% (18 genes) and 20% (45 genes). FC CI = FC 95% confidence interval.

Table S6. List of 393 genes that are significantly differentially expressed across both studies using Fisher's chi squared test with FDR=10%. S = chi-squared statistics; $P = P$ value.

Table S7. Enrichment analysis of genes differentially expressed in both GSK-HiTDiP and Janssen-BRC studies (Table S3). The top 10 gene ontology (GO) terms for Biological Processes (BP) are ranked according to their *P*-values from Fisher's exact test for significant enrichment. Bonferroni correction specifies a P-value threshold of $P = 4.94 \times 10^{-6}$ to achieve significance at q<0.05. Such a correction is well-known to be too stringent given that many of the GO terms are correlated, however the top 9 terms reported here remain significant even under Bonferroni correction.

Table S8. List of the 150 genes among the 165 genes in Table S5 that overlap with the microarray platform used in the NESDA study. The table displays fold-changes (FC) for the GSK-HiTDIP, Janssen-BRC and NESDA studies, as well as *P*-values (P) and false discovery rate estimates (FDR) for the NESDA study. The concordance of fold-changes is also provided (1 encodes concordance whereas 0 encodes non-concordance).

Table S9. List of 21 genes that are significantly differentially expressed (q2 = 0.0084) with consistent sign of fold change in both the GSK-HiTDIP and Janssen-BRC studies when not correcting for anxiety. This list was defined using a Bayesian rule for finding the largest P-value threshold associated with twice as many differentially expressed genes in both studies as would be expected by random coincidence (implemented in sdef software; Blangiardo et al [14]). Genes are ranked according to the HiTDIP fold-change (FC). The other columns indicate: genes that were also reported within the list of 165 genes in Table S4 (column "In list of 165"), genes that were measured in the NESDA study (column "in NESDA") and genes which were statistically significant at 5%, 10% and 20% FDR thresholds in the NESDA study (columns "NESDA 5%", "NESDA 10%" and "NESDA 20%", respectively). The last column of the table provides the fold-changes of the genes within the NESDA study.

Table S10. Enrichment analysis of the MDD-21 consensus set of genes that were differentially over-expressed (UP) or under-expressed (DOWN) in MDD patients compared to healthy controls in both GSK-HiTDiP and Janssen-BRC studies when not correcting for anxiety. The top 15 gene ontology (GO) terms for Biological Processes (BP) are ranked according to their P-values by Fisher's exact test for significant enrichment. Bonferroni correction specifies a P-value threshold of $P = 4.94 \times 10^{-6}$ to achieve significance at q < 0.05. Such a correction is well-known to be too stringent given that many of the GO terms are correlated; however, the top 8 terms were significantly enriched in the overexpressed UP gene set after Bonferroni correction.

Table S11. Gene transcriptional network modules were tested for case-control differences in eigengene expression. The 17 module eigengenes were extracted from the normative transcriptional network estimated from the control groups pooled over both studies. The gene expression data for each individual participant, whether a case or control, was projected onto each eigengene to summarise their expression of modular genes. Twotailed t-tests were performed to compare the mean eigengene score between groups for each module: positive *t*-statistics indicate that "on average" over all genes in each module there was relative over-expression in MDD cases compared to controls; negative *t*-statistics indicate that "on average" over all genes in each module there was relative under-expression in MDD cases compared to controls. There were significant case-control differences in eigengene expression for four modules, as shown below: module colours and functional labels correspond to **Figure 2**.

Figure S1. Schematic of study design and analysis

Figure S2. Bayesian analysis of genes differentially expressed in patients with MDD compared to healthy controls in both GSK-HiTDiP and Janssen-BRC studies. The ratio, *R*, between the observed and randomly expected number of genes differentially expressed in both studies (*y*-axis; dark blue line = median, light blue area = 95% credibility interval) increases and becomes more variable as the *P*-value threshold (x-axis) used to define significant case-control differences in each study becomes smaller or more conservative. The threshold $q_2 = 0.025$ (red line) is the *P*-value at which the ratio $R(q) = 2$ (dotted line), i.e., the number of genes differentially expressed in both studies is twice the number expected by chance under the null hypothesis. It was previously shown by an extensive simulation that this choice of threshold gives a good compromise between specificity and sensitivity (13, 14).

Figure S3. Statistical correction for effects of body mass index (BMI) on significance and effect size of case-control differences in the MDD-165 consensus gene set. A. Comparison of –log10 *P*-values for BMI-adjusted vs. BMI-unadjusted ("raw") gene expression data. B. Comparison of log2 fold change difference between cases and controls for BMI-adjusted vs. BMI-unadjusted gene expression data. C. Comparison of effect sizes of case-control differences, for BMI-adjusted vs. BMI-unadjusted gene expression data.

Supplementary References

- 1. Domenici E, Willé DR, Tozzi F, Prokopenko I, Miller S, McKeown A, et al. (2010): Plasma protein biomarkers for depression and schizophrenia by multi analyte profiling of case-control collections. . *PLoS ONE*. 5:e9166.
- 2. Muglia P, Tozzi F, Galwey NW, Francks C, Upmanyu R, Kong XQ, et al. (2010): Genome-wide association study of recurrent major depressive disorder in two European case–control cohorts. *Molecular Psychiatry*. 15:589-601.
- 3. Tilahun A, Lin D, Shkedy Z, Geys H, Alonso A, Peeters P, et al. (2010): Genomic biomarkers for depression: Feature-specific and joint biomarkers. *Statistics in Biopharmaceutical Research* 2:419-434.
- 4. Zoon H, Veth C, Arns M, Drinkenburg W, Talloen W, Peeters P, et al. (2013): EEG alpha power as an intermediate measure between brain-derived neurotrophic factor Val66Met and depression severity in patients with major depressive disorder. *J Clin Neurophys* 30:261-267.
- 5. Liu Y, Yieh L, Yang T, Drinkenburg W, Peeters P, Steckler T, et al. (2016): Metabolomic biosignature differentiates melancholic depressive patients from healthy controls. *BMC Genomics*. 17:669.
- 6. Wing JK, Babor T, Brugha T, Burke J, Cooper JE, Giel R, et al. (1990): SCAN: Schedules for Clinical Assessment in Neuropsychiatry. *Arch Gen Psychiatry*. 47:589- 593.
- 7. Wittchen HU, Höfler M, Gander F, Pfister H, Storz S, Üstün B, et al. (1999): Screening for mental disorders: performance of the Composite International Diagnostic–Screener (CID–S). *International Journal of Methods in Psychiatric Research*. 8:59-70.
- 8. Parker G, Hadzi-Pavlovic D, Boyce P, Wilhelm K, Brodaty H, Mitchell P, et al. (1990): Classifying depression by mental state signs. *British Journal Psychiatry*. 157:55-65.
- 9. Gautier L, Cope L, Bolstad BM, Irizarry RA (2004): affy—analysis of Affymetrix GeneChip data at the probe level *Bioinformatics*. 20:307-315.
- 10. Kauffmann A, Gentleman R, Huber W (2009): arrayQualityMetrics—a bioconductor package for quality assessment of microarray data. . *Bioinformatics*. 25:415-416.
- 11. Ritchie ME, Phipson B, Wu D, Hu Y, Law CW, Shi W, et al. (2015): limma powers differential expression analyses for RNA-sequencing and microarray studies. *Nucleic Acids Research*. gkv007.
- 12. Li Q, Birkbak NJ, Gyorffy B, Szallasi Z, Eklund AC (2011): Jetset: selecting the optimal microarray probe set to represent a gene. *BMC Bioinformatics*. 12:1.
- 13. Blangiardo M, Richardson S (2007): Statistical tools for synthesizing lists of differentially expressed features in related experiments. *Genome Biology*. 8:R54.
- 14. Blangiardo M, Cassese A, Richardson S (2010): sdef: an R package to synthesize lists of significant features in related experiments. . *BMC Bioinformatics*. 11:270.
- 15. Benjamini Y, Hochberg Y (1995): Controlling the false discovery rate: a practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society Series B (Methodological)*. 57:289-300.
- 16. Langfelder P, Horvath S (2008): WGCNA: an R package for weighted correlation network analysis. *BMC Bioinformatics*. 9:1.
- 17. Freeman TC, Goldovsky L, Brosch M, Van Dongen S, Mazière P, Grocock RJ, et al. (2007): Construction, visualisation, and clustering of transcription networks from microarray expression data. *PLoS Comput Biol*. 3:e206.
- 18. Theocharidis A, van Dongen S, Enright A, Freeman T (2009): Network visualization and analysis of gene expression data using BioLayout Express (3D). *Nature Protocols*. 4:1535-1550.
- 19. Jansen R, Penninx BWJH, Madar V, Xia K, Milaneschi Y, Hottenga JJ, et al. (2016): Gene expression in major depressive disorder. *Molecular Psychiatry*. 21:444.
- 20. Mostafavi S, Battle A, Zhu X, Potash JB, Weissman MM, Shi J, et al. (2014): Type I interferon signaling genes in recurrent major depression: increased expression detected by whole-blood RNA sequencing. *Molecular Psychiatry*. 19:1267-1274.
- 21. Spijker S, Van Zanten JS, De Jong S, Penninx BW, van Dyck R, Zitman FG, et al. (2010): Stimulated gene expression profiles as a blood marker of major depressive disorder. *Biological Psychiatry*. 68:179-186.
- 22. Savitz J, Frank M, Victor T, Marino J, McJinney B, Teague T, et al. (2013): Inflammatory, apoptotic, and neurological disease-related genes are differentially expressed in currently depressed patients with mood disorders and correlate with morphometric and functional imaging abnormalities. *Brain Behavior & Immunity*. 31:161-171.
- 23. Segman RH, Goltser-Dubner T, Weiner I, Canetti L, Galili-Weisstub E, Milwidsky A, et al. (2010): Blood mononuclear cell gene expression signature of postpartum depression. *Molecular Psychiatry*. 15:93-100.
- 24. Yi Z, Li Z, Yu S, Yuan C, Hong W, Wang Z, et al. (2012): Blood-based gene expression profiles models for classification of subsyndromal symptomatic depression and major depressive disorder *PLoS ONE*. 7:p.e31283.
- 25. Glahn DC, Curran JE, Winkler AM, Carless MA, Kent JW, Charlesworth JC, et al. (2012): High dimensional endophenotype ranking in the search for major depression risk genes. *Biological Psychiatry*. 71:6-14.