

Genetic mapping of transcriptomic response to *in vivo* immune  
perturbations

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# Abstract

The human immune system plays a central role in defense against infection, but its dysregulation is implicated in immune-mediated diseases. The past decade has seen increasing application of high-throughput technologies to profile, predict, and understand immune response to perturbation. The ability to measure immune gene expression at scale has led to the identification of transcriptomic signatures that predict clinical phenotypes such as antibody response to vaccines. It has also been recognised that both expression and phenotypic responses are traits with complex genetic architectures. This thesis examines the longitudinal transcriptomic response to immune perturbations, and its association with clinical response phenotypes and common genetic variation.

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**Chapter 2** explores transcriptomic response to pandemic influenza vaccine in a multi-ethnic cohort of healthy adults. The success of vaccination in controlling influenza is indisputable, but it is not completely understood why some individuals fail to mount protective antibody responses. I meta-analysed blood microarray and **RNA-sequencing (RNA-seq)** datasets, identifying a distinct transition from innate immune response at day 1 after vaccination, to adaptive immune response at day 7. Heterogeneity between measurement platforms made it difficult to identify single-gene transcriptomic associations with antibody response. Using a gene set approach, I found expression modules related to the inflammatory response, the cell cycle, CD4<sup>+</sup> T cells, and plasma cells to be associated with vaccine-induced antibody response.

In **Chapter 3**, I map **response expression quantitative trait loci (reQTLs)** in the same cohort to investigate regulation of transcriptomic response by common genetic variants. Rather than driving differential expression post-vaccination, the strongest **reQTL** appear to be explained by changes in cell composition revealing cell type-specific **expression quantitative trait locus (eQTL)** effects. For example, a **reQTL** identified for *ADCY3* specific to day 1 was driven largely by high monocyte proportions at day 1 compared to other timepoints. Changes in cell composition present a significant challenge to interpreting **reQTLs** found through bulk sequencing of heterogeneous tissues.

Finally, **Chapter 4** applies an analogous longitudinal study design to explore **Crohn's disease (CD)** patient response to anti-**tumour necrosis factor (TNF)** drugs: infliximab and adalimumab. Anti-**TNF** treatment has revolutionised patient care for **CD**, but 20-40% of patients show primary non-response soon after starting treatment. I identified baseline expression modules associated with primary non-response, but also significant heterogeneity in associations between the two drugs. Expression changes post-treatment in non-responders were largely magnified in responders, suggesting there may be a continuum of response. Distinct expression trajectories identified for responders and non-responders revealed sustained expression differences up to week

54. A set of interferon-related genes were regulated in opposing directions in responders and non-responders, presenting an attractive target for future studies of the biological mechanisms underlying non-response.

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# Chapter 1

## Introduction

Observable human characteristics or traits are called phenotypes. Variation in phenotype emerges from the interplay of genetics, environment and pure chance. The contributions of each vary from phenotype to phenotype. Traits for which genetic variation explains a non-zero percentage of phenotypic variation are heritable. Virtually all phenotypic traits are heritable to some degree, and twin studies provide upper bounds on this heritability by partitioning phenotypic variation into genetic and environmental components [1].

Genetic variation presents a unique opportunity to probe the causal molecular mechanisms underlying phenotypes. Information encoded in the genome can have phenotypic consequences only after flowing through multiple molecular layers. This guiding principle is the central dogma, whereby the flow is directed from DNA to RNA to protein, via transcription and translation. Barring somatic mutation, an individual's genome is fixed at conception, thus providing a causally upstream anchor that can be measured with relatively little error. A mainstay of the field of human genetics is uncovering the specific genetic variants that contribute to the heritability of phenotypes through statistical association of variants and phenotypes. Although not immune to population-level biases like stratification [2] and collider bias [3], genetic association has intrinsic resistance to reverse causality, an issue that permeates observational studies on the causes of human phenotypes.

### 1.1 Genetic association studies of complex traits

#### 1.1.1 Structure and variation of the genome

The human genome is almost three billion bp (base pairs) in length, containing 20 000–25 000 protein-coding genes that span 1–3 % of its length, with the remaining sequence being non-coding [4, 5]. Each diploid cell contains two copies of the genome, organised into 46 chromosomes comprised of 23 maternal-parental pairs—22 pairs of homologous autosomes and one pair of sex chromosomes. Variation in the genome between individuals in a population exists in the form of **single nucleotide polymorphisms (SNPs)**, short indels, and structural variants. For common population variants with **minor allele frequency (MAF) >1–5 %**, the vast majority (>99.90 %) are **SNPs** and short indels [5]. On average, a pair of genomes differs by one **SNP** per 1000–2000 bp

I agree the intro is built around genetics. I have tried to keep the genetics parts concise while elaborating on gene expression more in the later two sections.

[6]. Each version of a variant is called an allele; each individual has a maternal and parental allele at each variant.

The large number of variants in a population are inherited in a smaller number of haplotypes—contiguous stretches of the genome passed through generations via meiotic segregation. The fundamental sources of genetic diversity are mutation and meiotic recombination, generating new alleles and breaking apart haplotypes into shorter ones over evolutionary time. Variants that are physically close on a chromosome are less likely to flank a recombination event, hence more likely to cosegregate on the same haplotype (genetic linkage). Genetic linkage is one source of **linkage disequilibrium (LD)**—the non-random association of alleles at two variants, differing from expectation based on their population frequencies and the law of independent assortment. LD can be quantified by  $r^2$ , the squared correlation coefficient between alleles in that specific population [7].

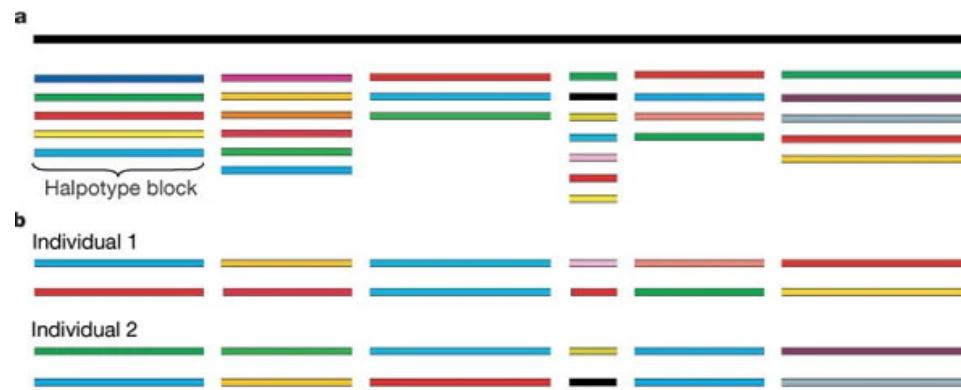
Recombination events are not distributed uniformly throughout the genome. The genome is a mosaic of haplotype blocks delimited by recombination hotspots, characterised by strong LD within blocks, and little LD between blocks [8, 9] (Fig. 1.1). The structure of correlated haplotypes reflects a population’s unique evolutionary history, and can be used to trace the demography of populations back through time [10].

### 1.1.2 Lessons from the past fifteen years

Genetic variants can affect heritable traits by impacting the function or regulation of target genes. How genetic variation contributes to a particular trait defines its genetic architecture—the number of genes affecting that trait; and the frequencies, effect sizes, and interactions of trait-associated alleles [12, 13]. The number of genes defines a spectrum of traits from monogenic (where inheritance follows simple Mendelian patterns) to polygenic (where inheritance is complex). Proposed architectures differ strikingly among complex traits, even for traits with phenotypic similarities like **type 1 diabetes (T1D)** and **type 2 diabetes (T2D)** [12]. What is consistent, is that the number of genes and genetic variants affecting a complex trait is large (ranging from dozens to many thousands), thus the average effect size of trait-associated variants is small [14–16].

Since the 1980s, linkage analysis has been used to map the chromosomal positions and regions (loci) affecting traits by tracing the cosegregation of markers (variants with known position) with the trait in family pedigrees [17–19]. They were complemented by early genetic association studies, which largely focused on variants in or near candidate genes selected on the basis of prior biological knowledge [20]. These methods saw much success for Mendelian traits, but application to most complex traits proved challenging. Small average effect sizes meant penetrance was too low to reliably observe cosegregation problems in pedigrees [19]. Early candidate gene studies were also underpowered to detect small effects [21].

The past fifteen years have seen the rise of **genome-wide association studies (GWASs)** that systematically test common variants selected in a comparatively hypothesis-free manner across the whole genome (Fig. 1.2). Using large sample sizes to overcome small effects and large multiple testing burden, thousands of associations have been discovered for complex traits and diseases, many robustly replicated across populations [19, 22]. A number of take-home messages have emerged. Most genetic variance is additive—the contribution of dominance and epistatic



**Figure 1.1: The mosaic structure of human genetic variation.** Large parts of the genome can be divided into haplotype blocks between 5–200 kbp in length, with strong intra-block LD. For each block, three to seven common haplotypes (indicated by different colors) represent the majority of variation found in humans. An individual carries two haplotypes per block, one inherited from each parent. The exact structure and diversity of the blocks varies between populations. Information on the haplotypes, their locations in the genome, and their frequencies in different populations form a “haplotype map” of the genome. Figure reprinted by permission from Springer Nature: Springer Nature, Nature, Pääbo [11], © 2003.

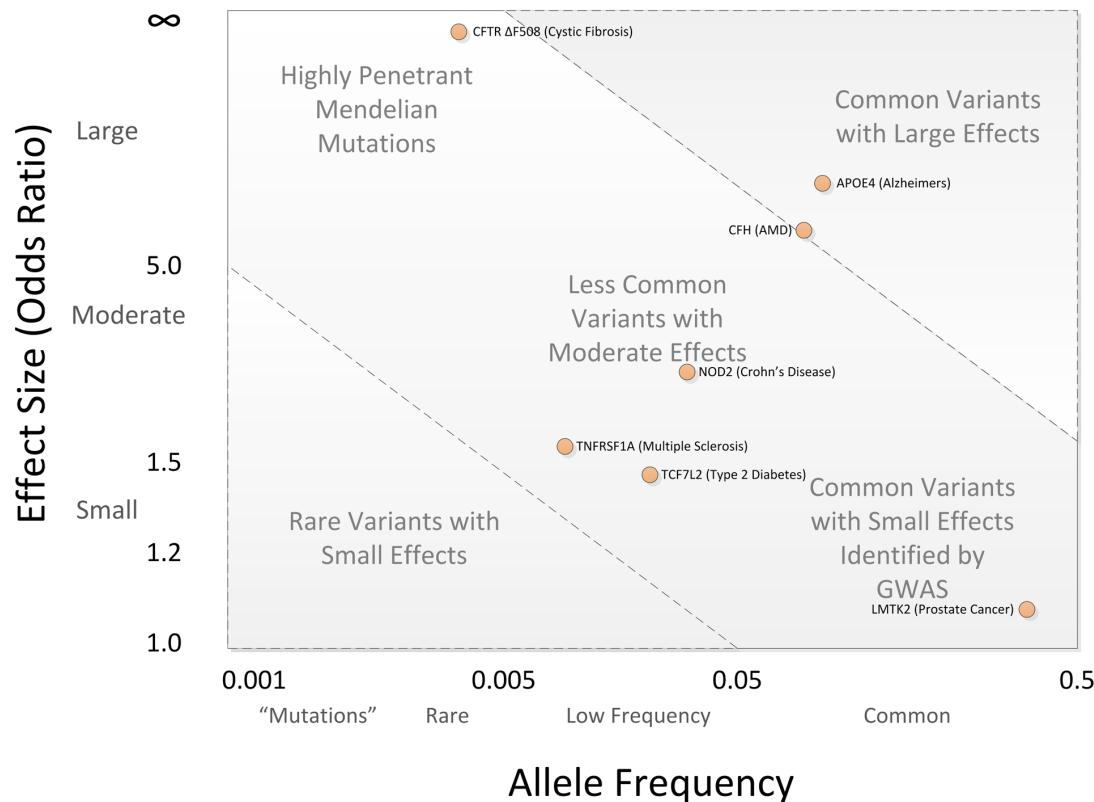
interactions is small [13]. Variants with effects on multiple phenotypes (pleiotropy) are widespread [19]. Even traits that are molecular rather than whole-organism phenotypes can be remarkably polygenic, with hundreds to thousands of associated loci [23]. GWAS sample sizes in the millions are increasingly commonplace, and the discovery of new associations with ever smaller effects as sample sizes increase shows no sign of plateauing [24, 25].

### 1.1.3 From complex trait to locus

GWASs rely on the tendency of common variants on the same haplotype to be in strong LD. As the number of haplotypes is relatively few, it is possible to select a subset of tag variants such that all other known common variants are within a certain LD threshold of that subset. In practice, there is enough redundancy that the number of variants measured on a modern genotyping array (in the order of  $10^5$ – $10^6$ ) is sufficient to tag almost all common variants [27, 28]. Associations with unmeasured variants are indirectly detected through correlation with a tag variant. Furthermore, as unrelated individuals still share short ancestral haplotypes, study samples can be assigned haplotypes from a panel of haplotypes derived from reference samples by matching on the directly genotyped variants. This process of genotype imputation allows ascertainment of many more variants not directly genotyped [29], and helps to recover rarer variants that are poorly-tagged [22]. Modern imputation panels enable cost-effective GWASs testing tens of millions of variants as rare as 0.01–0.1 % in diverse populations [30].

Testing large numbers of variants incurs a massive multiple testing burden, but acknowledging the correlation between variants due to LD, there are only the equivalent of  $\sim 10^6$  independent tests in the European genome, regardless of the number of tests actually performed [31]. The field has thus converged on a fixed discovery threshold of  $0.05/10^6 = 5 \times 10^{-8}$  for genome-wide significance in European populations [32], akin to controlling the type I family-wise error rate (FWER) to below  $\alpha = 0.05$  using the Bonferroni correction\*.

\*The Bonferroni correction makes no assumptions about the dependence structure of the *p*-values, controlling



**Figure 1.2: Effect size and frequency of trait-associated genetic variants.** Complementary methods are suitable for different trait architectures. Linkage analysis is suited to detecting Mendelian variants with large effects. **GWAS** is suited to detecting common variants with small effects. There are few common variants of large effect due to selection. Rare variants with small effects are hard to distinguish from noise without very large samples. As LD depends on frequency, rare variants are poorly tagged by genotyping arrays and difficult to impute. Studies focusing on rare variants often employ **whole-exome sequencing (WES)** or **whole-genome sequencing (WGS)**. Figure reproduced from Bush *et al.* [26] under the CC BY 4.0 license ([creativecommons.org/licenses/by/4.0/legalcode](http://creativecommons.org/licenses/by/4.0/legalcode)).

### 1.1.4 From locus to causal variant

By design, a significantly-associated variant from a **GWAS** needs not be a variant that causally affects the trait, and may only tag a causal variant. The resolution of the associated locus depends on the local **LD** structure. Fine-mapping is the process of determining which of the many correlated variants in an associated locus are most likely to be causal. The causal variants in a locus are not necessarily the ones with the strongest associations. Bayesian fine-mapping methods take a variable selection approach, assigning each variant a posterior probability of causality. A credible set of variants likely to contain all causal variants in the locus with some probability can then be determined [34, 35]. The ability to separate causal and tag variants depends on factors like **LD**, sample size, and the effect size and number of causal variants [22, 34]. It is important that the causal variant is observed, by direct genotyping or confident imputation.

### 1.1.5 From causal variant to target gene

Most causal variants for Mendelian traits are coding variants (nonsense, missense, or frameshift) that impact protein sequence [36]. In contrast, over 90 % of **GWAS** loci fall in non-coding regions [37], and often too far from the nearest coding region to be in **LD** [38]. Even if the causal variants at a locus are fine-mapped, one of the greatest challenges following **GWAS** is prioritising the target genes through which those variants affect the trait. A reasonable heuristic is to assign the nearest gene **transcription start site (TSS)** or body as the target, particularly for metabolite traits [39]. For improved accuracy across a variety of complex traits, integrative methods gene prioritisation combine variant-to-gene distance with other metrics and data types drawn from numerous external sources [39–41].

## 1.2 Gene expression as an intermediate molecular phenotype

### 1.2.1 Regulation of gene expression

Gene regulation data are indispensable for gene prioritisation. Rather than directly impacting the coding sequence of a gene, many non-coding **GWAS** loci are hypothesised to affect traits by affecting the regulation of target gene expression [37, 42]. Unlike genotype, expression is dynamic across time and space. Diverse expression programs are responsible for the myriad of cell and tissue types generated during development, and enables adaptation in response to environmental stimuli.

Expression is the product of eukaryotic transcription, a multi-step process involving interactions between DNA, RNA, and hundreds of proteins [43]. Transcription of the **pre-messenger RNA (mRNA)** is initiated when RNA polymerase and **transcription factors (TFs)** form part of a protein complex around the promoter region and **TSS** of a gene. **TFs** can also bind to more distant *cis*-regulatory elements such as enhancers and repressors. Distant regulatory elements interact with the promoter region via DNA looping. Transcription can only happen in regions of open chromatin, where the packing of DNA-histone complexes (nucleosomes) is loose enough that the

the **FWER** (probability of at least one type I error) exactly under any structure. It is conservative (i.e. controls the **FWER** at a stricter level than the chosen  $\alpha$ ) even for independent tests. In fact it is always conservative unless the  $p$ -values have strong negative correlations [33].

DNA is physically-accessible to the transcriptional machinery. Chromatin accessibility is partially determined by histone modifications such as methylation, acetylation, phosphorylation, and ubiquitination [44]. The DNA itself can also be modified; methylation at CpG sites in promoters tends to repress transcription [45].

To form a mature mRNA, the pre-mRNA is capped at the 5' end by a modified nucleotide, and at the 3' end by a poly(A) tail. Introns are removed, and the exons spliced together by spliceosomes that cut and rejoin the RNA at splice sites. Different ways this occurs determines which of many alternatively-spliced transcripts is produced. Post-transcription regulation of mature mRNAs is also possible, via RNA editing and regulatory elements in the 5' and 3' untranslated regions (UTRs).

In line with the regulatory hypothesis, GWAS variants are heavily enriched in regulatory elements annotated by functional genomics projects (e.g. ENCODE [4]), including regions of open chromatin, histone binding sites, TF binding sites, enhancers, splice sites, and UTRs [46–50]. Furthermore, enrichment is often observed in particular contexts (tissues, cell types, or cell states [22, 37, 42]). An example is the enrichment of fine-mapped immune-mediated inflammatory disease (IMID) SNPs in CD4<sup>+</sup> T cell enhancers, particularly to enhancers activated after stimulation [48]. These results put forth expression as an important intermediate linking non-coding GWAS variants to their associated traits, and help nominate trait-relevant contexts.

### 1.2.2 Expression quantitative trait loci (eQTLs)

Expression is a complex molecular phenotype in itself, with a heritability of 15–30 % [51]. Genome-wide assays for expression, such as microarrays and RNA-sequencing (RNA-seq), were among the earliest high-throughput technologies developed for quantifying molecular phenotypes. Genetic loci associated with quantified gene expression are called expression quantitative trait loci (eQTLs). Large-scale efforts such as the Genotype-Tissue Expression (GTEx) project [52] have pioneered the study of eQTLs and other molecular quantitative trait loci (molQTLs) over the past decade [53].

eQTL effect sizes are large relative to variants associated with whole-organism phenotypes, with the average eQTL explaining 5–18 % of additive genetic variance for its associated gene [51]. The eQTLs with the largest effects tend to be concentrated near the TSS of their target gene (*cis*-eQTLs), affecting TF binding sites and other local regulatory elements. eQTLs further away or on a different chromosome are called *trans*-eQTLs. The exact threshold separating *cis*- from *trans*- on the same chromosome is arbitrary; <1 Mbp and >5 Mbp are commonly used thresholds for *cis*- and *trans*-eQTLs respectively [54–56]\*. In general, eQTL effect size declines with distance to the TSS, and *trans*-eQTLs have smaller effects compared to *cis*-eQTLs [53]. *Trans*-eQTL often represent *cis*-eQTLs of regulatory molecules like TFs and RNA-binding proteins that may target many genes in *trans* as master regulators [55, 57]. Gathering large enough samples to detect

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\*Having a threshold is often a matter of practicality to reduce the number of variants tested. Assaying expression is still more costly than array genotyping, so eQTL sample sizes are small compared to GWAS. Even though eQTLs effects are relatively large, eQTL mapping genome-wide is still equivalent to performing GWASs thousands of continuous phenotypes, incurring enormous computational and multiple testing burdens. Studies focused specifically on *trans*-eQTL mapping reduce the number of tests in other ways, such as testing only trait-associated variants [56].

*trans*-eQTLs remains a priority, as most expression heritability is driven by *trans*- rather than *cis*- effects, perhaps due to small but wide-reaching effects [58].

### 1.2.3 Context-dependent eQTLs

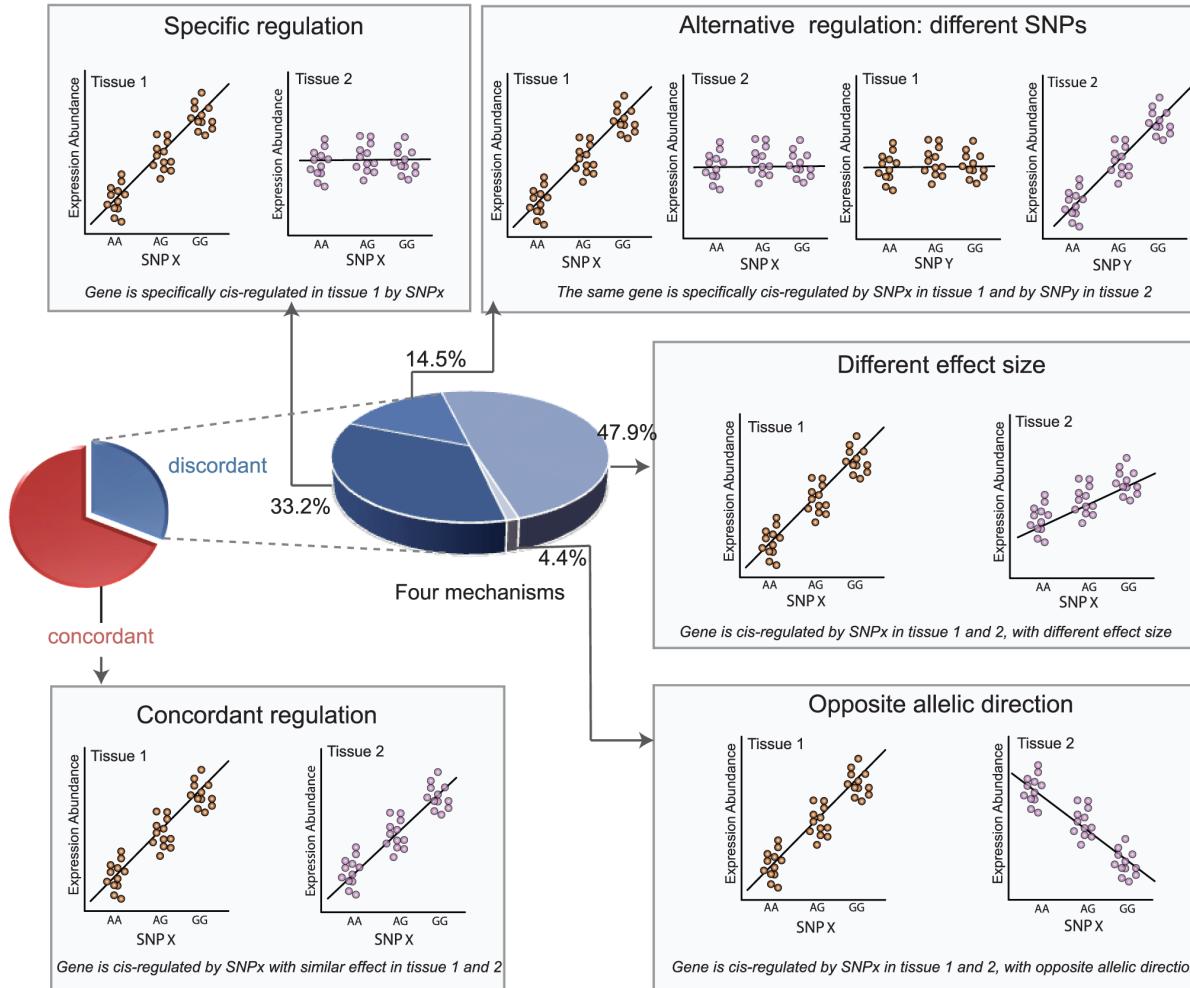
Like expression itself, the effects of eQTLs are highly context-dependent [53, 55]. When the effect size of an eQTL is not the same in all environments, but differs depending on the environment, the eQTL is said to interact with those environments. This can manifest as a *statistical* interaction in a regression model with a multiplicative genotype-environment term, where the effects of environment and genotype on expression are not additive at the chosen scale for measuring expression. A non-exhaustive list of environmental contexts that have been found to interact with eQTLs includes sex [59], age [59], ancestry [60–62], tissue [63, 64], purified cell type [60, 65–68], cell type composition in bulk samples [69–72], cell differentiation stage [73], disease status [66], and experimental stimulation (see Section 1.2.4). These contexts can be interdependent. For example, tissue-dependent effects may arise from a combination of cell type-dependence and varying cell composition between tissues.

A multitude of molecular mechanisms could facilitate genotype-environment interactions at eQTLs. Fu *et al.* [74] mapped eQTLs in blood and four non-blood tissues (Fig. 1.3), and proposed mechanisms that might explain discordant effects of an eQTL allele on target gene between tissues, assuming the eQTL disrupts a regulatory factor's binding site. Different effect sizes of same or opposite signs could arise from tissue-dependent effects of the same factor, such as activating expression in one tissue and repressing it in another e.g. due to cofactors, or from binding of different factors in different tissues at the same site. Tissue-specific effects could arise from tissue-specific expression of a regulatory factor. A tissue-specific effect could also reflect tissue-specific target gene expression, as the eQTL effect will be zero in a tissue where the target is not expressed e.g. due to chromatin inaccessibility. Tagging of different causal variants in the two tissues, potentially with differing tagging efficiency (LD), could generate all the above scenarios.

Furthermore, the complexity of human gene regulation means these mechanisms might be acting at epigenetic, pre-, co-, or post-transcriptional levels eQTLs [51]. Detection of context-dependent effects merely exposes differences in regulatory architecture between contexts. Determining the underlying mechanisms may well require data types beyond just genotype and expression.

### 1.2.4 Immune response expression quantitative trait loci (reQTLs)

A important class of context-dependent eQTLs are response expression quantitative trait loci (reQTLs), where the interacting environment is experimental stimulation, potentially revealing regulatory effects not detectable at baseline [53, 75]. The vast majority of reQTL studies to date have been conducted on immune cells. This is not only due to the abundance of immune cells easily accessible in peripheral blood, amenable to purification and stimulation, but because the immune system is specialised for mounting different responses depending on the pathogen or perturbation. Done *in vitro*, variables such as cell type and abundance; and the nature, length, and intensity of stimulation can be precisely controlled.



**Figure 1.3: Types of tissue-dependent *cis*-eQTL effects.** The effect size of an eQTL SNP on expression can be concordant or discordant between tissues. Discordant effects represent genotype-tissue interactions, and can be classified into four subtypes. Specific regulation refers to a gene with a significant eQTL in only one tissue. Alternative regulation refers to regulation of the same gene by independent SNPs in the two tissues—genes can have multiple eQTL with tissue-specific effects. Different effect size refers to an eQTL having tissue-dependent effects with concordant sign but discordant magnitude. Opposite allelic direction is a tissue-dependent effect where the sign is discordant. Pie charts show the proportion of different types of effects in pairwise comparisons of blood and four non-blood tissues by Fu *et al.* [74]. Figure reproduced from Fu *et al.* [74] under the CC BY 4.0 license ([creativecommons.org/licenses/by/4.0/legalcode](http://creativecommons.org/licenses/by/4.0/legalcode)).

A seminal study by Barreiro *et al.* [76] mapped eQTLs in monocyte-derived **dendritic cells (DCs)** before and after 18 h infection with *Mycobacterium tuberculosis*. reQTLs were detected for 198 genes, 102 specific to the uninfected state, and 96 specific to the infected state. They observed a 1.4-fold enrichment of reQTLs among **GWAS** variants associated with susceptibility to pulmonary tuberculosis, but no enrichment of eQTLs shared between uninfected and infected DCs. From overlap of reQTLs and GWAS variants, three genes (*DUSP14*, *ATP6V0A2*, *RIPK2*) were prioritised as candidates affecting tuberculosis susceptibility. Since then, numerous *in vitro* reQTL studies have been conducted with a variety of stimulations (often cytokines, pathogens, or **pathogen-associated molecular patterns (PAMPs)**), applied to purified [68, 77–89] or mixed cell types [81, 90].

A complementary approach is **reQTL** mapping with *in vivo* stimulation. An *in vitro* mixture of cells cannot hope to replicate the innumerable interactions involved in human immune response. *In vivo* designs suit whole-organism stimulations and response phenotypes, such as vaccination and vaccine-induced antibody response.

Published *in vivo* reQTL studies are comparatively few. Idaghdour *et al.* [91] mapped whole blood **eQTL** in 94 West African children admitted to hospital for malaria, and 61 age-matched controls. reQTLs with a significant case-genotype interaction were detected for five genes: *PRUNE2*, *SLC39A8*, *C3AR1*, *PADI3*, and *UNC119B*. As *SLC39A8* is upregulated with T cell activation, a postulation was made that T cell activation is important to malaria infection response. In Franco *et al.* [92], whole blood **eQTLs** were mapped in 247 healthy adults given **trivalent inactivated influenza vaccine (TIV)**. Twenty genes involved in membrane trafficking and antigen processing were prioritised to be important to vaccine response, having **reQTL** or differential expression post-vaccination, and expression correlation with antibody response. Lareau *et al.* [93] focused on epistatic effects of **SNP-SNP** interactions on expression fold-change after smallpox vaccination in 183 individuals. Eleven significant interactions were found where the effect of two independent **SNPs** on expression was non-additive. Apoptosis-related genes (e.g. *TRAPPC4*, *ITK*) were enriched among target genes. Most recently, Davenport *et al.* [94] mapped whole blood **eQTLs** in 157 **systemic lupus erythematosus (SLE)** patients in a phase II clinical trial of an anti-IL-6 monoclonal antibody. Nine **reQTLs** where the effect was magnified in drug-exposed versus unexposed groups were found to disrupt the binding site of *IRF4*, highlighting it as key regulatory factor downstream of IL-6.

Overall, *in vivo* **reQTL** studies have delivered insight into the biology of a diverse set of whole-organism phenotypes. However, ethical requirements can limit sample size and choice of stimulation. Many environmental factors (e.g. diet, lifestyle, immune exposures) cannot be controlled, potentially leading to greater experimental noise, and complicating interpretation of results.

### 1.2.5 Gene prioritisation using eQTLs

eQTLs are enormously valuable for target gene prioritisation after **GWAS**. They propose both target gene and mechanism of action, where the effect of variant on complex trait is mediated through expression. **GWAS** variants for many traits are indeed enriched for eQTLs [95], but care must be taken to avoid false positives due to the abundance of eQTLs. At current sample

Prioritisation of context is mentioned shortly.

sizes, 60–80 % of genes have at least one detectable eQTLs [53, 56], and half of common variants are *cis*-eQTLs for at least one gene [96]. Assuming that a locus is associated with both a trait of interest and with expression of a particular gene, how can one separate the scenario where the same causal variants affect both trait and expression (pleiotropy), from coincidental overlap between distinct sets of causal variants that may possibly in LD? Bayesian colocalisation methods address this by extending fine-mapping to multiple phenotypes [97–99]. Using information from all variants in the locus, they estimate the posterior probability that the same causal variants are associated with both phenotypes, distinguishing pleiotropy from LD.

Given the effect of an eQTL can be starkly context-dependent, eQTL datasets from trait-relevant contexts are most useful for gene prioritisation. For instance, immune *in vitro* reQTL are enriched more so than non-reQTL among GWAS associations for immune-related phenotypes such as susceptibility to infectious [76, 90] and immune-mediated diseases [83, 90]. Knowledge of cell type-specific in addition to shared eQTL effects finds many additional colocalisations with complex traits [72, 100]. The increasing number of context-dependent eQTL datasets available for large-scale colocalisation analyses means eQTLs can propose not just target gene and mechanism, but also the specific environments most relevant to a trait.

## 1.3 Phenotypes of immune response

### 1.3.1 An overview of the immune system

Immunology began as the study of host defense against infection [101]. It is now recognised that the immune system is also involved in pathogenesis of diverse conditions encompassing allergic, autoimmune, and other immune-mediated diseases. This subsection provides a basic overview of parts of the immune system relevant to this thesis.

The two major arms of the immune response are the innate and adaptive response. The innate response is rapid and non-specific, occurring in the first few minute to days after the initial (primary) exposure to infection. This triggers the adaptive response, which takes days to weeks to develop, but delivers a powerful and specific response capable of eliminating pathogens that have evaded the innate response. The adaptive response can also create immunological memory lasting years to decades, where re-exposure to the same pathogen induces a faster and more powerful recall response\*. Both arms distinguish self from non-self through complex interaction of many cell types via surface receptors and signalling molecules.

Immune cell types differentiate from common myeloid progenitor or common lymphoid progenitors, which themselves are descended from pluripotent hematopoietic stem cells (HSCs) in the bone marrow. By in large, the cells of the innate response are of the myeloid lineage, and the cells of the adaptive response are of the lymphoid lineage. Immune cells are also called leukocytes or white-blood cells, as many types can be found in peripheral blood, but certain types are confined to tissues or parts of the lymphatic system.

Innate response begins with the detection of pathogens by phagocytotic sensor cells—primarily neutrophils, tissue-resident macrophages, and DCs. These cells express pattern recognition receptors (PRRs) that recognise conserved PAMPs not present in host cells, then secrete small

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\*There is increasing evidence the innate immune system also has a form of immunological memory [102].

proteins (cytokines) that trigger the inflammatory response: a massive recruitment of multiple cell types from blood into infected tissues. Recruitment is partially mediated by a family of cytokines called chemokines, which chemically attract immune cells by creating a concentration gradient (chemotaxis). Recruited neutrophils clear pathogens by phagocytosis, and secrete antimicrobial molecules by degranulation. **Natural killer (NK)** cells detect and kill virus-infected and tumour cells. Circulating monocytes migrate and differentiate into macrophages and **DCs**. Macrophages perform phagocytosis, modulate inflammation, and can also engage in antigen-presentation, but it is **DCs** that are considered specialised **antigen-presenting cells (APCs)**. Antigen-presentation by **DCs** is a key link between the innate and adaptive responses.

The main forces of the adaptive response comprise B and T lymphocytes. **Naive lymphocytes** express antigen receptors that recognise parts of specific antigens called epitopes. When they encounter this antigen, they activate, proliferate (clonal expansion), then differentiate into effector cells. To initiate adaptive response, **CD4<sup>+</sup>** (helper) T cells recognise peptide fragments from the antigen presented in a complex with **major histocompatibility complex (MHC)** class II on the surface of **APCs**. **CD4<sup>+</sup>** T cells then differentiate into several subsets that activate and regulate other cell types, including macrophages, **CD8<sup>+</sup>** T cells and B cells. Activated **CD8<sup>+</sup>** (cytotoxic) T cells recognise antigens presented by **MHC** class I on infected cells and directly kill the cell. Activated B cells differentiate into plasma cells that secrete large quantities of antibodies, the soluble form of the **B cell receptor (BCR)**. Antibody-mediated immunity is also called humoral immunity, whereas T cells and innate immune responses comprise cell-mediated immunity. A small subset of activated B and T cells can become memory cells, responsible for long-term immunological memory.

maintain a pool naive lymphocytes, each having a receptor specific for a different possible antigen  
add TCR

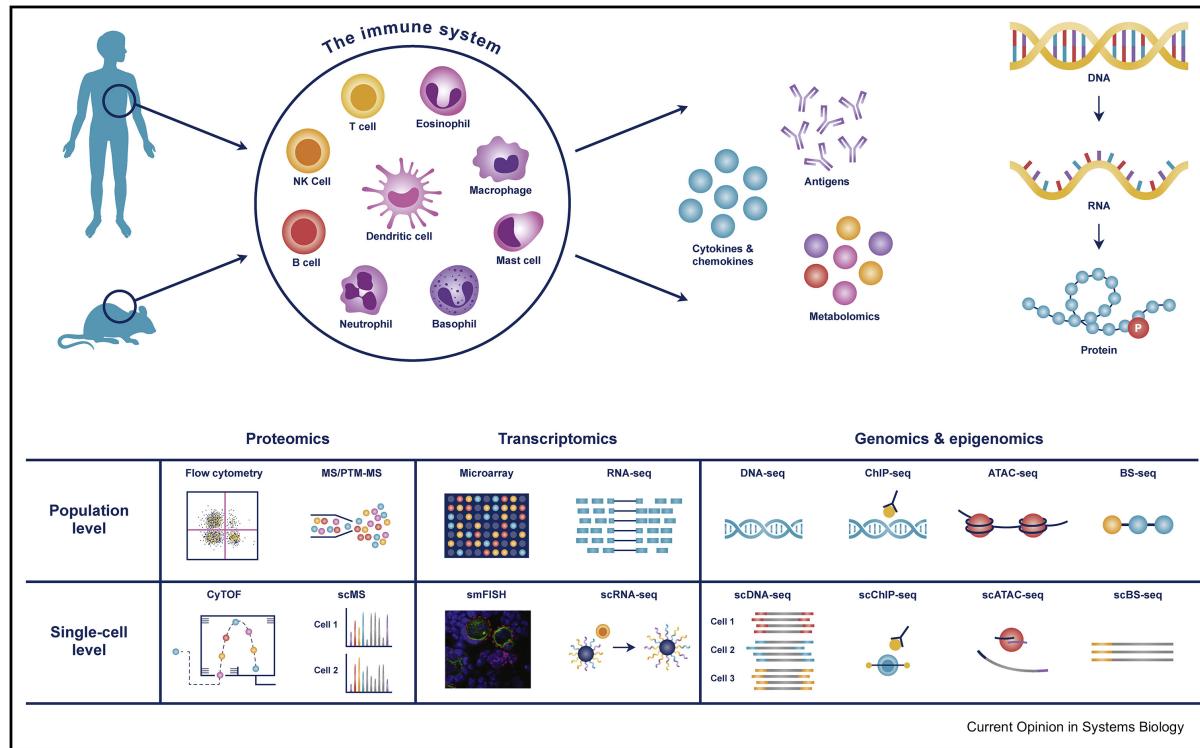
distinguish plasmablast/-plasma cell and add long lived plasma cells

add B cell activation mechanism by cd4, BCR

### 1.3.2 High-throughput immunology

To understand the immune system and its intricate interactions, “systems immunology” studies take a holistic rather than reductionist approach [103–105]. The basic principle is the same—experimentally perturb the system and observe its response. Drugs and vaccines can be used as safe and synchronised perturbations. A range of high-throughput technologies can be applied to measure response at many layers of the immune system (Fig. 1.4). Longitudinal designs are common, aiming to sample timepoints corresponding to baseline, innate and adaptive immunity. The complexity of the immune response still presents a major challenge: the richness of sampling required often restricts sample size due to cost and logistics.

There are three major themes to systems immunology. Initial studies of a particular response phenotype are often descriptive, aiming to find correlations between the components of the immune system and other components, or with phenotypic response. Predictive studies then evaluate the ability to use relevant measurements to predict individual response. Feature sets that are molecular phenotypes (e.g. gene expression) with validated predictive accuracy are known as molecular signatures. Causal inference is the third and most difficult goal. Fortunately, the heritability of immune parameters (e.g. cell counts, surface marker expression, serum protein levels) is substantial, between 20–40 % [107–110], with greater heritability for innate versus adaptive immune parameters [109]. Much akin to **GWAS** and **quantitative trait locus (QTL)** studies, to identify causal links in the immune system, one can leverage genetic variation as naturally-



**Figure 1.4: High-throughput technologies for systems immunology.** Profiling can be done in multiple humans and model organisms, at multiple levels of the immune system, and at bulk or single-cell resolutions. An additional dimension not shown is profiling at multiple timepoints before and after perturbation. Figure reprinted from Yu *et al.* [106], © 2019, with permission from Elsevier.

occurring perturbations [104, 111]. Controlled variation can also be systematically generated by RNA interference or genome editing [112]. Obtaining causal understanding is essential for clinical translation, to determine the interventions that can be made to promote effective response to pathogens and vaccines, and impede pathways that lead to immune dysregulation in disease.

## 1.4 Thesis outline

This thesis examines longitudinal response to *in vivo* immune perturbations by vaccine and drug. Chapter 2 is a descriptive differential gene expression (DGE) study of transcriptomic and antibody responses to pandemic influenza vaccine in the Human Immune Response Dynamics (HIRD) cohort of healthy adults. Chapter 3 integrates HIRD genotype data to map the regulation of expression response to vaccine using an *in vivo* reQTL design. In Chapter 4 I mirror the design of the previous two chapters, exploring clinical response to biologic anti-tumour necrosis factor (TNF) therapy for Crohn's disease (CD) patients in the Personalised Anti-TNF Therapy in Crohn's Disease (PANTS) cohort. Finally, Chapter 5 presents an overview of shared themes and limitations, and provides recommendations for future analyses and study designs for immune response phenotypes.

## Chapter 2

# Transcriptomic response to Pandemrix vaccine

### 2.1 Introduction

#### 2.1.1 Influenza

Influenza is an infectious respiratory disease caused by the influenza virus family (*Orthomyxoviridae*) in a variety of vertebrate hosts. Of the four virus types (A, B, C, D) defined by antigenic specificity of the viral nucleoprotein, human infections are primarily caused by influenza A and influenza B. Each year, seasonal epidemics result in ~1 billion infections and 300 000–500 000 deaths worldwide. Peak seasonality is defined by low humidity, low temperature, and other climate factors. Risk factors for severe illness and death include extremes of age (infants <1 yr, elderly >65 yr), pregnancy, obesity, chronic illness, and host genetics (e.g. mutations in *IFITM3* and *IRF7*) [113, 114].

Influenza viruses are enveloped viruses with a negative-sense single-stranded RNA genome divided into segments (eight segments in influenza A and B), each encoding one or more viral proteins. There are two glycoproteins both occurring on the surface of the viral envelope that are the main antigens targeted by the host immune system. **haemagglutinin (HA)**, with its characteristic head-stalk structure, facilitates viral entry by binding sialic acid-containing surface receptors on host cells. **neuraminidase (NA)** facilitates viral release, cleaving sialic acids to prevent newly-synthesised viruses aggregating to each other—viral proteins can be sialylated post-translation—and to the dying host cell in the final stages of the viral life cycle. The gradual accumulation of mutations in these surface protein genes is known as antigenic drift, and can lead to evasion of antibody-mediated immunity acquired during previous exposures. As the virus type with the greatest prevalence, host range, and genetic diversity, influenza A is classified into a number of subtypes based on the antigenic properties of its **HA** and **NA**. At least 18 **HA** subtypes and 11 **NA** subtypes exist [115]. Although these **HA** and **NA** subtypes are all antigenically-dissimilar, there can still be cross-reactivity between subtypes, and considerable drift within subtypes [116]. Influenza B viruses are less diverse, classified into two antigenically-distinct lineages: Victoria-like and Yamagata-like [113].

On occasion, reassortment of genome segments between viruses infecting the same cell can

quickly generate new strains (antigenic shift). Antigenic shifts are associated with pandemics due to lack of pre-existing population immunity [113]. Pandemics have occurred four times in modern history: 1918 (“Spanish”), 1957 (“Asian”), 1968 (“Hong Kong”), and 2009 (“swine”). Each was caused by influenza A, involving reassortment of human and animal strains, or zoonotic transmission of animal strains [117]. For instance, the 2009 pandemic was due to an influenza A strain with **HA** subtype 1 and **NA** subtype 1 gene segments of swine origin [118]: A(H1N1)pdm09\*. Pandemic strains tend to enter seasonal circulation post-outbreak, potentially replacing previously-circulating strains; A(H1N1)pdm09-like strains are now the predominant seasonal A(H1N1) strain [113].

### 2.1.2 Seasonal influenza vaccines

Vaccination is the primary method for prevention and control of influenza. Antigenic drift and decline of vaccine-induced immunity over time means annual vaccination is recommended. Seasonal vaccines are multivalent, usually formulated against three (trivalent) or four (quadrivalent) influenza strains anticipated to circulate in upcoming influenza seasons. The **World Health Organization (WHO)**’s Global Influenza Surveillance Response System (GISRS) makes recommendations on the most representative strains for the Northern and Southern hemispheres each year, about six months before the start of the respective seasons.

There are three classes of licensed vaccines against seasonal influenza: **inactivated influenza vaccines (IIVs)**, **live attenuated influenza vaccines (LAIVs)**, and recombinant **HA** vaccines [115, 120]. **IIVs** can be split virion, containing virions disrupted with detergent, or subunit, containing further purified **HA** protein. **LAIV** contain low-virulence, cold-adapted viruses that replicate well only in the cool upper respiratory tract. Recombinant **HA** vaccines contain purified recombinant **HA** expressed in insect cell lines rather than relying on traditional viral propagation in embryonated chicken eggs. Cell-based **IIVs** are also available. Cell-based vaccines are faster to manufacture in pandemic situations, not dependent on egg supply, and avoids egg-adaptation (mismatches between vaccine and circulating strains caused by adaptation to growth in eggs).

Licensed seasonal vaccines are effective and well-tolerated in healthy adults, but particular subclasses of vaccine are recommended for different demographics [121–124]. **LAIVs** are delivered via nasal spray and are more effective than **IIVs** at mitigating transmission. They are recommended for children—the major drivers of transmission due to high viral loads and prolonged shedding [113, 121]—but are contraindicated for young children <2 yr at risk of wheezing, and immunocompromised individuals. Trials also suggest **LAIV** has superior efficacy compared to **IIVs** in children. High-dose and adjuvanted **IIV** vaccines are recommended to enhance immunogenicity in the elderly. Cell-based and egg-free vaccines are suitable for people with egg allergies. No vaccines are licensed for use in infants <6 mo, but passive immunity can be conferred through vaccinating the mother.

Point estimates of seasonal vaccine efficacy range from 50–90 % in healthy adults in controlled trials. Real-world effectiveness can be as low as 10 %, depending greatly on vaccine class, choice of endpoint, the match between vaccine and circulating strains, and host factors [114, 125]. In

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\*“pdm09” was a unique suffix added to distinguish the 2009 pandemic strain from the circulating seasonal A(H1N1) strains at the time [119].

general, efficacy is comparable or better in children versus young adults, and lowest in the elderly due to immunosenescence. Females mount higher antibody responses than males, regardless of age **IIVs**, potentially mediated by sex steroid levels [114, 126]. Immune history has major effects on vaccine response due to immune memory. Adults primed by past exposures to seasonal influenza strains have qualitatively different responses to unprimed adults or influenza-naïve children. For example, influenza-naïve children mount much higher serum antibody responses to seasonal **LAIV** than primed adults [122]; antibody responses to **IIV** peak later in unprimed individuals, and require two doses to reach optimal concentrations [121]. Immune history also impacts response via antigenic seniority (also known as immune imprinting), where the antibody response is biased towards recall against strains encountered in early childhood, rather than generating a *de novo* response. This is beneficial if strains with the same epitopes come back into circulation, and harmful against strains still similar enough to trigger immune memory, but with drifted epitopes [114, 127]. Host genetic variation in cytokine genes, immunoglobulin genes and the **human leukocyte antigen (HLA)** region are associated with antibody responses—reviewed in more depth in Section 3.1.1.

### 2.1.3 Quantifying immune response to influenza vaccines

The efficacy of **IIVs** are mostly mediated by induction of strain-specific anti-**HA** antibodies, although other antibodies (e.g. anti-**NA**) may also contribute in the case of non-purified vaccines. **Antibody-secreting cells (ASCs)** in peripheral blood around one week after vaccination, and serum antibodies peak around two to four weeks after vaccination. Antibody-mediated protection may last up to a year in healthy adults [121, 128]. The immunodominance of the **HA** head over the stalk means most anti-**HA** antibodies have epitopes in the head domain. Unsurprisingly, the resulting immune selection pressure concentrates antigenic drift in the head domain. The stalk domain is relatively conserved, hence anti-stalk antibodies can be broadly neutralising, effective against multiple virus subtypes (heterosubtypic immunity) [129].

The **haemagglutination inhibition (HAI)** assay is an inexpensive method for quantifying serum anti-**HA** antibody concentrations. A serial dilution of serum is created and mixed with standardised concentrations of **red blood cells (RBCs)** and influenza virus. Without the presence of antibodies, the receptor site on the **HA** head binds to membrane-bound sialic acid on **RBCs**, agglutinating them into a lattice that appears as a cloudy red solution. Anti-**HA** antibodies inhibit agglutination, allowing the **RBCs** to settle, creating a clear solution with a dark red pellet. The titre value is the least dilute concentration of serum that completely inhibits agglutination [130]. The value is relative to the concentrations of reagents, requiring standardised protocols for comparability. A standardised **HAI** titre of 40 (1:40 dilution) is deemed seroprotective, and is an accepted correlate of protection for **IIVs**, representing 50 % clinical protection rate against infection [121, 131]. Reliable correlates of protection are useful in vaccine trials to reduce resource requirements (e.g. time, sample size, cost) compared to disease or infection-based endpoints like clinical protection [132]. For seasonal **IIVs**, regulatory agencies define target criteria based on the minimum proportion of individuals achieving **HAI** seroprotection ( $\geq 40$ ) and seroconversion ( $\geq 4$ –fold increase in titre after vaccination, indicating the vaccine is immunogenic) [115, 129, 131].

An alternative method is the **microneutralisation (MN)** assay, which quantifies concentrations of serum antibodies capable of neutralising viral infectivity. Neutralising antibodies may be anti-**HA** antibodies quantifiable by **HAI**, but may also be anti-**HA** stalk antibodies or antibodies with non-**HA** targets not detectable by **HAI** [115]. The assay involves a serial dilution of serum incubated with virus. The serum-virus mixtures are then inoculated into host cells *in vitro*. After incubation, an **enzyme-linked immunosorbent assay (ELISA)** can be run to detect virus-infected cells, the lack of which indicates neutralising activity [130]. A **MN** assay value of 160 (1:160 dilution) is considered equivalent to the seroprotective **HAI** value of 40 [121].

**IIVs** primarily induces serum antibodies of the IgG isotype. The cellular response has not been extensively studied, but the induction of CD8<sup>+</sup> T cells by unadjuvanted subunit **IIVs** is considered poor [121, 133]. In contrast, **LAIVs** can induce serum IgG, but also efficiently induces mucosal IgA and T cell responses [122]. Protection may also have greater duration than that afforded by **IIVs**, but the longevity still pales in comparison to natural infection, which can grant strain-specific protection that is lifelong [115, 120–122]. Different facets of response play different roles in immunity: serum IgG is important for limiting severity of systemic infection, mucosal IgA in the upper respiratory tract inhibits initial infection and transmission, CD8<sup>+</sup> T cells promote viral clearance and recovery, and CD4<sup>+</sup> T cells help induce humoral and CD8<sup>+</sup> T cells Krammer *et al.* [113], Bresee *et al.* [121], Sano *et al.* [129], and Renegar *et al.* [134]. Correlates of protection for **LAIV** have not yet been defined; licensed **LAIVs** have all been licensed on the basis of clinical protection. Their comparable efficacy to **IIVs** in adults despite low **HAI** titres and seroconversion rates are presumed to be mediated by mucosal and cell-mediated immunity [115, 122]. Clearly, a broader view of immunity than granted by serological antibody assays is needed to understand the mechanisms leading to efficacious influenza vaccine responses.

#### 2.1.4 Systems vaccinology of seasonal influenza vaccines

Vaccinology has historically been driven by the “isolate-inactivate-inject” paradigm [135]. Many vaccines have been developed and licensed through expensive, large-scale, and largely empirical trials that deliver highly effective vaccines, but little understanding on the immunological mechanisms of protection. In response, the last decade has seen the rise of systems vaccinology, a subfield of systems immunology dedicated to the analysis of high-throughput data measured at multiple levels of the immune system to characterise response to vaccination [132, 136–142]. Traditional serological assays (e.g. **HAI**, **MN**) are complemented with a raft of other technologies to give a broader view of immune response [136–138, 141, 142]. Flow (e.g. **fluorescence-activated cell sorting (FACS)**) and mass cytometry (e.g. **cytometry by time-of-flight (CyTOF)**) are used to quantify immune cell subpopulations by their surface markers using fluorescent and heavy metal tags. These technologies can also be used to quantify intracellular markers (e.g. cytokines) by cell staining. Frequencies of cells secreting specific proteins (e.g. cytokines or antibodies) can also be quantified (e.g. **enzyme-linked immune absorbent spot (ELISPOT)**), useful for monitoring activated cell populations involved in both humoral and cell-mediated. The transcriptome of peripheral blood is extremely popular to assay (e.g. expression array, **RNA-sequencing (RNA-seq)**), providing an accessible, global measure of gene expression in dozens of immune cell subtypes without the need to select specific genes of interest in advance. Recently, there has been a growing

interest in targeted sequencing of B cell and T cell repertoires, responsible for the specificity of the adaptive immune system. Serum proteins can be quantified in a low-throughput (e.g. **ELISA**) or multiplex manner (e.g. Luminex). Modern proteomics platforms also embrace a global philosophy, simultaneously quantifying thousands of proteins (e.g. SOMAscan). Finally, although not often considered due to small cohort sizes, host genetic variation can be accurately measured by genotyping arrays and sequencing.

Longitudinal study design is key, not only to profile different stages of innate and adaptive immunity, but also for determining correlates of protection. Correlates are known for some but not all established vaccines [143, 144]. For novel and emerging diseases, there may be no prior knowledge of correlates for use in vaccine development. The term “molecular signature” was coined to refer to transcriptomic responses induced early after vaccination that correlate with, and importantly, are predictive of later immune phenotypes (e.g. antibody titres) [132]. Non-transcriptomic data types can also be used to form signatures. The ultimate goal is baseline prediction, where the immune state immediately prior to vaccination predicts response, and could potentially be modulated to enhance response in a similar manner to adjuvanting the vaccine itself [145].

Work in the field thus far focused on established vaccines. One can learn from the success of highly-efficacious vaccines like yellow fever vaccine (YF-17D), where interferon, complement and inflammasome expression signatures measured 3–7 days post-vaccination predict CD8<sup>+</sup> T cell and neutralising antibody responses 60 days post-vaccination [137, 146]. Much has also been learnt from the study of vaccines with suboptimal efficacy in challenging populations: infants and the elderly, pregnant women, immunocompromised patients, ethnically-diverse populations, developing countries [147]. The field has not yet identified completely novel correlates for many vaccines, partially because protection itself can be difficult to measure. One promising system is the human challenge trial, applied by Vahey *et al.* [148] to identify genes in the immunoproteasome pathway associated with protection from malaria challenge after adjuvanted RTS,S malaria vaccination. If correlates for novel vaccine candidates could be routinely established based on shared immune mechanisms leading to efficacy and long-lasting protection derived from multiple successful vaccines, there is enormous potential for optimising trials to be fast and cost-effective [132, 149], and informing rational, mechanism-based design for diseases that have thus far proved intractable to empirically-designed vaccines (e.g. HIV, malaria, non-childhood tuberculosis) [135, 139, 142, 149].

Seasonal influenza vaccines have been well-studied by systems approaches. One of the earliest studies by Zhu *et al.* [150] found that expression of type I interferon-modulated genes at day 7 was more prominent for **LAIV** than **trivalent inactivated influenza vaccine (TIV)** in children (total cohort size  $n = 85$ ). A subsequent study found that both **LAIV** and **TIV** could induce interferon-related genes in children ( $n = 37$ ), but much earlier in **TIV** (day 1) than in **LAIV** (day 7) [151]. As serum antibody titres are an established correlate for **TIV**, studies have been done to identify its molecular basis. Bucasas *et al.* [152] ( $n = 119$ ) found a 494-gene expression signature (including *STAT1*, *CD74*, and *E2F2*) measured at day 1 and 3 correlated with serum antibody titres measured 14 and 28 days after vaccination. Signatures including day 3 kinase *CaMKIV* expression are a strong predictor of day 28 **HAI** antibody titres in independent trials

over three consecutive influenza seasons ( $n = 67$ ) [153]. Expression of gene sets related to B cell proliferation at day 7 are also predictive of day 28 HAI ( $n = 15$ ) [154]. Work has also been done to understand the heterogeneity in response due to host factors like sex [126] and age [155–158].

In some cases, signatures can be derived from predictors measured pre-vaccination [145]. A gene module enriched in apoptosis-related genes measured at baseline was found to predict day 28 HAI response ( $n = 89$ ) [159]. Tsang *et al.* [160] used not gene expression, but FACS measurements to establish signatures for day 70 neutralising antibody titres ( $n = 63$ ). Frequencies of several B cell, myeloid dendritic cell (DC), CD4 $^{+}$  memory T cell, and a number of other activated T cell populations were not only predictive, but also stable over a period of two months. [156] used data collected over five consecutive seasons ( $n = 212$ ) to identify associations between B cell (positive), T cell (positive), and monocyte (negative) baseline expression modules with day 28 HAI. They were able to replicate these associations using published data from Franco *et al.* [92] and Furman *et al.* [159]. Another multi-cohort, multi-season study ( $n > 500$ ) [158] found baseline expression of genes (*RAB24*, *GRB2*, *DPP3*, *ACTB*, *MVP*, *DPP7*, *ARPC4*, *PLEKHB2*, *ARRB1*) and gene modules to be associated with antibody response. Again, the authors were able to validate the associations in an independent cohort. To conclude, it must be noted that the utility of molecular signature for influenza or other vaccines in clinical trials has not yet been validated, and it is difficult to draw causal insights from studies that are largely descriptive or predictive (molecular signatures). The existence of temporally-stable and replicable signatures is, however, encouraging.

### 2.1.5 The Human Immune Response Dynamics (HIRD) study

For studies of seasonal influenza vaccines in adults, responses are heavily influenced by immunological memory built by past vaccination or infection with antigenically-similar strains [136, 161]. Dependence on exposure is reflected in high variability of baseline vaccine-specific antibody titres and memory B cell numbers [160]. There have also been few systems vaccinology studies of adjuvanted influenza vaccines, known to have greater immunogenicity and efficacy than non-adjuvanted vaccines in children and the elderly [157, 162, 163]. The Human Immune Response Dynamics (HIRD) study conducted by Sobolev *et al.* [161] was conceived as a unique opportunity to study response to an adjuvanted pandemic influenza vaccine (Pandemrix), where responses are more likely to be primary than recall, and variability due to prior exposure is minimised.

Pandemrix was one of several vaccines rapidly developed and licensed in response to the 2009 influenza pandemic [164]. It is a monovalent split-virion IIV against the pandemic influenza A/California/07/2009 (H1N1)pdm09 strain\*, developed by GlaxoSmithKline, containing 3.75 µg HA and adjuvant AS03 (oil-in-water emulsion with DL- $\alpha$ -tocopherol, squalene, polysorbate 80). Subsequent studies estimated its effectiveness to be ~80% after a single dose [165]. As the H1N1 subtype had not circulated since the 1918 pandemic, the majority of the HIRD cohort would have been immunologically-naive at the time of sampling (March 2010 to August 2011).

\*The WHO nomenclature for isolates specifies influenza type (A, B, C, D), host of origin (human if omitted), geographical origin, strain number, year of isolation, and isolate subtype (combination of HA and NA subtypes) [116].

The **HIRD** study is an longitudinal, prospective cohort study. A total of 178 healthy adults in the UK were vaccinated with a single dose of Pandemrix. Clinical, transcriptomic, immune cell frequency, cytokine level, antibody titre, and adverse event phenotypes were collected. Genes associated with both myeloid and lymphoid effector functions had increased expression at day 1 versus baseline, most prominently for genes associated with the interferon response. Day 1 gene expression was impacted by age. Significant global differences were observed in individuals older than 30–40 yr, considerably earlier than usually considered in studies of immunosenescence in old age. The early myeloid responses—increase in blood monocyte levels and cytokines associated with innate activation e.g. CCL4—were overall consistent with studies of unadjuvanted seasonal influenza vaccines. However, the early lymphoid responses—driven by a five-fold increase in serum interferon gamma levels at day 1—were unique to this adjuvanted pandemic vaccine.

Vaccine (antibody) response was defined as a  $\geq 4$ -fold increase in either **HAI** or **MN** titres after vaccination. Genes related to plasma cell development and antibody production were more highly expressed in 23 vaccine responders compared to 18 non-responders at day 7 post-vaccination. However, due to high variability among the vaccine non-responders in expression trajectory over time, a predictive model that segregated the two groups could not be built, even considering other predictors such as frequencies of immune cell subsets, and serum cytokine levels. There appeared to be many “routes to failure”, rather than any single determining factor leading to poor antibody response.

### 2.1.6 Chapter summary

Transcriptomic measurements in the original **HIRD** study were restricted to a relatively small number of individuals ( $n = 46$ ), limiting power to detect expression signatures associated with antibody response. In addition, the binary responder versus non-responder definition used does not account for variation in baseline titres, and dichotomisation of a continuous variable loses information, implies a discontinuity in response at the cutoff.

In this chapter, I combine the existing array data with newly generated **RNA-seq** data ( $n = 75$ ) on additional individuals from the **HIRD** cohort, using Bayesian random-effects meta-analysis to account for between-platform heterogeneity. I also compute a baseline-adjusted, continuous phenotype of antibody response to vaccination, the **titre response index (TRI)** [152]. Leveraging the greater sample size, more statistically efficient definition of vaccine response, and greater sensitivity of rank-based gene set enrichment analysis over gene-wise analysis, I identify gene expression modules associated with magnitude of antibody response. The strongest associations are seen at day 7, but also significant module associations are also seen at baseline.

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## 2.2 Methods

### 2.2.1 Existing HIRD data and additional data generation

The design of the **HIRD** study is fully described in Sobolev *et al.* [161]. In brief, blood samples were collected from each individual on each of six visits: two pre-vaccination (days -7 and 0), and four post-vaccination (days 1, 7, 14 and 63). The Pandemrix dose was administered after blood

sampling on day 0. Serum antibodies were measured for all individuals ( $n = 178$ ) on days -7 and 63 using both HAI and MN assays. peripheral blood mononuclear cell (PBMC) gene expression was profiled for 46 individuals by expression array on days -7, 0, 1 and 7.

In addition to the existing data, PBMC RNA-seq data was generated for 75 individuals at days 0, 1, and 7; and 169 individuals were genotyped. The sets of individuals with gene expression assayed by array and RNA-seq are disjoint, as no biological material for RNA extraction remained for the array individuals. An overview of datasets is shown in Fig. 2.1.

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pany the figure

### 2.2.2 Computing baseline-adjusted measures of antibody response

There were 166/178 individuals with HAI and MN titres available at both baseline (day -7) and post-vaccination (day 63). Sobolev *et al.* [161] defined Pandemrix vaccine responders as individuals with  $\geq 4$ -fold titre increases from day -7 to day 63 in either the HAI or MN assays. This is a typical threshold for HAI and MN seroconversion used to assess the immunogenicity of seasonal IIVs [115], and has also been recommended for pandemic IIVs [166]. However, they also noted there was “a complete spectrum” of baseline titres of non-responders, citing “glass ceiling” non-responders whose high baseline titres “enhancements by  $\geq 4$ -fold harder to achieve”. This may be referring to the dynamic range of the assays. In the full data, the range of HAI titres is 84096, and the range of MN titres is 105120 (Fig. 2.2a, Fig. 2.2b). In just the day -7 baseline titres, the range of HAI titres is 8512, and the range of MN titres is 105120\*. For example, it is impossible for an individual with higher than 1280 MN at day -7 to achieve a 4-fold increase in MN after vaccination if the maximum MN value is 5120. This ceiling effect can be seen in Fig. 2.2d, where for a given baseline MN titre, there is a limit to the maximum observable fold change.

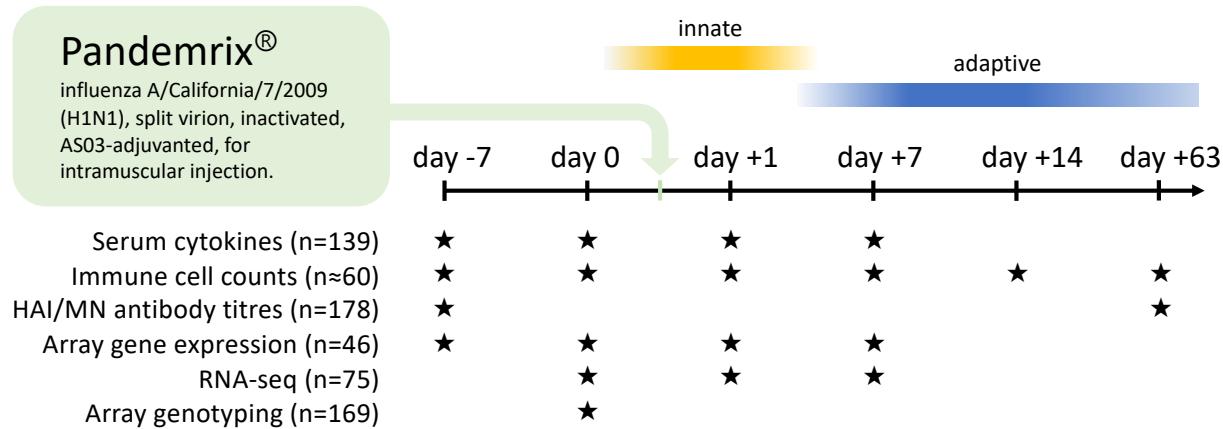
Another perspective is to consider that day 63/day -7 fold change is a change score on the log scale. It is well-known that change scores are usually negatively correlated to baseline. This can be due to individual-level regression to the mean<sup>†</sup>, where an extreme observation is more likely to be followed by less extreme ones in the same individual [167], but is also due to the mathematical relationship between change score and baseline when the variance of the post-test score is large compared to the variance of the baseline [169]. The negative correlation of titre fold change and baseline is visible in the HIRD data (Fig. 2.2c, Fig. 2.2d).

Dichotomisation of continuous variables can also result in loss of information [170–173]. Cohen [170] presents a classic example where dichotomising a continuous independent variable reduces statistical power akin to throwing away a third of the samples—and this is the optimal case when the cutpoint is the mean. Lastly, a discontinuous cutpoint is biologically implausible, implying that a 4.01-fold antibody titre change would be dramatically more protective than a 3.99-fold change.

To address these concerns, I computed the TRI as defined in Bucasas *et al.* [152]. For each assay, a linear regression was fit with the  $\log_2$  day 63/day -7 titre fold change as the response, and the  $\log_2$  day -7 baseline titre as the predictor. The residuals from the two regressions were

\*The distribution of pre-existing titres would be expected to be higher if this were a seasonal vaccine [160].

<sup>†</sup>Cf. Group-level regression to the mean, which is prominent if the baseline measurement is used as a selection criteria for follow-up [167, 168].



**Figure 2.1: Overview of study data.** The total **HIRD** cohort size was 178 individuals. Serum cytokines were quantified by 16-plex Luminex panel. Immune cell subsets were quantified by **FACS**. Serum antibodies were quantified by both **HAI** and **MN** assays. Array and **RNA-seq** gene expression were quantified in the **PBMC** compartment.

each standardised to zero mean and unit variance, then averaged with equal weight. The **TRI** is a single variable that expressed a continuous measure of change in antibody titres averaged across both assays post-vaccination, compared to individuals with a similar baseline titre. It is no longer correlated with baseline (Fig. 2.2e, Fig. 2.2f), and remains comparable to the original binary definition (Fig. 2.2g, Fig. 2.2h).

Descriptive statistics for the 114 individuals with both gene expression and antibody titre data are presented in Table 2.1. Although the proportion of responders between array (32/44) and **RNA-seq** (59/70) individuals is similar ( $p$ -value = 0.16, Fisher's exact test), the variance of **TRI** in array individuals is higher ( $p$ -value = 0.00, Levene's test), suggesting more extreme antibody response phenotypes are present (Fig. 2.3). The cause of this is unknown, there is a possibility that individuals with more extreme phenotypes were prioritised for array transcriptomics in the original **HIRD** study\*.

### 2.2.3 Genotype data generation

DNA was extracted from frozen blood using the Blood and Tissue DNeasy kit (Qiagen), and genotyping was done using the Infinium CoreExome-24 BeadChip array (Illumina). In total, 192 samples from 176 individuals in the **HIRD** cohort were genotyped at 550 601 markers, including replicate samples submitted for individuals where extracted DNA concentrations were low.

192 and 176 should be correct, 169 is the number after QC.

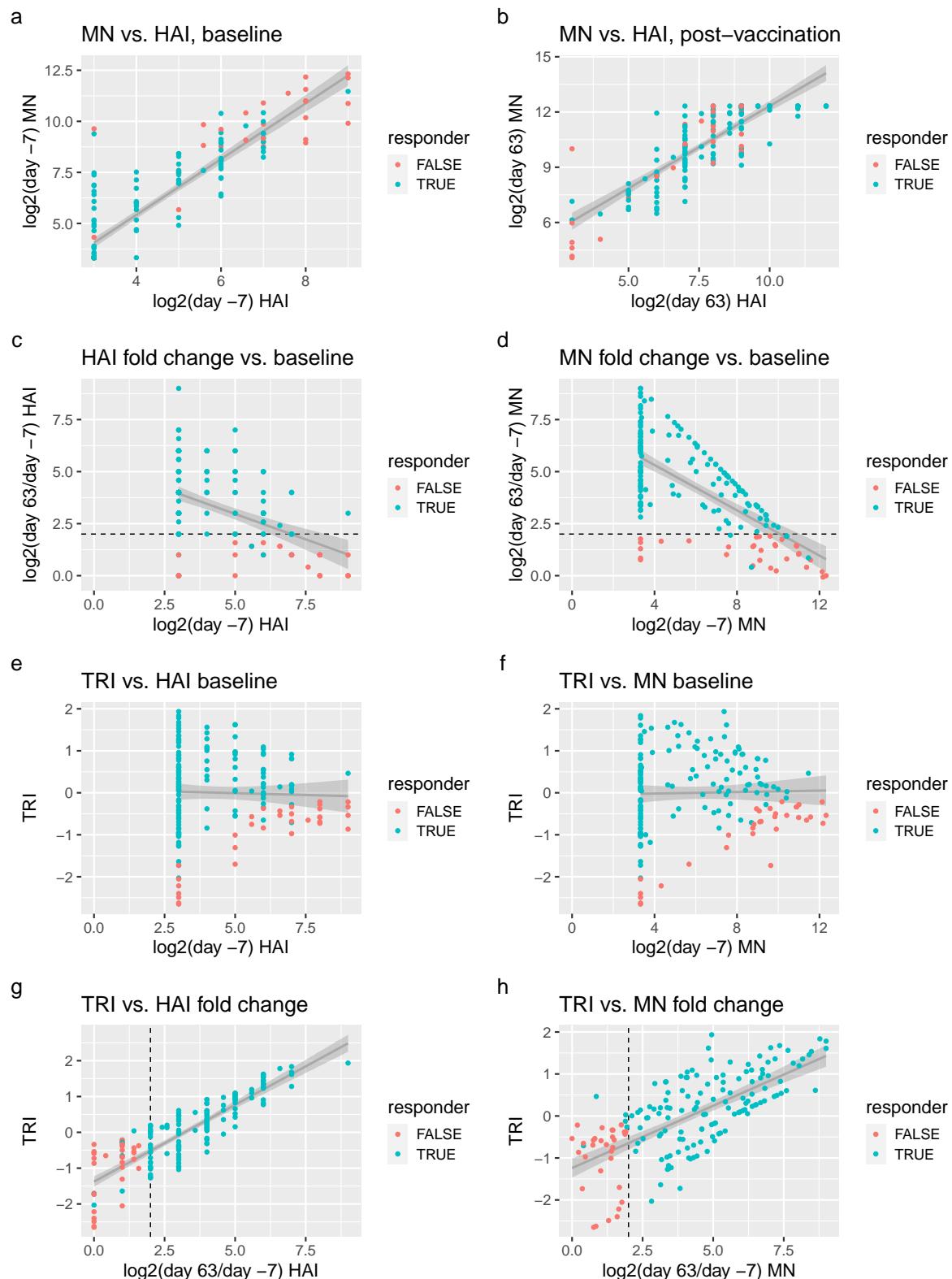
### 2.2.4 Genotype data preprocessing

Using PLINK (v1.90b3w), genotype data underwent the following quality control filters to remove poorly genotyped samples and markers:

- maximum marker missingness across samples <5 %;
- maximum sample missingness across markers <1 % (Fig. 2.4);

still some missing software versions and references

\*Personal communication with Sobolev *et al.* [161] authors.



**Figure 2.2: Antibody titre data and responder definitions.** Titre values are on the  $\log_2$  scale. Individuals are colored by binary responder status:  $\geq 4$ -fold increase in either HAI or MN titres from baseline (day -7) to post-vaccination (day 63). Dashed lines show the  $\geq 4$ -fold thresholds. (a, b) HAI and MN titres are correlated at baseline (a) and post-vaccination (b). Comparison of TRI to HAI (left column) and MN (right column) titres and binary responder/non-responder status (colored) in 166 HIRD individuals. Row 1: baseline titres are positively correlated to post-vaccination titres. (c, d) Baseline titres are negatively correlated to fold change. (e, f) TRI is computed from the standardised residuals from c and d, adjusting for baseline titre. (g, h) TRI remains comparable in ordering to binary response status.

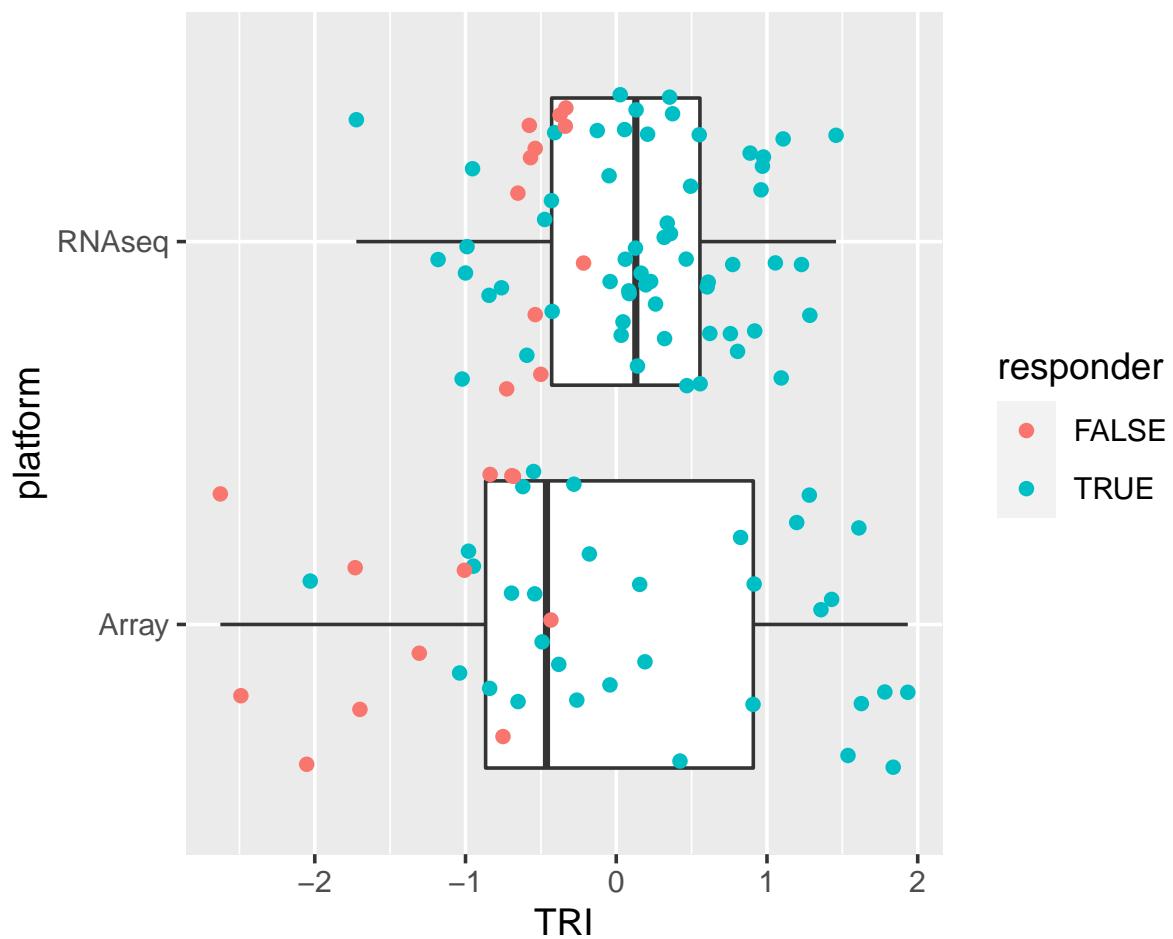


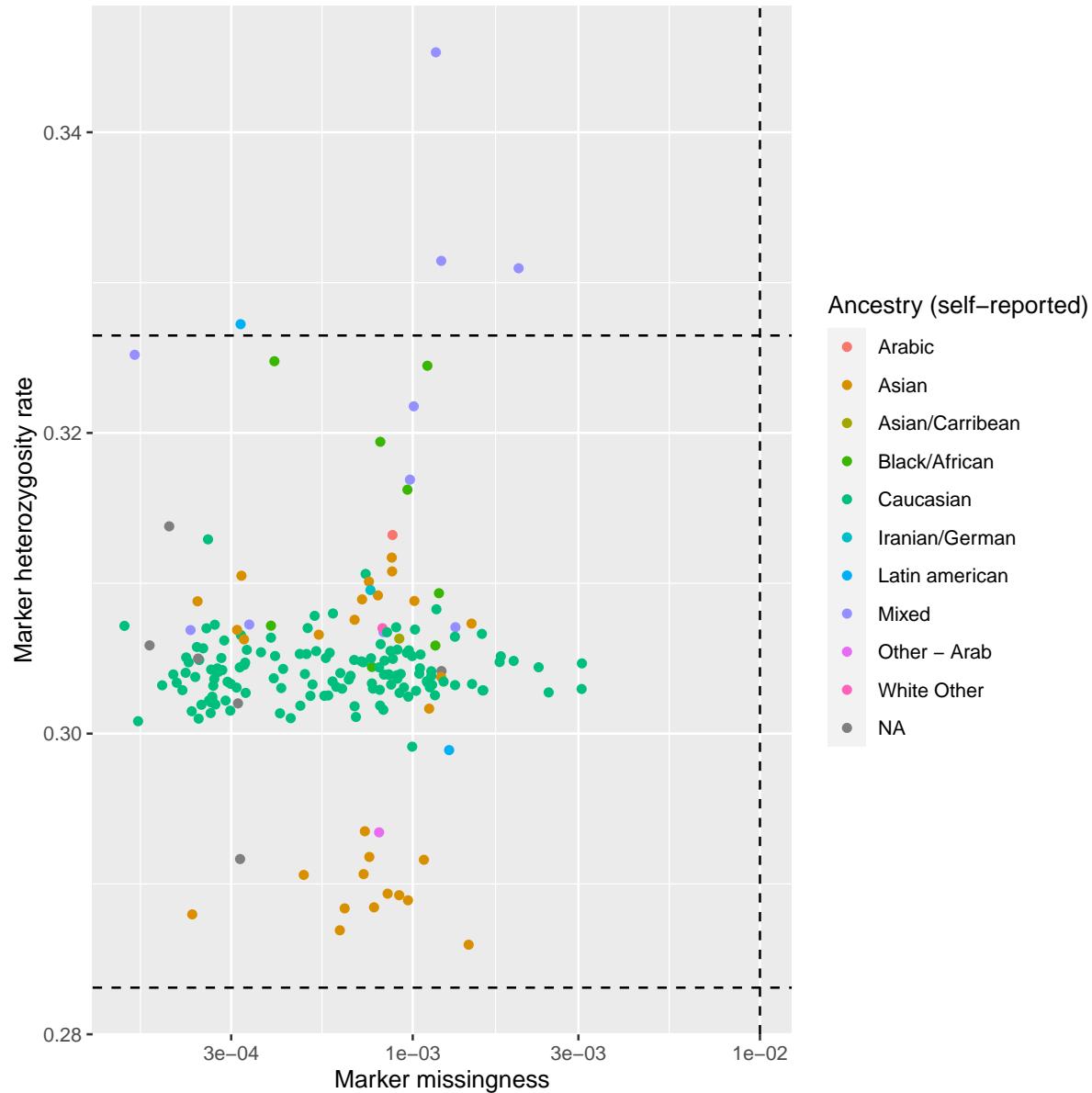
Figure 2.3: Distribution of **TRI**, stratified by platform.

**Table 2.1: Descriptive statistics for individuals with both expression and antibody data.** Values are count and percentage for categorial variables; mean and standard deviation for continuous variables.

	Total n = 114	Platform Array n = 44	RNA-seq n = 70
Gender			
F	72 (63.2%)	27 (61.4%)	45 (64.3%)
M	42 (36.8%)	17 (38.6%)	25 (35.7%)
Age at vaccination (years)	29.2 (11.8)	32.9 (14.1)	26.8 (9.4)
Ancestry (self-reported)			
Asian	14 (12.3%)	5 (11.4%)	9 (12.9%)
Black/African	9 (7.9%)	4 (9.1%)	5 (7.1%)
Caucasian	82 (71.9%)	33 (75%)	49 (70%)
Latin American	2 (1.8%)	1 (2.3%)	1 (1.4%)
Mixed	5 (4.4%)	1 (2.3%)	4 (5.7%)
Other - Arab	1 (0.9%)	0 (0%)	1 (1.4%)
White Other	1 (0.9%)	0 (0%)	1 (1.4%)
log2 day -7 HAI	4.4 (1.8)	4.2 (1.6)	4.5 (1.9)
log2 day 63 HAI	7.6 (1.8)	7.4 (2.2)	7.6 (1.5)
log2 HAI fold change	3.2 (1.9)	3.2 (2.4)	3.1 (1.6)
log2 day -7 MN	6.2 (2.8)	5.4 (2.4)	6.6 (3.0)
log2 day 63 MN	10.4 (2.0)	9.5 (2.2)	10.9 (1.6)
log2 MN fold change	4.2 (2.3)	4.1 (2.6)	4.3 (2.1)
Responder (binary definition)			
FALSE	23 (20.2%)	12 (27.3%)	11 (15.7%)
TRUE	91 (79.8%)	32 (72.7%)	59 (84.3%)
TRI	-0.0 (0.9)	-0.2 (1.2)	0.1 (0.7)

- maximum sample heterozygosity rate within 3 standard deviations of the mean (threshold selected visually to exclude outliers, Fig. 2.4);
- sample sex mismatches based on X chromosome marker heterozygosity (`--check-sex` option);
- and marker deviation from Hardy-Weinberg equilibrium (HWE), an indication of genotyping or genotype calling errors [174, 175] (`--hwe` option,  $p$ -value  $< 1 \times 10^{-5}$ )<sup>\*</sup>.

\*A wide range of thresholds for the HWE marker filter in controls between  $1.00 \times 10^{-3}$  and  $5.70 \times 10^{-7}$  are reported in the literature [175]. The quality control pipeline thresholds used here are from de Lange *et al.* [176]. Since the HIRD cohort is two orders of magnitude smaller in size, this is a relaxed threshold, so additional vigilance for genotyping errors downstream is required. In principle, it may be possible to select a more appropriate threshold from the empirical distribution of HWE  $p$ -values [174].



**Figure 2.4: Sample filters for marker missingness and marker heterozygosity rate.** Thresholds for missingness (1 %) and heterozygosity rate (mean  $\pm$  3 standard deviations) are shown by dashed lines.

To exclude closely-related individuals and deduplicate samples from the same individual, pairwise kinship coefficients were computed using KING (v1.4). As rare variation is not generally required to determine relatedness, markers were filtered to **minor allele frequency (MAF) >0.05** for computational efficiency. For each pair of samples with pairwise kinship coefficient  $> 0.177$  (first-degree relatives or closer), the sample with lower marker missingness was selected. After all filters, 169/176 samples and 549 414/550 601 markers remained.

### 2.2.5 Computing genotype principal components as covariates for ancestry

As shown in [Table 2.1](#), the **HIRD** cohort is multi-ethnic. Large-scale population structure explains variation in gene expression [177, 178], so including genotype **principal components (PCs)** that reflect that structure as covariates can increase statistical efficiency for detecting associations with expression. I used HapMap 3 samples [179] as a reference population where the major axes of variation in genotypes are ancestry. Genotypes were first **linkage disequilibrium (LD)-pruned** (PLINK `--indep-pairwise 50 5 0.2` i.e. in a sliding window of 50 kbp, step size of 5 variants, remove variants at each step until no pair of variants has **LD >0.20**), to avoid regions with many redundant markers being overrepresented [180, 181]. Eighteen genomic regions with especially strong and/or long-range **LD** that contain many highly correlated markers were excluded, otherwise some **PCs** may reflect those just regions rather than genome-wide ancestry [180, 182]. **principal component analysis (PCA)** was performed using smartpca (v8000), then **HIRD** sample **PCs** were computed by projection onto the HapMap 3 **PCA** eigenvectors. For non-genotyped individuals with expression data, **PC** values were imputed as the mean value for all genotyped individuals with the same self-reported ancestry. The top **PCs** indeed separate samples by ancestry ([Fig. 2.5](#)). Significant **PCs** with large eigenvalues unlikely to be due to sampling noise were selected by Tracy-Widom test [183]. The fourth **PC** had an eigenvalue of 1.01 ( $p\text{-value} = 0.02$ ), so the top four **PCs** were retained as continuous covariates for ancestry downstream.

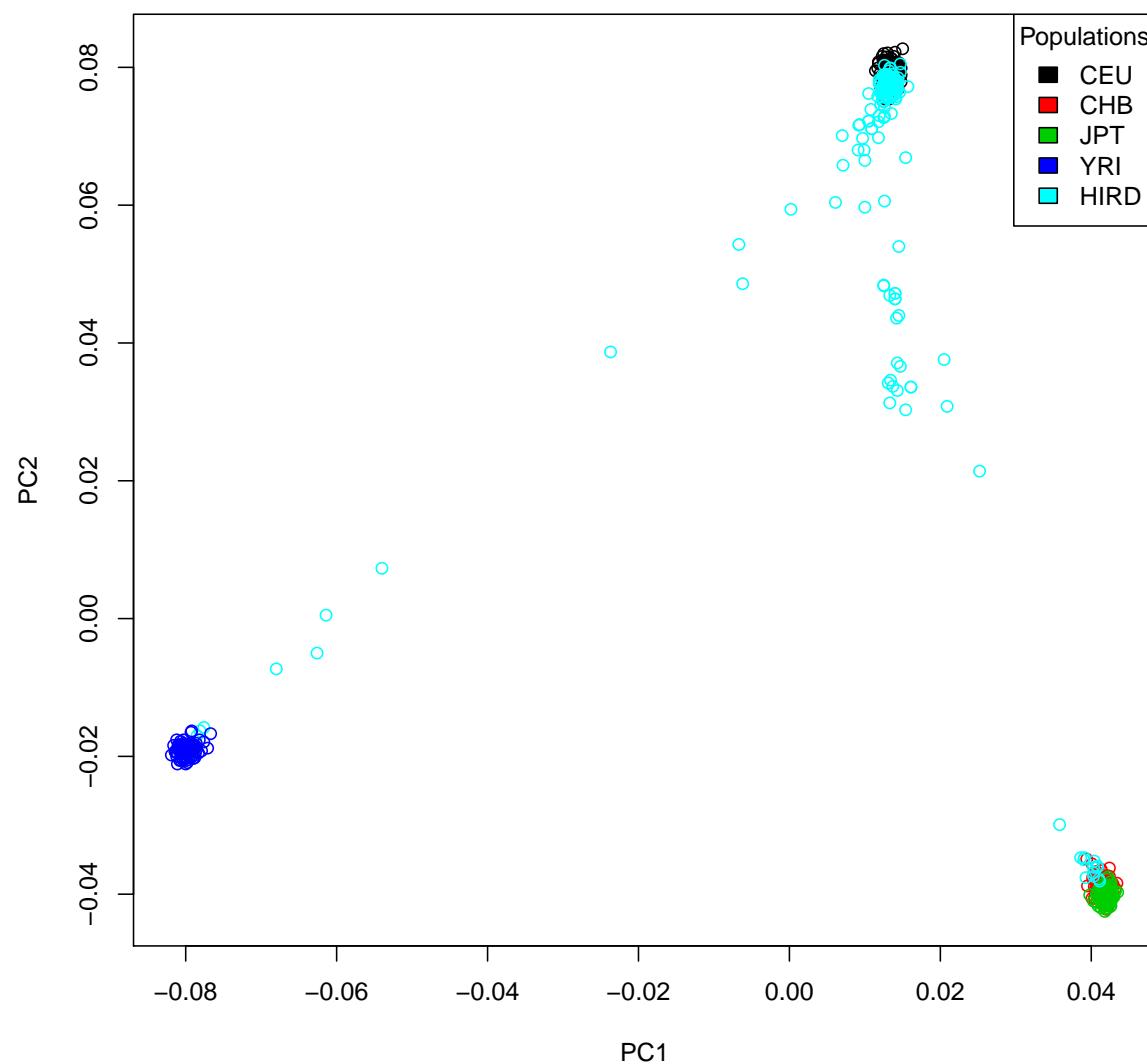
### 2.2.6 RNA-seq data generation

Total RNA was extracted from **PBMCs** using the Qiagen RNeasy Mini kit, with on-column DNase treatment. RNA integrity was checked on the Agilent Bioanalyzer and mRNA libraries were prepared with the KAPA Stranded mRNA-Seq Kit (KK8421), which uses poly(A) selection. To avoid confounding of timepoint and technical effects from library preparation and sequencing, samples were pooled by library prep plate (three pools) ensuring libraries from all timepoints of an individual were in the same pool, then sequenced across multiple lanes as technical replicates (HiSeq 4000, 75 bp paired-end).

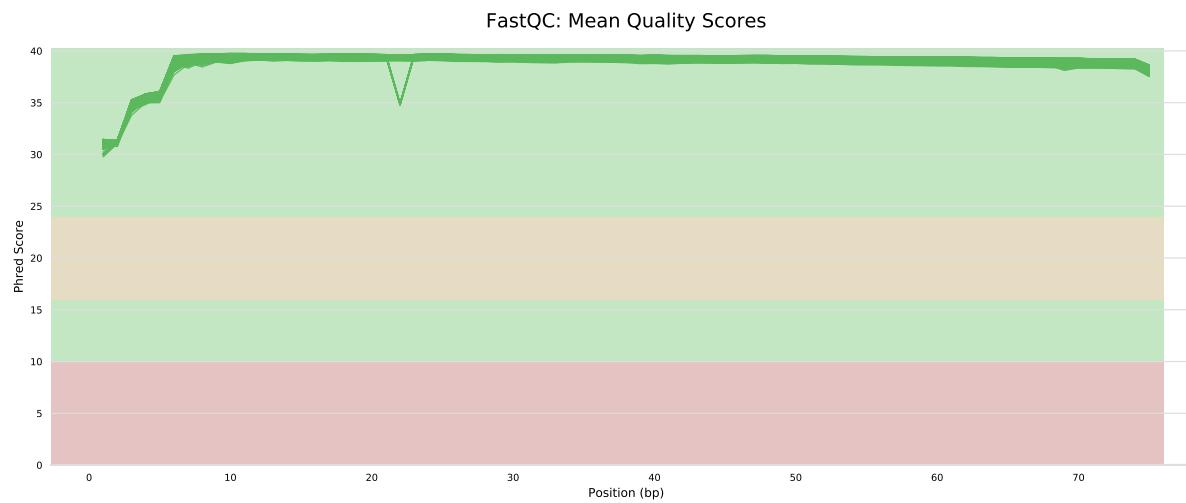
**RNA-seq** quality metrics were assessed using FastQC\* and Qualimap [184], then visualised with MultiQC [185]. Sequence quality was high, as measured by mean per-base Phred scores across sample reads ([Fig. 2.6](#)). The unimodal GC-content distribution suggested negligible levels of non-human contamination ([Fig. 2.7](#)).

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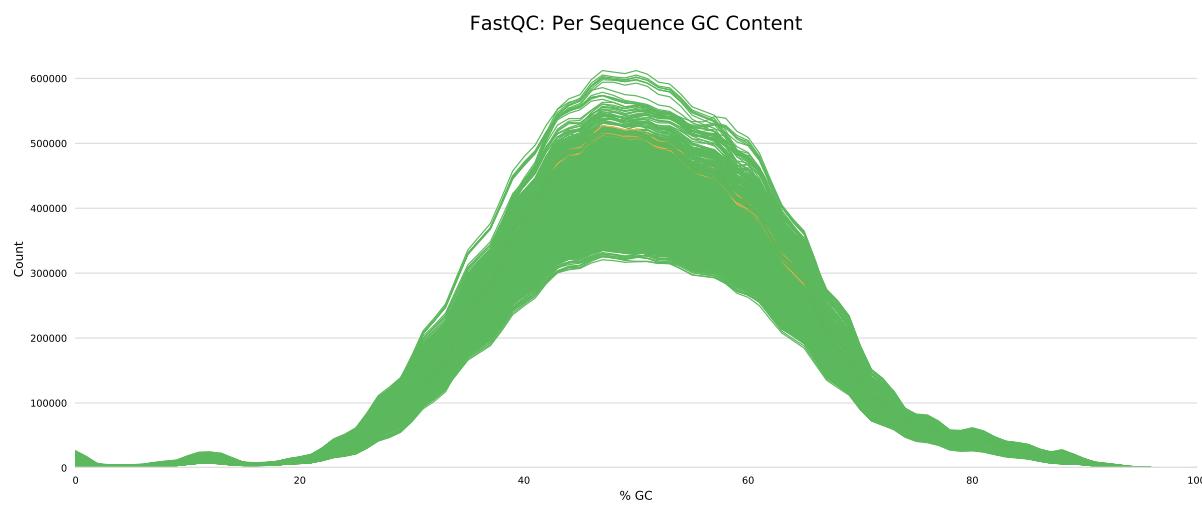
\*<https://www.bioinformatics.babraham.ac.uk/projects/fastqc/>



**Figure 2.5:** HIRD samples (cyan) projected onto PC1 and PC2 axes defined by PCA of HapMap 3 samples. The first two PCs separate individuals of European (CEU, upper-right) from Asian (CHB and JPT, lower-right) and African (YRI, lower-left) .



**Figure 2.6:** FastQC per-base sequence quality (Phred scores) versus read position for RNA-seq samples. Visualised with MultiQC [185].



**Figure 2.7:** FastQC per-read GC distributions for RNA-seq samples. Visualised with MultiQC [185].

### 2.2.7 RNA-seq quantification and preprocessing

Reads were quantified against the Ensembl reference transcriptome (GRCh38.p15) using Salmon [186] in quasi-mapping-based mode, which internally corrects for transcript length and GC composition by computing an effective length for each transcript. The mean number of mapped read pairs per sample after summing was 27.09 million read pairs (range 20.24-39.14 million), representing a mean mapping rate of 80.73% (range 75.57-90.10%), within sequencing depth recommendations for differential gene expression (DGE) experiments (e.g. diminishing returns after 10 million single-end reads [187]) and mapping rate expectations (e.g. 70–90 % [188]). Relative transcript abundances were summarised to Ensembl gene-level (release 90) count estimates using tximport (`scaledTPM` method, which scales Salmon transcripts per millions (TPMs) up to the library size [189, 190]) to improve statistical robustness and interpretability [189]. To combine technical replicates, as the sum of Poisson distributions remains Poisson-distributed, counts for technical replicates were summed for each sample.

Genes with short non-coding RNA (ncRNA) biotypes\* were filtered out. These are generally not polyadenylated, depleted by size selection during library preparation, and shorter than the 75 bp read length, so expression estimates for these genes can reflect misassignment of counts from overlapping protein-coding or long ncRNA genes [191]. Globin genes, which are highly expressed in RBCs and reticulocytes, cell types expected to be depleted in PBMC [192], were also filtered out. Given the proportion of removed counts at this stage was low for most samples (Fig. 2.8), poly(A) selection and PBMC isolation were deemed to have been efficient.

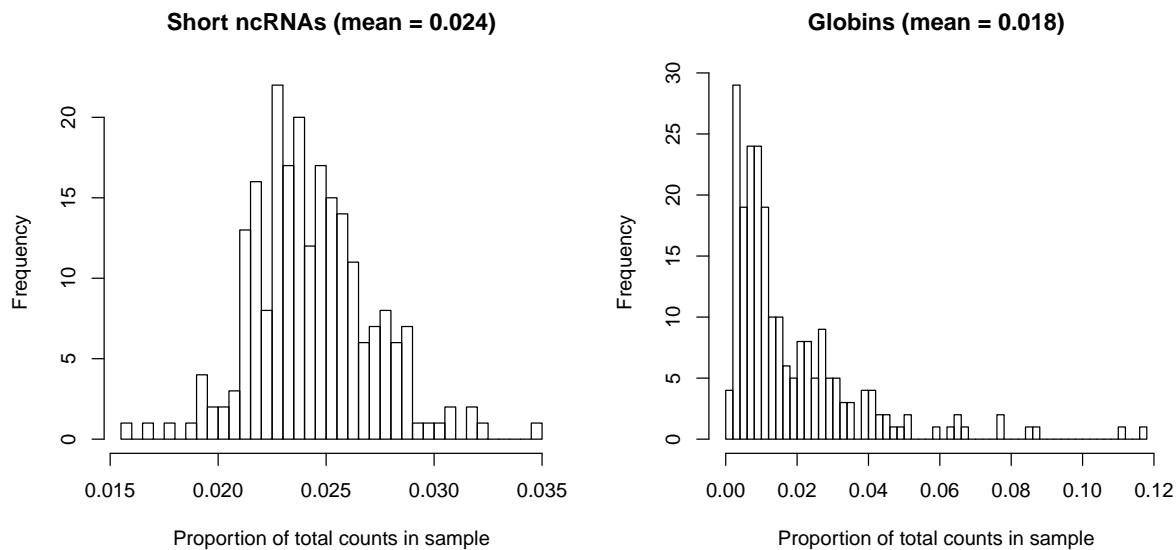
Many of the genes in the reference transcriptome are not expressed in PBMC (Fig. 2.9), and many genes are expressed at counts too low for statistical analysis of DGE. Genes were filtered to require a minimum of 0.5 counts per million (CPM) in at least 20 % of samples. The 0.5 CPM threshold was chosen to correspond to approximately 10 counts in the smallest library, where 10-15 counts is a rule of thumb for considering a gene to be robustly expressed [193, 194]. Genes were further filtered to require detection (non-zero expression) in at least 95 % of samples to lessen the impact of low-expression outliers. The change in the distributions of gene expression among samples before and after filtering shows a substantial number of low expression genes are removed (Fig. 2.10).

RNA-seq produces compositional data due to sequencing a fixed number of reads per library; if one gene's expression goes up in a library, another's must go down. In order for expression values to be comparable between different libraries (samples), it is important to account for composition bias, the dependence of expression estimates on the expression properties of other genes in each library [195]. Effective library sizes were computed as between-sample normalisation factors using the trimmed mean of M-values (TMM) method [195, 196] from edgeR::calcNormFactors [197]. Precision weights for each (gene by sample) observation were computed with `voom` [198] to account for the mean-variance relationship in RNA-seq data; `voom` also transforms expression values to the  $\log_2$  CPM scale, accounting for composition bias using effective library sizes.

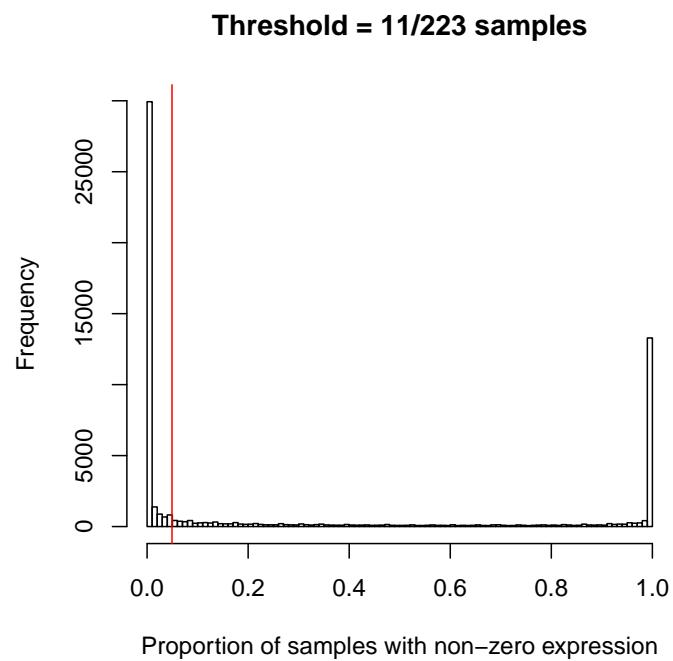
Finally, 15 samples were excluded for having missing HAI or MN data. After the application of all filters, expression values were available for 21 626 genes over 208 samples (70/75 individuals

no in both cases, I mean the genes are removed from the analysis, no use increasing the multiple testing burden

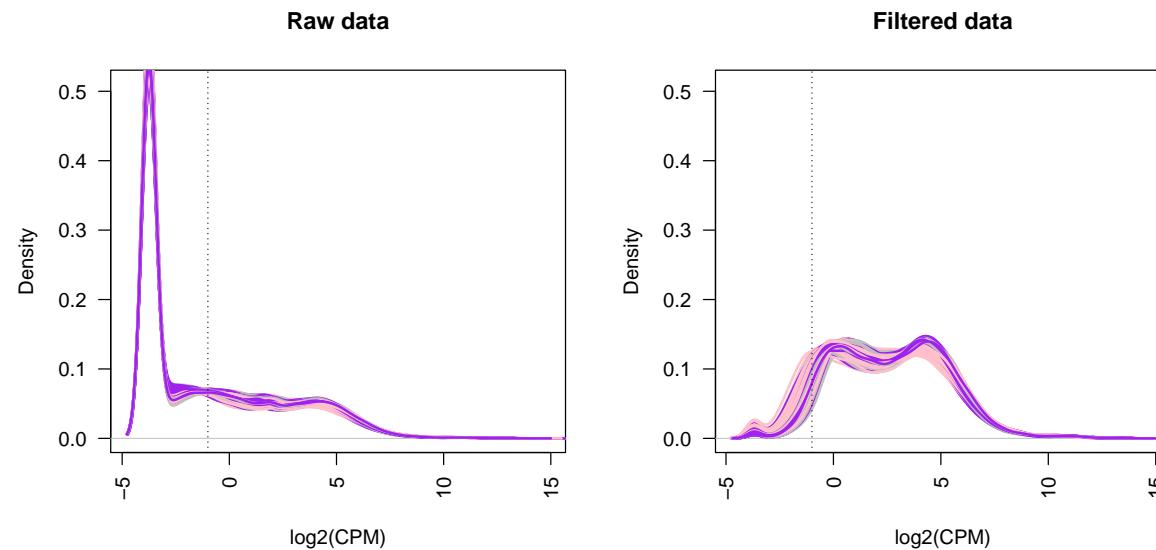
\*miRNA, miRNA\_pseudogene, miscRNA, miscRNA\_pseudogene, Mt rRNA, Mt tRNA, rRNA, scRNA, snlRNA, snoRNA, snRNA, tRNA, tRNA\_pseudogene. List from <https://www.ensembl.org/Help/Faq?id=468>



**Figure 2.8:** Distributions of removed short ncRNA and globin counts as a proportion of total counts in RNA-seq samples.



**Figure 2.9:** Distribution of the proportion of samples in which genes were detected (non-zero expression). Many genes are not detected in any samples (left-hand side). Vertical line shows 5% threshold below which genes were discarded.



**Figure 2.10:** Distributions of gene expression for **RNA-seq** samples before and after filtering low expression and non-detected genes. Vertical line shows **CPM** = 0.5 threshold.

on day 0, 68/75 on day 1, and 70/75 on day 7).

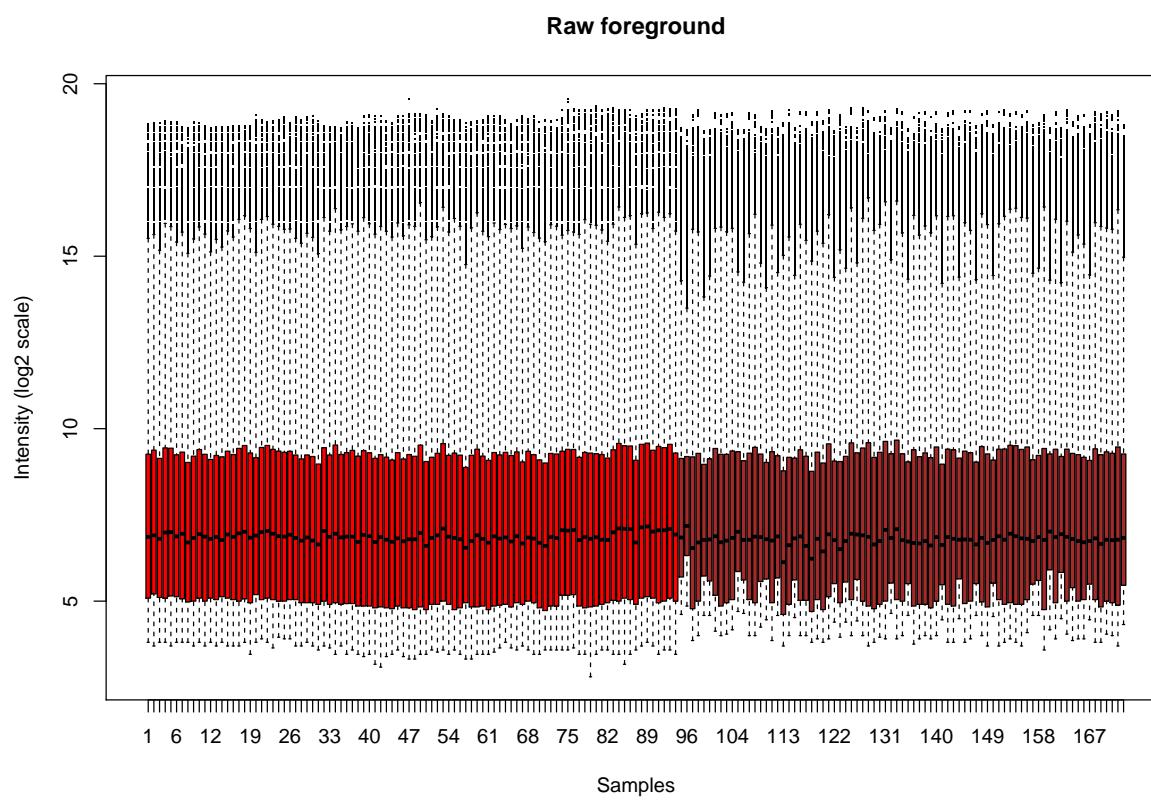
### 2.2.8 Array data preprocessing

Single-channel Agilent 4x44K expression array (G4112F, 60-mer oligonucleotide probes) data for 173 samples from Sobolev *et al.* [161] were downloaded from ArrayExpress (<https://www.ebi.ac.uk/arrayexpress/experiments/E-MTAB-2313/>). These arrays were originally processed in two batches, the effect of which can be seen in the raw foreground intensities (Fig. 2.11).

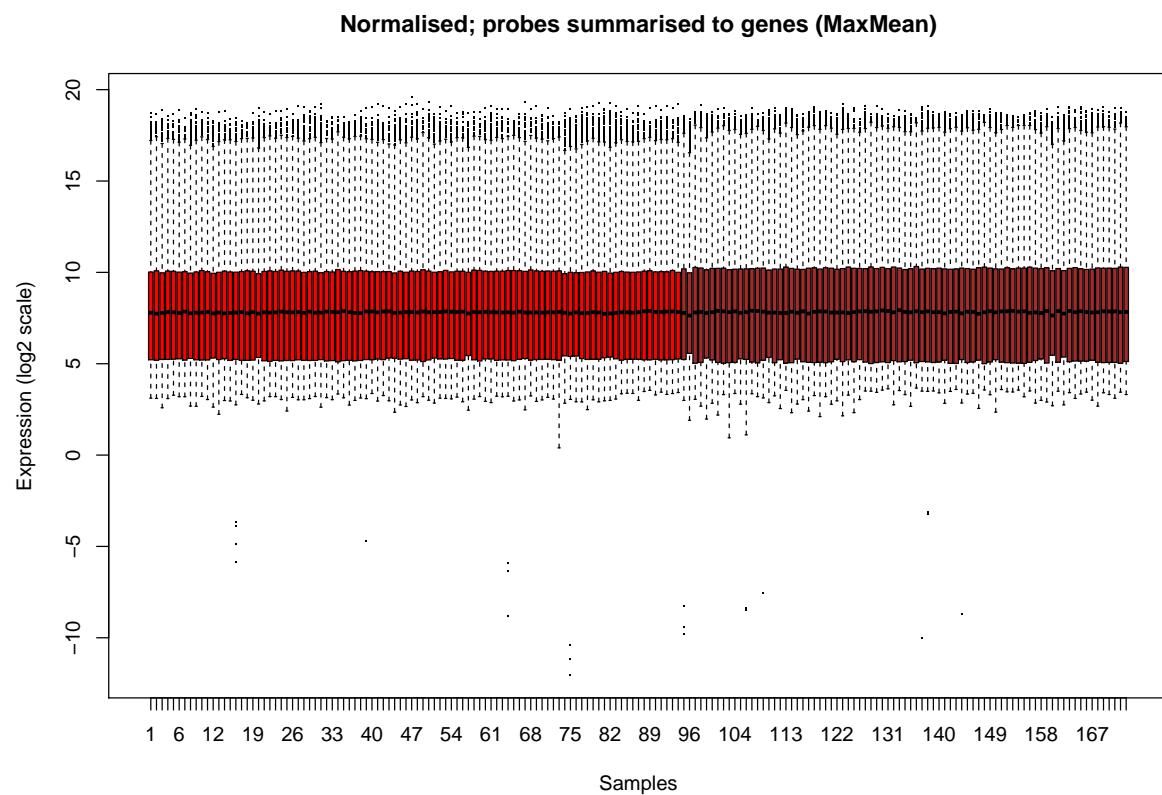
**VSN::normalizeVSN** [199] was used to simultaneously perform background correction, between-array normalisation (affine transformation, centers and scales each array to control for systematic experimental factors), and variance-stabilisation (generalised logarithm, similar to  $\log_2$  with better performance for small values) of intensity values, resulting in expression values on a  $\log_2$  scale. As systematic experimental factors might differ between batches, requiring different centering and scaling factors, normalisation was done per-batch, then the two batches were merged.

Probes were matched to genes using **hgug4112a.db**\*. Most genes were targeted by multiple array probes; 31 208 probes were collapsed into 18 216 Ensembl genes using by selecting the probe with the highest mean intensity for each gene (**WGCNA::collapseRows**(method=MaxMean), a method recommended for probe to gene collapsing by Miller *et al.* [200]). While it would be optimal to select a collapsing method to maximise the concordance between array and **RNA-seq** expression values, there were no samples assayed by both platforms in the **HIRD** dataset. The final normalised  $\log_2$  intensity values for these 18 216 genes over 173 samples is shown in Fig. 2.12. Finally, **limma::arrayWeightsQuick** [201] was used to compute per-sample quality weights used to downweight unreliable arrays (samples) in the **DGE** analyses.

\*<https://bioconductor.org/packages/release/data/annotation/html/hgug4112a.db.html>



**Figure 2.11:** Distribution of raw foreground intensities for 173 **HIRD** array samples. Colored by array processing batch.



**Figure 2.12:** Distribution of per-sample expression estimates after normalisation and collapsing of probes to genes. Colored by array processing batch.

### 2.2.9 Differential gene expression (DGE)

#### 2.2.9.1 Platform and batch effects

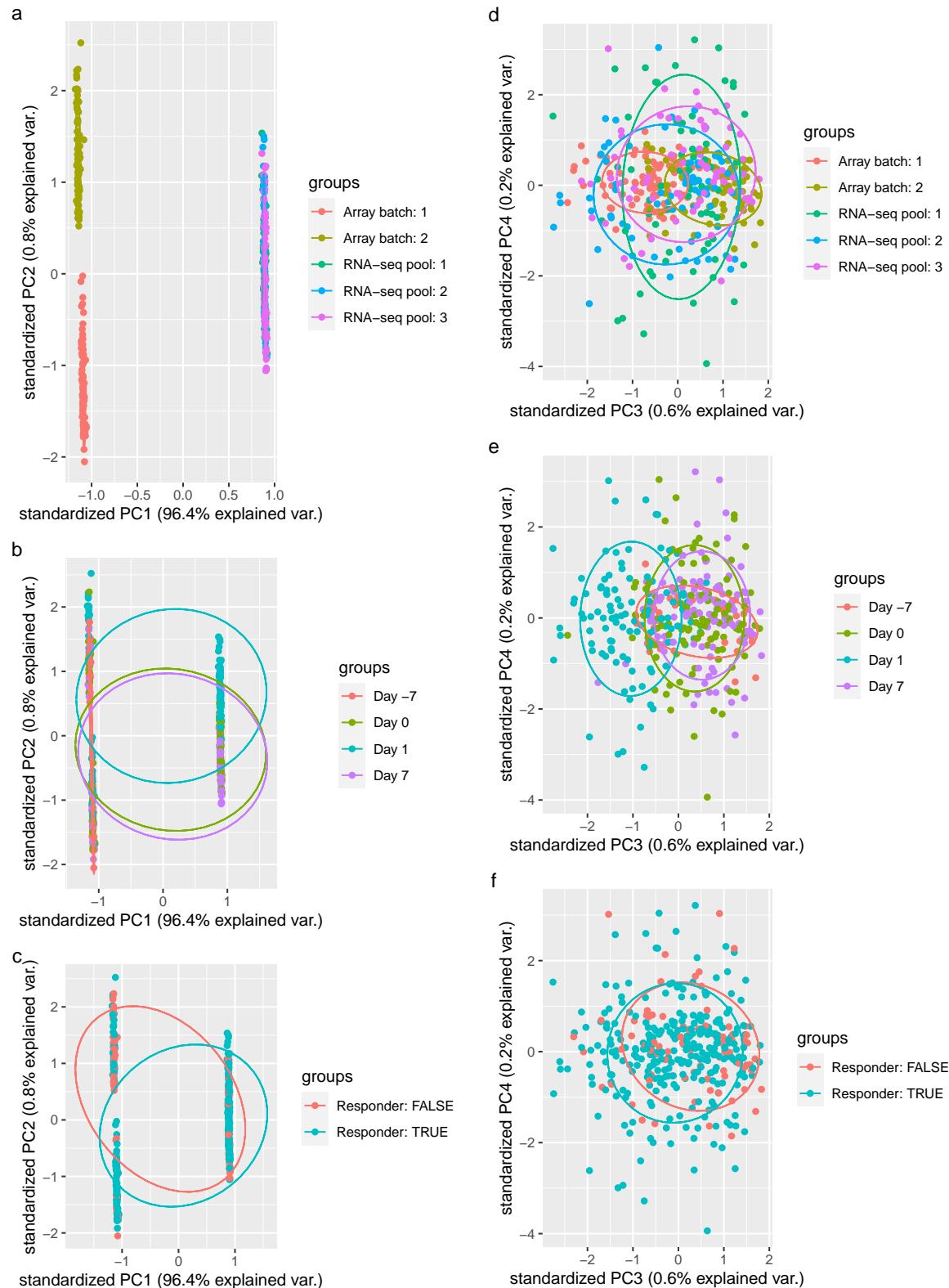
Combining the normalised array and **RNA-seq** data resulted in expression values for 13 593 genes assayed in both platforms, and a total of 374 samples. **PCA** revealed that although samples separate by experimental timepoint along **PC3** (Fig. 2.13d), measurement platform is by far the largest source of variation. Normalisation was also not able to completely remove the batch effect within the array data (Fig. 2.13a). The large platform effect likely stems from systematic technological differences in how each platform measures expression. **RNA-seq** has a higher dynamic range, resulting less bias at low expression levels, but estimates are more sensitive to changes in depth than array estimates are to changes in intensity [202]. Agreement between the two platforms is poor at extremes of expression [203, 204]. The preprocessing done for the two platforms (Sections 2.2.7 and 2.2.8) is also vastly different.

Despite the shortcomings of array data detailed above, the array dataset contains individuals with more extreme antibody response phenotypes (Fig. 2.3), hence the data should not be excluded. Given the magnitude of the platform effect, I concluded that the appropriate approach should be a two-stage approach that meta-analyses per-platform **DGE** effect estimates while explicitly accounting for between-platform heterogeneity.

Regarding the batch effect within the array data, a popular adjustment method is ComBat [205], which estimates per-gene, per-batch centering and scaling parameters, which are shrunk towards the per-batch mean parameters over all genes using empirical Bayes to improve robustness. ComBat was the method used by Sobolev *et al.* [161]. In comparisons of array batch effect adjustment methods, ComBat performed favourably (versus five other adjustment packages) [206] or comparably (versus fitting batch as a fixed or random effect in the linear model, which are centering-only corrections) [207]. However, where batches are unbalanced in terms of sample size [208] or distribution of study groups that have an impact on expression [209], ComBat can overcorrect batch differences or bias estimates of group differences respectively. In our data, sample size and timepoint groups are fairly balanced between the two array batches (Table 2.2); The proportion of responders is not, but response status does not have as prominent an impact on global expression as timepoint (Fig. 2.13). For the **DGE** analyses in this chapter, I chose to model batches (array batch and **RNA-seq** pool) as fixed effects rather than pre-adjusting with Combat, ensuring the **degrees of freedom (df)** in the **DGE** model were correct. In practice, results from the analyses were not substantially affected by the choice of whether to use a ComBat pre-adjustment or a fixed effect.

#### 2.2.9.2 Per-platform DGE model

As a meta-analysis is proposed, **DGE** analyses are restricted to the 13593 genes assayed by both the array and **RNA-seq** platforms. Linear models were fit using limma [210], which is computationally fast, performs well for sufficiently large ( $n \geq 3$  per group) sample sizes [211], and internally considers the precision weights computed for **RNA-seq** observations in Section 2.2.7, and the array quality weights computed for array samples in Section 2.2.8. As Sobolev *et al.* [161] already found there was no global dissimilarity in array expression between day -7 and



**Figure 2.13: First four standardised PCs in the expression data, colored by array batch/RNA-seq pool (a, c), and timepoint (b, d) and binary response status (e, f). Expression of each gene was standardised across samples within each platform before PCA.**

**Table 2.2: Balance of timepoint and responder groups between array batches and RNA-seq pools.** Values are count and percentage for categorial variables; mean and standard deviation for continuous variables.

	Total n = 374	Array 1 n = 87	Array 2 n = 79	RNA-seq 1 n = 70	RNA-seq 2 n = 69	RNA-seq 3 n = 69
<b>Day</b>						
-7	40 (10.7%)	20 (23%)	20 (25.3%)	0 (0%)	0 (0%)	0 (0%)
0	114 (30.5%)	24 (27.6%)	20 (25.3%)	24 (34.3%)	23 (33.3%)	23 (33.3%)
1	109 (29.1%)	21 (24.1%)	20 (25.3%)	22 (31.4%)	23 (33.3%)	23 (33.3%)
7	111 (29.7%)	22 (25.3%)	19 (24.1%)	24 (34.3%)	23 (33.3%)	23 (33.3%)
<b>Responder</b>						
FALSE	80 (21.4%)	12 (13.8%)	36 (45.6%)	11 (15.7%)	9 (13%)	12 (17.4%)
TRUE	294 (78.6%)	75 (86.2%)	43 (54.4%)	59 (84.3%)	60 (87%)	57 (82.6%)
<b>TRI</b>	-0.1 (1.0)	-0.1 (1.0)	-0.4 (1.4)	0.1 (0.6)	-0.0 (0.8)	0.2 (0.6)

day 0, for the DGE analyses in this chapter, array day -7 and day 0 are treated as repeated measurements taken at a single “baseline” timepoint.

For each gene and platform, I fit a model (model 1) with expression as the response variable; with an intercept, timepoint (baseline, day 1, day 7), TRI, batch/pool, sex, age, and the first 4 genotype PCs as fixed-effect predictors; and individual as a random-effect predictor. Within-individual correlations for the random effect were estimated using `limma::duplicateCorrelation`. A second model (model 2) was also fit, the only difference being two additional predictors for the multiplicative interactions between day 1 and day 7 with TRI. Model 1 was used for testing differences in expression between pairs timepoints, and for testing association between TRI and expression overall. Model 2 was used for testing association between TRI and expression at specific timepoints.

Contrasts were used, testing if linear combinations of estimated model coefficients are different from zero. From model 1, I defined contrasts for day 1 vs. baseline, day 7 vs. baseline, day 7 vs. day 1, TRI, sex, and age. For example, to test for association between TRI and expression, I used a contrast where the weight for the TRI coefficient was 1, with all other coefficient weights set to 0; to test for differences between day 7 vs. day 1, I used a contrast where the weight for the day 7 coefficient was 1, the weight for the day 1 coefficient was -1, and all other coefficient weights were 0. From model 2, I defined contrasts for the TRI, TRI-day 1, and TRI-day 7 interaction terms, which test for association between TRI and expression at specifically at baseline, day 1, and day 7. Corresponding coefficients and standard errors for the contrasts were extracted from the `limma` models, which represent effect size in units of  $\log_2$  expression fold change per unit change in predictor value.

### 2.2.9.3 Choice of DGE meta-analysis method

Two popular frameworks for effect size meta-analysis are fixed-effect and random-effects [212, 213]. The fixed-effect model assumes a single true effect size  $\theta$  common to all studies. Given  $k$  studies ( $i = 1, \dots, k$ ), the observed effect size in the  $i$ th study is commonly assumed to be

$y_i \sim \mathcal{N}(\theta, \sigma_i^2)$ , where observed variation is explained only by within-study sampling error  $\sigma_i$ . In meta-analysis, the effects are combined with some weighting, commonly the inverse variance (precision)  $1/\sigma_i^2$ .

The random-effects model assumes a distribution of true effects centered around a common mean  $\mu$ . Each of the  $k$  studies estimates its own study-specific true effect size  $\theta_i$ . These are distributed around  $\mu$  with variance  $\tau^2$  (standard deviation  $\tau$ ), representing an additional source of variation: the between-studies heterogeneity. Then we have  $y_i \sim \mathcal{N}(\theta_i, \sigma_i^2)$  for the first level of variation,  $\theta_i \sim \mathcal{N}(\mu, \tau^2)$  for the second level of variation, and assuming these distributions, we have a normal-normal multilevel model [214]. Study weights include both within and between-study variance  $1/(\sigma_i^2 + \tau^2)$ , reducing to the fixed-effect model when  $\tau = 0$ .

The choice of fixed or random effects depends on whether it is tenable to assume studies are identical enough that they all estimate a common effect\*. In the HIRD data, there are  $k = 2$  studies: array and RNA-seq. The between-platform differences described in Section 2.2.9.1 represent considerable sources of between-study heterogeneity. For DGE, arrays also suffer from ratio compression of fold change estimates due to cross-hybridisation and probe saturation [204, 216, 217]. The assumption of  $\tau = 0$  is unrealistic and a random-effects model is more appropriate.

Unfortunately, there is no optimal solution for directly estimating  $\tau$  in random-effects meta-analyses with small  $k$  [218], and especially in the case of  $k = 2$  [219]. Many estimators are available [220], but lack of information with small  $k$  causes estimation to be imprecise, and often results in boundary values of  $\tau = 0$  that are incompatible with the assumed positive heterogeneity [221, 222]. In such circumstances, the most sensible approach may be to incorporate prior information about hyperparameters  $\mu$  and  $\tau$  in a Bayesian random-effects framework [220–223]. For this study, I use the implementation in bayesmeta [214].

#### 2.2.9.4 Prior for between-studies heterogeneity

The choice of prior for between-studies heterogeneity  $\tau$  is influential when  $k$  is small [223]. Gelman [224] considers the case of  $k = 3$ , showing that a flat prior places too much weight on implausibly large estimates of  $\tau$ , and recommends a weakly informative prior that acts to regularise the posterior distribution, constraining it away from implausible values. Since I assumed zero estimates for  $\tau$  are unrealistic, I use a weakly informative gamma prior, as recommended by Chung *et al.* [221], which has zero density at  $\tau = 0$  but increase gently as  $\tau$  increases (a positive constant derivative at zero). This constrains  $\tau$  to be positive, but still permits estimates close to zero if the data support it. This is in contrast to priors used in other studies from the log-normal (e.g [225, 226]) or inverse-gamma (e.g. [227]) families that have zero density at zero and derivatives of zero close to zero, ruling out small values of  $\tau$  no matter what the data suggest; and in contrast to half- $t$  family priors (e.g. [223, 224]), which have their mode at zero, and do not rule out  $\tau = 0$ .

Instead of constraining the value of  $\tau$  for a gene's effect size to be a single, unreliable estimate from  $k = 2$  data points, assuming a prior distribution recognises that other genes may be

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\*A common misinterpretation is that random-effects meta-analysis assumes studies *themselves* are sampled from a population of studies. This is rarely appropriate since the design of new studies is influenced by existing studies [215]. The required assumption is exchangeability of study *effects*, which informally states effects are neither completely identical nor completely independent, but “similar” [215].

informative of the range of plausible values for between-platform heterogeneity. To estimate the appropriate shape and scale parameters for the gamma empirically, a frequentist random-effects model using the **restricted maximum likelihood (REML)** estimator for  $\tau$  (recommended for continuous effects [220]) was fit for each gene using `metafor::rma.uni` [228]. Depending on the contrast, over half of resulting per-gene  $\tau$  estimates could be boundary values of zero. Small estimates of  $\tau < 0.01$  were excluded, and a gamma distribution fit to the remaining estimates using `fitdistrplus` [229].

#### 2.2.9.5 Prior for effect size

While the choice of prior on  $\tau$  is influential when  $k$  is small, there is usually enough data to estimate the effect size  $\mu$  such that any reasonable non-informative prior can be used [222, 224]. `bayesmeta` implements both flat and normal priors for  $\mu$ . Assuming that most genes are not differentially expressed with effect sizes distributed randomly around zero, I selected a normal prior with  $N(\mu = 0, \sigma^2)$ , over a flat prior. As in the section above, to determine an appropriate scale, a normal distribution with mean  $\mu = 0$  was fit to the distribution of effect sizes from the gene-wise frequentist models to empirically estimate  $\sigma$ .

Heavy-tailed Cauchy priors have been proposed for effect size distributions in **DGE** experiments to avoid over-shrinkage of true large effects in the tails [230]. Since `bayesmeta` does not implement a Cauchy prior, to avoid over-shrinkage, I flatten the normal prior considerably by scaling up the standard deviation by a factor of 10:  $N(0, (10\sigma)^2)$ . This places a 95% prior probability that effects are less extreme than approximately 20 times the observed  $\sigma$ , sufficient to allow for extreme fold-changes.

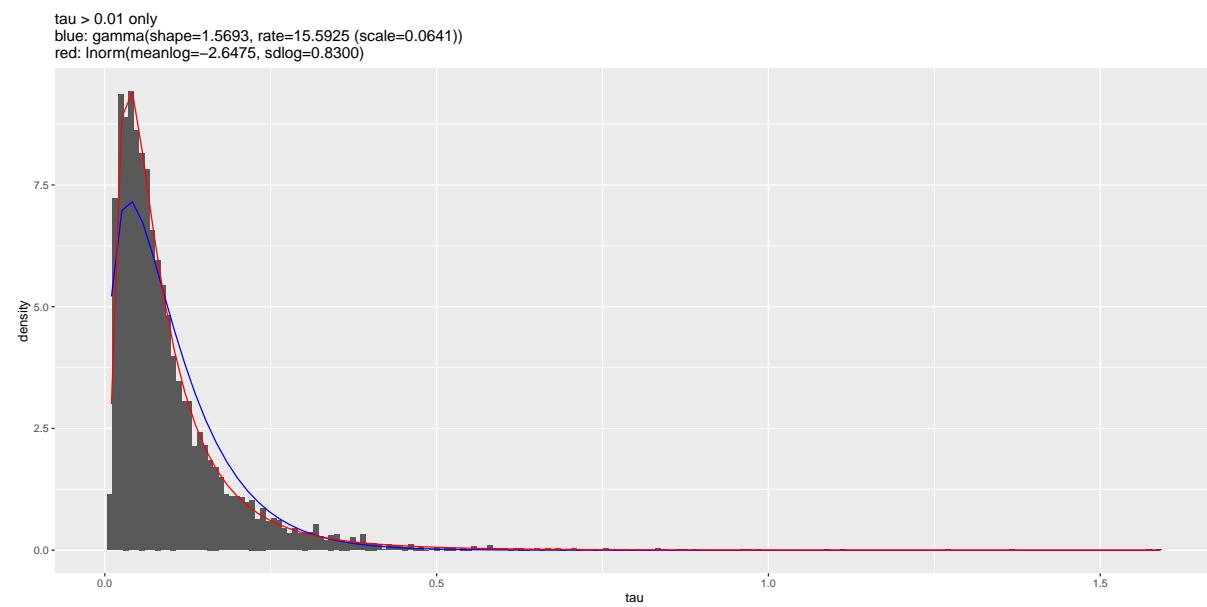
#### 2.2.9.6 Evaluation of priors

An example of the empirically estimated hyperparameters for the priors for the day 1 vs. baseline contrast are shown in Fig. 2.14 (for  $\tau$ ) and Fig. 2.15 (for  $\mu$ ). For  $\tau$ , the final prior used was  $\text{Gamma}(\text{shape} = 1.5693, \text{scale} = 0.0641)$ . This is comparable to the default recommendation from Chung *et al.* [221] of a  $\text{Gamma}(\text{shape} = 2, \text{scale} = \lambda)$  prior where  $\lambda$  is small. For  $\mu$ , the final prior used was  $N(0, (0.3240 * 10)^2)$ . The tails of the non-scaled normal fit (black) are light compared to the Cauchy fit (red), which may lead to over-shrinkage, especially since there are many genes with high positive fold changes for the day 1 vs. baseline effect.

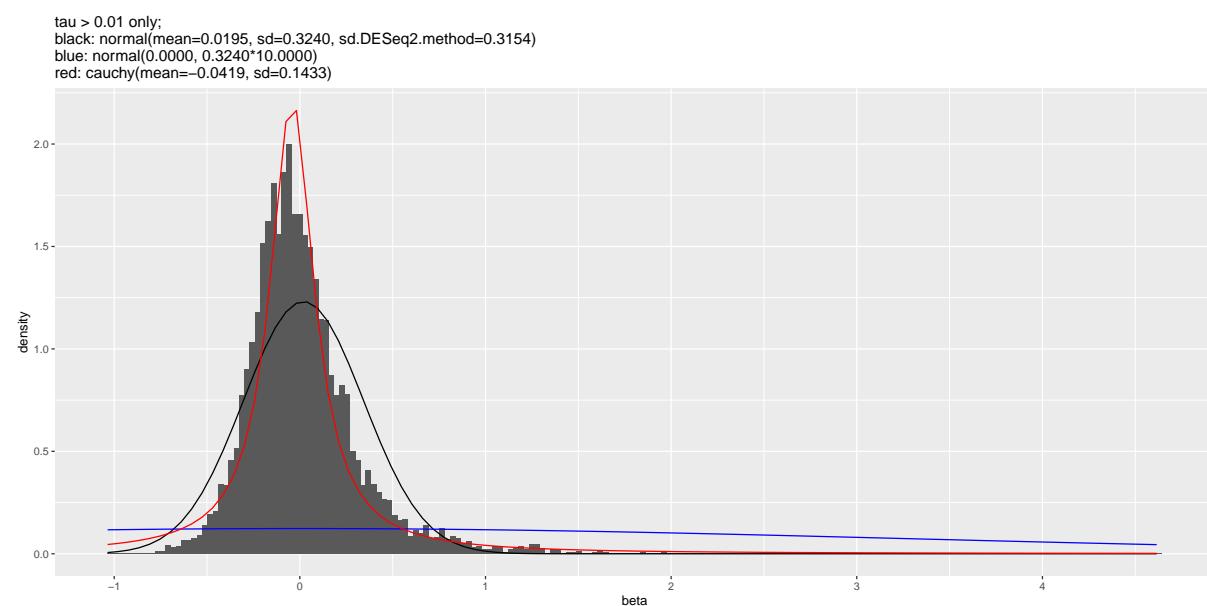
#### 2.2.9.7 Multiple testing correction

For per-platform **DGE**, **false discovery rate (FDR)** control was done with `limma::decideTests` using the **Benjamini-Hochberg (BH)** procedure. For the frequentist random-effects meta-analysis, nominal gene-wise  $p$ -values are converted to **FDR** estimates using `p.adjust(method='BH')` in R.

For the Bayesian random-effects meta-analysis, the effect sizes and standard errors from the per-gene meta-analysis output from `bayesmeta` were supplied to `ashr`, which models the distribution of effects under the assumption of unimodality [232]. `ashr` applies empirical Bayes shrinkage to improve the accuracy of effect estimation (e.g. against winner's curse), returning



**Figure 2.14:** Gamma prior for  $\tau$  (blue) used for `bayesmeta` analyses of the day 1 vs. baseline effect, compared to the empirical distribution of per-gene frequentist `metafor::rma.uni` estimates for  $\tau$ . Genes with small estimates of  $\tau < 0.01$  were first excluded. Empirical log-normal fit also shown (red). Distribution parameters are listed.



**Figure 2.15:** Normal prior for  $\mu$  (blue) used for `bayesmeta` analyses of the day 1 vs. baseline DGE effect, compared to the empirical distribution of per-gene frequentist `metafor::rma.uni` estimates for  $\tau$ . Genes with small estimates of  $\tau < 0.01$  were first excluded. The original non-scaled normal fit is shown (black), as well as a Cauchy fit (red). Distribution parameters are listed. Alternative estimate of the Normal standard deviation more robust to outliers using a quantile matching method from `DESeq2` [231] is also shown. In this case, it was comparable to the maximum likelihood (ML) estimate from `fitdistrplus`.

posterior effect sizes, posterior standard errors, and their significance ([local false sign rate \(lfsr\)](#)). [lfsr](#) is analogous to [FDR](#), but quantifies the probability, given the data, of calling the wrong sign for an effect, rather than the confidence of a non-zero effect [232]. Unless otherwise stated, correction was done at the 5 % level separately for each contrast, as control is for the proportion of positives expected to be false positives, which is scalable to multiple contrasts.

### 2.2.10 Gene set enrichment analysis using blood transcription modules

The gene sets used were [blood transcription modules \(BTMs\)](#) from Chaussabel *et al.* [233] (prefixed “DC”) and Li *et al.* [234] (prefixed “LI”). Modules are sets of genes with transcriptional and functional similarities across a variety of healthy, diseased and stimulated conditions. The 260 modules from Chaussabel *et al.* [233] were constructed by unsupervised clustering of 239 [PBMC](#) transcriptomes from multiple disease datasets, then annotated by data mining of gene names in PubMed abstracts. The 334 modules from Li *et al.* [234] were constructed from coexpression analysis of approximately 30 000 blood transcriptomes, then annotated making use of Gene Ontology terms, cell type-specific markers, pathway databases, and manual literature searches. These datasets are particularly suitable for systems vaccinology studies, given their focus on the blood transcriptome. Li *et al.* [234] modules are better annotated in general, and were used for the majority of gene set enrichments in this chapter.

Gene set enrichment analyses were conducted using `tmod::tmodCERNOtest` [235], which assesses the enrichment of small ranks within specific sets of genes compared to all genes, when the genes are ranked by some metric—here I used effect sizes from `bayesmeta`. The CERNO statistic for a gene set is:

$$-2 \sum_{i=1}^n \ln \frac{r_i}{N} \sim \chi^2(2N) \quad (2.1)$$

where  $n$  is the number of genes in the set,  $r$  is the rank of the  $i$ th gene in the set, and  $N$  is the number of measured genes (intersection between genes in the experiment and genes in the set of [BTMs](#) used). CERNO is relatively robust to the ranking metric [236]. [FDR](#) control for the number of gene sets tested was done using [BH](#), again separately for each contrast. Since `tmod::tmodCERNOtest` only considers enrichment of small ranks which computing significance, but genes can be down or upregulated, separate tests were done sorting in ascending and descending order, and the more significant result was used to determine the overall direction of effect for each gene set. As the approach is rank-based and considers all measured genes, no filters on effect size were applied before testing.

The effect size of an enrichment is given by the [area under the curve \(AUC\)](#). It can be computed from  $U$ , the test statistic from a Mann-Whitney U test (also known as the Wilcoxon rank-sum test):

$$U = nN + \frac{n(n+1)}{2} - \sum_{i=1}^n \frac{r_i}{N} \quad (2.2)$$

This is a non-parametric test for whether genes in the set have smaller ranks than genes not in the set on average. Finally, [AUC](#) =  $U/(nN)$ , which takes values from 0 to 1.

## 2.3 Results

### 2.3.1 Extensive global changes in expression after vaccination

To gain an overview of how the transcriptome changes after vaccination, linear models were fit to identify genes differentially expressed at day 1 or day 7 compared to baseline (day -7 and day 0) in the **HIRD** array and **RNA-seq** expression data, accounting for covariates such as batch effects, sex, age, **TRI**, and ancestry. At the 13 593 genes with expression measured by both platforms, models were fit within each platform. A frequentist random-effects meta-analysis was initially run to generate plausible values for **DGE** effect size and between-platform heterogeneity. These were used to form empirical priors for a Bayesian random-effects meta-analysis, producing final posterior estimates of effect size and standard errors.

Vaccination induced changes in a large proportion of the **PBMC** transcriptome; 6257/13 593 gene were differentially expressed between any pair of timepoints ( $\text{lfsr} < 0.05$ ). Using an absolute **FC**  $> 1.5$  cutoff identified 857 genes with the strongest effects. Their expression clustered into three general patterns: upregulation from baseline to day 1, then downregulation from day 1 to day 7 back to baseline levels; upregulation from baseline to day 1, sustained at day 7; and downregulation from baseline to day 1, the upregulation from day 1 to day back to baseline levels (Fig. 2.16).

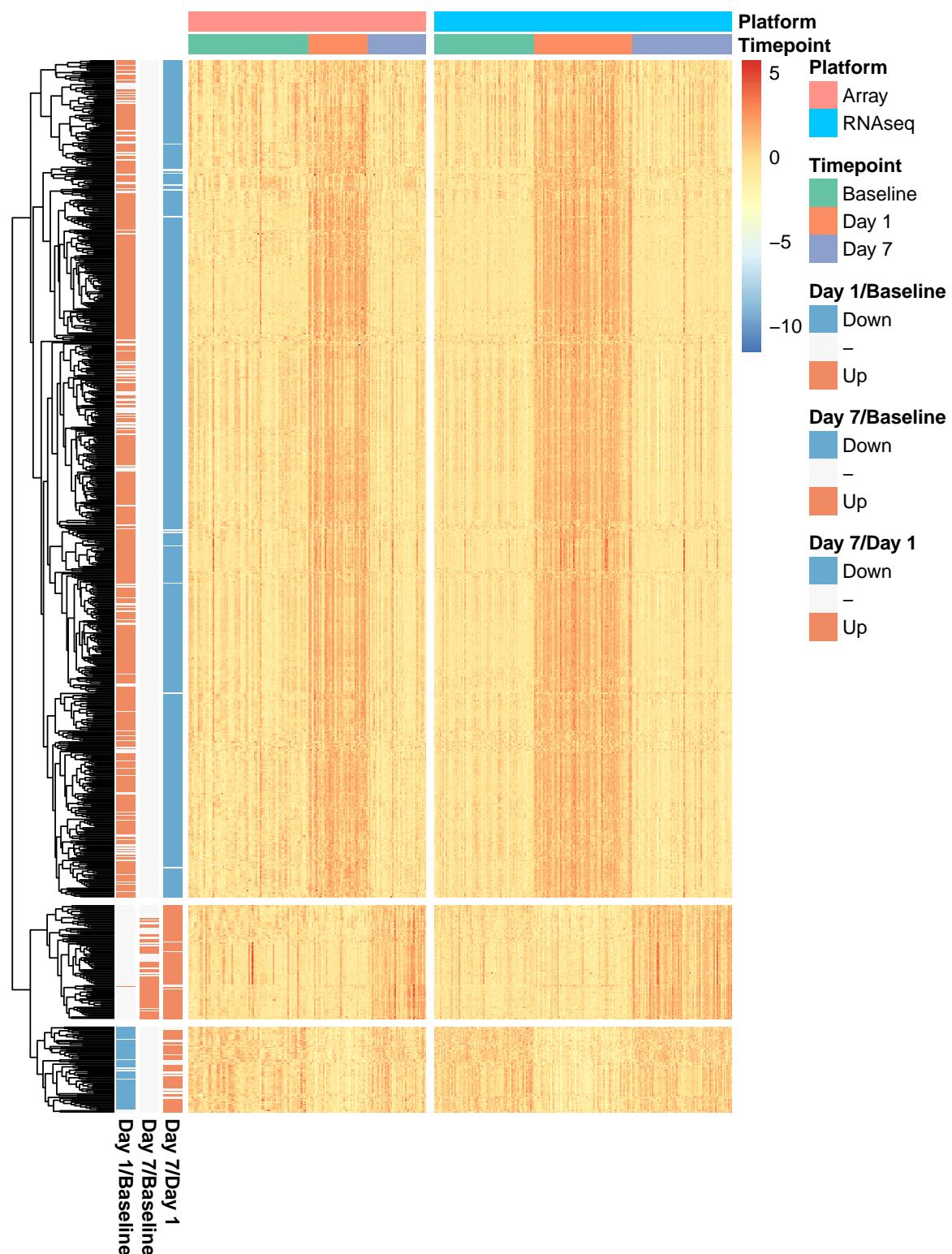
#### 2.3.1.1 Innate immune response at day 1 post-vaccination

Consistent with global expression at day 1 being markedly different from expression at other timepoints (Fig. 2.13), the highest numbers of differentially expressed genes are observed at day 1, with 644 genes differentially expressed vs. baseline. The majority of these (580/644) were upregulated. The gene with the highest **FC** increase at day 1 compared to baseline was *ANKRD22* ( $\log_2 \text{FC} = 4.49$ ), an interferon-induced gene in monocytes and **DCs** involved in antiviral innate immune pathways [237]. Other key genes in the interferon signalling pathway [238] such as *STAT1* ( $\log_2 \text{FC} = 2.17$ ), *STAT2* ( $\log_2 \text{FC} = 0.95$ ), and *IRF9* ( $\log_2 \text{FC} = 0.82$ ) are also upregulated at day 1. Rank-based gene set enrichment analysis using tmod [235] revealed that genes with the large **FC** increases at day 1 were enriched in modules associated with interferon, activated **DCs**, monocytes, and **Toll-like receptors (TLRs)** and inflammatory signalling (Fig. 2.17). Sobolev *et al.* [161] reported only a 1.6-fold ( $\log_2 1.6 = 0.68$ ) increase in blood monocytes from baseline to day 1, as measured by **FACS**, so these changes reflect active, per-cell upregulation as well as proliferation.

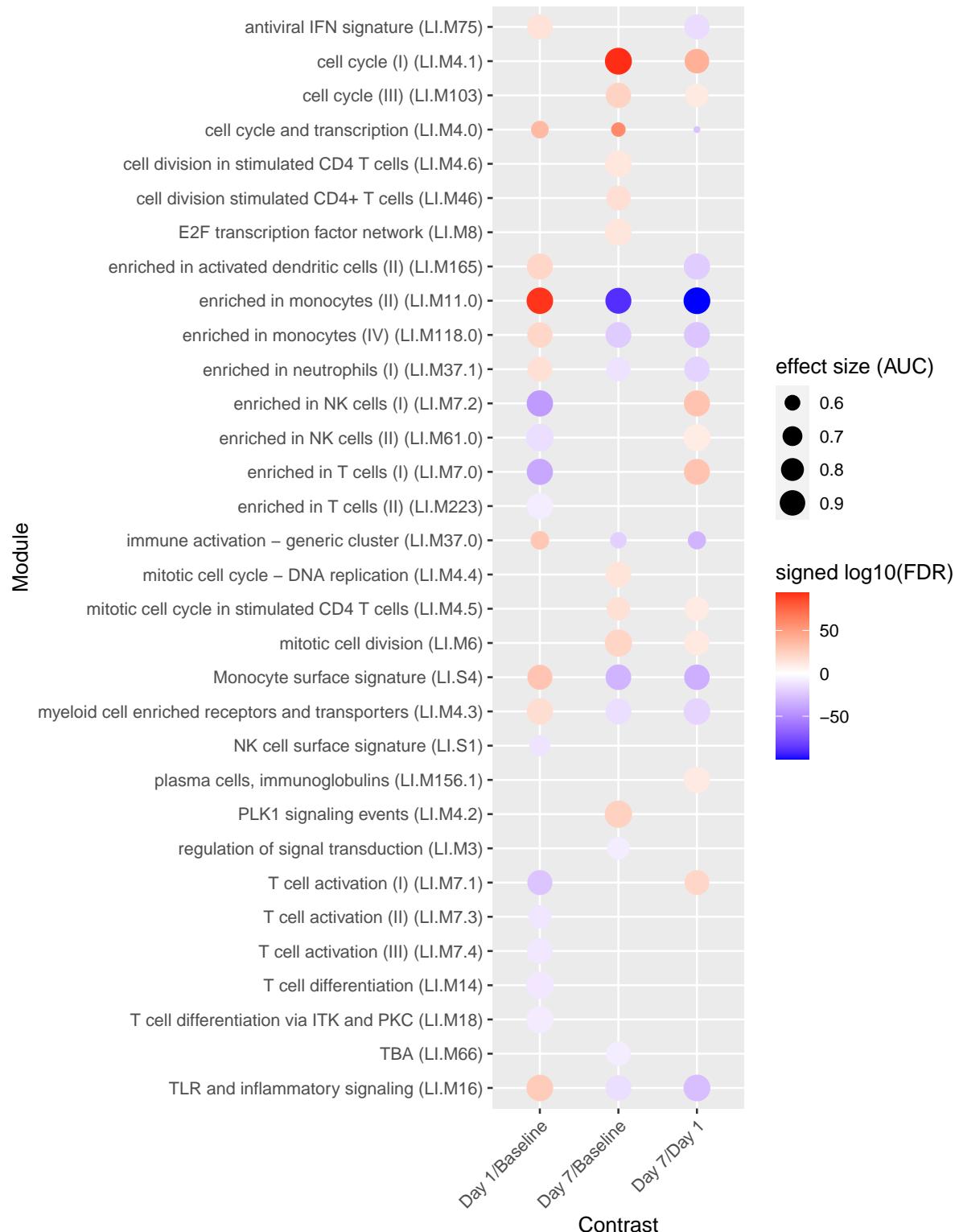
will get to consistency of top hits in the next section when i discuss meta-analysis results

Sixty-four genes were downregulated at day 1, enriched in modules associated with T cells and **natural killer (NK)** cells. The largest absolute fold change observed for *FGFBP2* ( $\log_2 \text{FC} = -0.91$ ), which encodes Ksp37, a secretory protein unique to CD8<sup>+</sup> T cells and **NK** cells [239]. Again, the fold changes in expression were of greater magnitude than observed for the abundance of these cell types, suggesting active downregulation Sobolev *et al.* [161].

As can be seen in Fig. 2.16, there was a general tendency for expression to return to baseline levels by day 7. This was the case for 566/644 upregulated genes and 44/64 downregulated genes, indicating the innate phase of response likely peaks in the first few days.



**Figure 2.16:** Normalised gene expression for 857 genes differentially expressed between any pair of timepoints ( $\text{lfsr} < 0.05$ ,  $|\text{FC}| > 1.5$ ). Rows are genes; columns are samples. Genes were standardised within-platform, hierarchically-clustered by Manhattan distance. Baseline timepoints were days -7 and 0. Row annotations show DGE between pairs of timepoints. Column annotations show sample platform and timepoint.



**Figure 2.17: Transcriptomic modules up or downregulated post-vaccination.** The top ten most significant modules for each contrast are shown. Size of circle indicates absolute effect size (AUC). Color of circle indicates significance ( $FDR < 0.05$ ) and direction of effect (red = upregulation, blue = downregulation). Absence of circle indicates non-significance.

### 2.3.1.2 Adaptive immune response at day 7 post-vaccination

Fifty-nine genes were differentially expressed at day 7 vs. baseline. The genes with the highest upregulation were genes associated with B cell differentiation and maturation: *TNFRSF17* (marginal zone B and B1 cell specific protein,  $\log_2 \text{FC} = 1.7538617$ ) and *MZB1* (B-cell maturation antigen,  $\log_2 \text{FC} = 1.7369668$ ). Plasma cell-specific Genes specific to plasma cells, including *SDC1* (which encodes CD138, required for plasma cell maturation [240]) ( $\log_2 \text{FC} = 1.3673081$ ) and *ELL2* (mediates antibody secretion [241]) ( $\log_2 \text{FC} = 0.8679659$ ) were also prominently upregulated. This matches an almost 5-fold increase in plasma cell abundance at day 7 compared to baseline [161]. Strongly enriched modules at day 7 were related to mitosis and cell proliferation, particularly in CD4<sup>+</sup> T cells (Fig. 2.17). Both the CD4<sup>+</sup> T cell and plasma cell response are indications of a shift toward an adaptive and primarily humoral immune response by day 7.

### 2.3.2 Expression associations with antibody response

#### 2.3.2.1 Detection of gene-level associations is hindered by between-platform heterogeneity

Using only array expression data, Sobolev *et al.* [161] identified a set of 62 genes with day 7 expression associated with antibody response, where response was defined as a binary phenotype based on 4-fold increases in HAI or MN titres from day -7 to day 63. Many of these genes were related to plasma cell development and antibody production. I also aimed to find genes associated with antibody response in the meta-analysis of array and RNA-seq expression data, and assess the replication of the 58/62 genes that fell into the set of 13 593 genes measured by both platforms.

I computed a baseline-adjusted, continuous measure of antibody response, the TRI [152]. The TRI is comparable to the binary definition in ranking (Fig. 2.2g, Fig. 2.2h), but as a continuous phenotype, it improves statistical efficiency to detect associations. Within just the array data, 51/58 genes were replicated ( $\text{FDR} < 0.05$ ), confirming TRI and the binary response phenotype were comparable. However, using only the RNA-seq data replicated 0/58 genes.

In the initial frequentist random-effects meta-analysis, with a significance threshold of  $\text{FDR} < 0.05$ , 6 genes had expression associated with TRI at baseline (Fig. 2.18f), 55 at day 7 (Fig. 2.18h), and 11 pooling samples over all timepoints (Fig. 2.18e). Of the day 7-specific associations reported by Sobolev *et al.* [161] (circled in Fig. 2.18h), 15/58 replicated, all with the same positive direction of effect (high expression with high TRI). However, almost all significant results displayed higher effect sizes in the array compared to RNA-seq (13/15 genes). This is in contrast to the associations identified with timepoint, where significant genes had more consistent effects between platforms along the diagonal (Fig. 2.18b,c,d). The likely cause is the presence of more extreme antibody response phenotypes (higher TRI range) in the array versus the RNA-seq dataset (Fig. 2.3). This represents an additional source of between-platform variation not due to technical factors, but inherent to the samples themselves.

In the Bayesian meta-analysis pipeline more robustly models between-study heterogeneity due to platform and sample-specific effects. Due to shrinkage of effects, few genes with effects closer to the dense center of the effect distribution are called as significant, and significant genes

no formal tests for heterogeneity of effect here,  
i don't think it's worth  
the effort unless reviewer  
2 says so.

tend to have outlying effect sizes in both platforms (compare Fig. 2.18b,c,d with Fig. 2.19b,c,d). No single gene was detected as significantly associated with **TRI** at  $\text{lfsr} < 0.05$  for any contrast: not in any single timepoint, nor when pooling samples across all timepoints (Fig. 2.19e,f,g,h). The frequentist meta-analysis is likely to use poor estimates of the between-platform heterogeneity, as there are only two data points to estimate it from. Indeed, all 15 significant genes with day 7 expression associated with **TRI** in the frequentist meta-analysis had unrealistic between-platform heterogeneity estimates of exactly zero (Fig. 2.20).

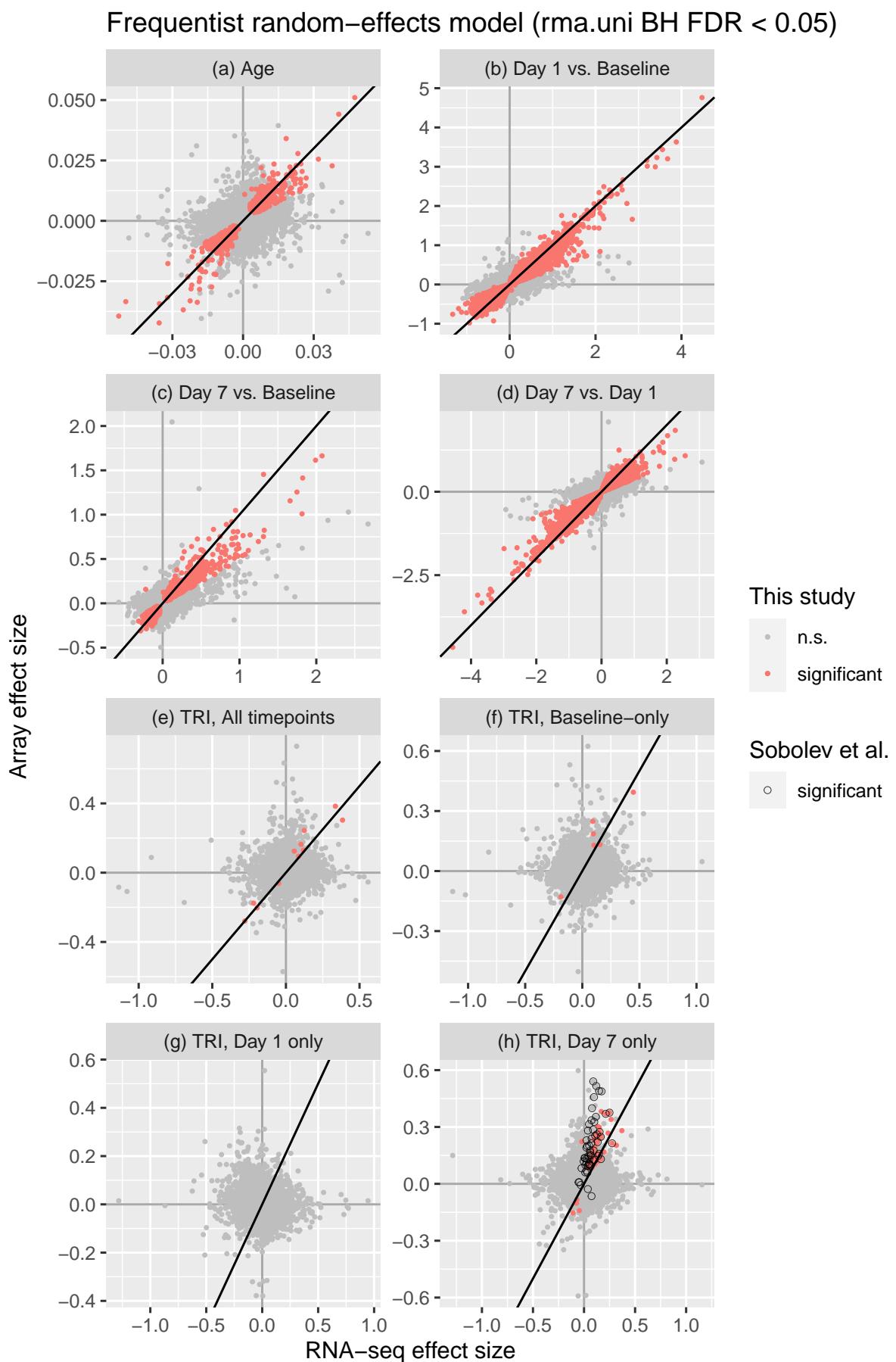
### 2.3.2.2 Module level associations with antibody response

Using effect sizes from the Bayesian meta-analysis, significant enrichments were detectable at the gene set level. The strongest effects were seen at day 7, where expression of modules related to the cell cycle, CD4<sup>+</sup> T cells, and plasma cells were positively associated with **TRI**—“cell cycle (I)” (LI.M4.1, **FDR** =  $6.81 \times 10^{-54}$ ), “Plasma cell surface signature” (LI.S3, **FDR** =  $1.78 \times 10^{-12}$ ), and “cell division stimulated CD4+ T cells” (LI.M46, **FDR** =  $5.54 \times 10^{-10}$ ) (Fig. 2.21).

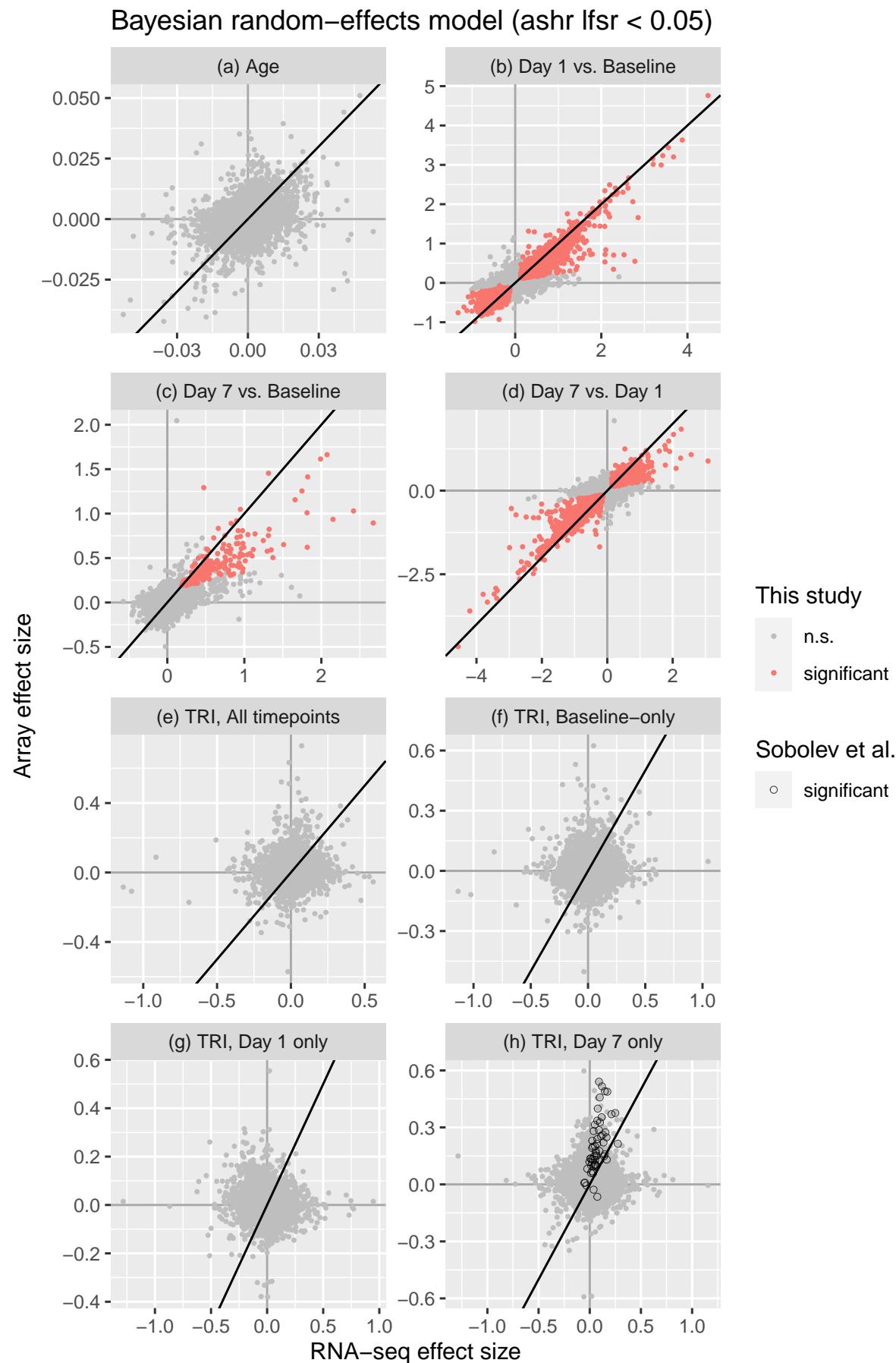
Associations with **TRI** were also detected at baseline. A diverse set of set of modules had positive associations, including “chemokines and inflammatory molecules in myeloid cells” (LI.M86.0, **FDR** =  $2.25 \times 10^{-11}$ ), “platelet activation - actin binding” (LI.M196, **FDR** =  $1.71 \times 10^{-8}$ ), “enriched in B cells (I)” (LI.M47.0, **FDR** =  $2.40 \times 10^{-7}$ ), “cell adhesion” (LI.M51, **FDR** =  $1.22 \times 10^{-10}$ ), “myeloid, dendritic cell activation via NFkB (I)” (LI.M43.0, **FDR** =  $4.68 \times 10^{-7}$ ), and “proinflammatory dendritic cell, myeloid cell response” (LI.M86.1, **FDR** =  $4.11 \times 10^{-7}$ ). Monocyte modules “enriched in monocytes (II)” (LI.M11.0, **FDR** =  $3.53 \times 10^{-4}$ ) and “Monocyte surface signature” (LI.S4, **FDR** =  $1.17 \times 10^{-3}$ ) were negatively association with **TRI**. Negative associations for these same modules were also maintained at day 1—“enriched in monocytes (II)” (LI.M11.0, **FDR** =  $1.41 \times 10^{-10}$ ), “Monocyte surface signature” (LI.S4, **FDR** =  $1.74 \times 10^{-6}$ )—and at day 7—“enriched in monocytes (II)” (LI.M11.0, **FDR** =  $5.54 \times 10^{-10}$ ).

## 2.4 Discussion

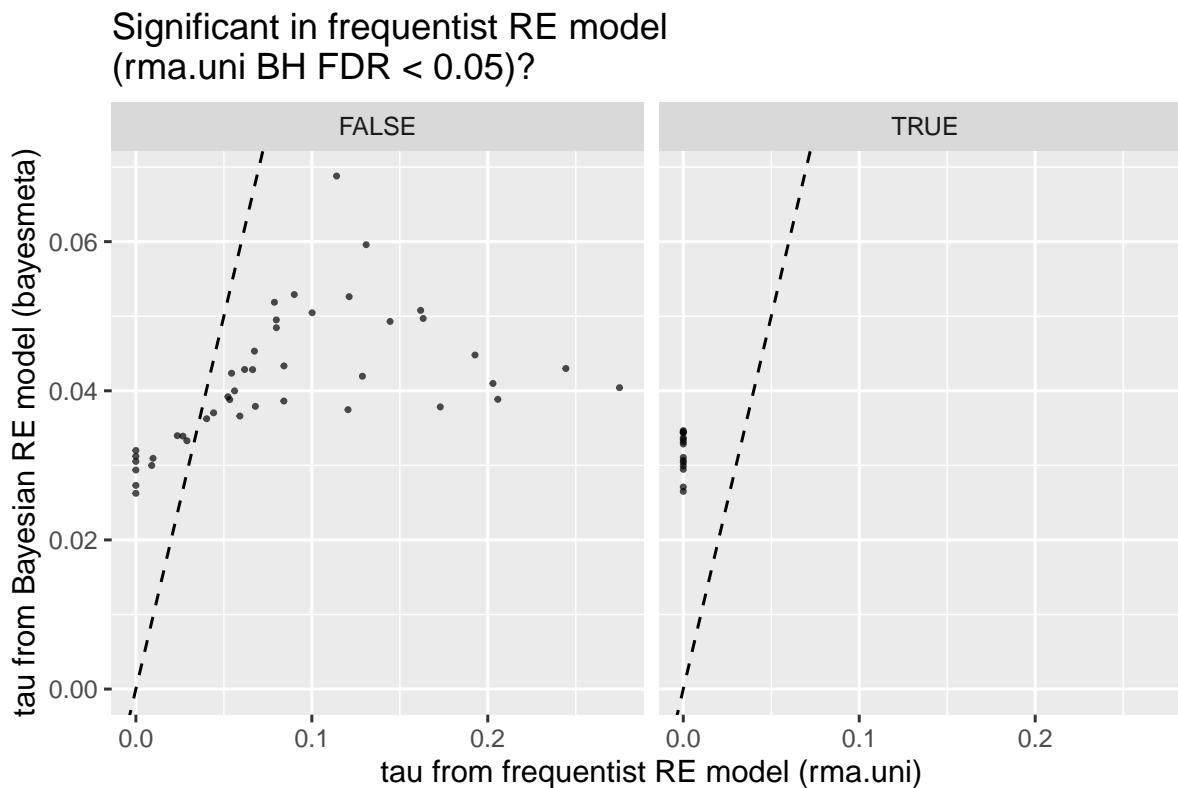
A meta-analysis of array and **RNA-seq** data revealed extensive transcriptomic response to Pandemrix vaccination in the **HIRD** cohort. At day 1, there was upregulation of genes and modules related to monocytes, interferon signalling, the inflammatory response; and downregulation of T cell and **NK** cell genes and gene modules. Concordant changes in these gene modules were also reported by Nakaya *et al.* [157] at day 1 after MF59-adjuvanted seasonal **TIV** in young children, but changes in these modules were not as consistent in children who received non-adjuvanted **TIV**. The AS03 adjuvant in Pandemrix is thought to act by promoting chemokine secretion, predominantly targeting monocytes and macrophages [162, 242], which concurs with the strong upregulation of monocyte and **DC** modules observed at day 1 after Pandemrix. A large component of the expression response at day 1 may be reflective of response to the adjuvant. Most genes differentially expressed at day 1 returned to baseline expression by day 7. Nakaya *et al.* [157] saw a similar trend comparing day 0 and day 3 for MF59-adjuvanted **TIV**. Unadjuvanted seasonal **TIV** also causes peak transcriptomic induction at day 1 Bucasas *et al.* [152]. Although the timepoint resolution here is coarse, the early innate response to Pandemrix is transient, peaking less 7



**Figure 2.18:** DGE effect sizes ( $\log_2 \text{FC}$ ) estimated in array versus RNA-seq samples, colored by significance in frequentist random effects meta-analysis using rma.uni at **BH FDR < 0.05**. Genes with day 7 expression associated with binary responder/non-responder status in Sobolev *et al.* [161] are circled for that contrast.



**Figure 2.19:** DGE effect sizes ( $\log_2 \text{FC}$ ) estimated in array versus RNA-seq samples, colored by significance in Bayesian random effects meta-analysis using `bayesmeta` at  $\text{ashr lfsr} < 0.05$ . Genes with day 7 expression associated with binary responder/non-responder status in Sobolev *et al.* [161] are circled for that contrast.



**Figure 2.20:** Estimates of between-platform heterogeneity  $\tau$  from frequentist and Bayesian meta-analysis, for the 58 genes with a significant association between day 7 expression and binary responder/non-responder status in Sobolev *et al.* [161]. Estimates from the frequentist method cover a wide range and can be zero. For this contrast testing association between day 7 expression and TRI, 8563/13593 of per-gene  $\tau$  estimates were zero, including all 15 significant results replicating [161] results. Significant results are array-driven, with 13/15 having higher effects in array (54/58 genes overall). Estimates from the Bayesian method are in a narrower range and constrained away from zero by the prior.



**Figure 2.21: Gene expression modules associated with antibody response (TRI).** Enrichments were performed with timepoints pooled, and at each day specifically. The top ten most significant modules for each contrast are shown. Size of circle indicates absolute effect size (AUC). Color of circle indicates significance ( $FDR < 0.05$ ) and direction of effect (red = expression positively correlated with TRI, blue = negatively correlated). Absence of circle indicates non-significance.

days, and likely less than 3 days post-vaccination. Upregulation of cell cycle, proliferating CD4<sup>+</sup> T cell, and B (plasma) cell genes and modules were detected at day 7. This indicates a shift to the adaptive immune response, likely involving CD4<sup>+</sup> T cell-supported differentiation and proliferation of **ASCs**.

Both day 1 and day 7 expression module changes were concordant with changes in cell populations seen in the **HIRD FACS** data. The greater magnitude of expression fold change of individual genes compared to cell abundance fold changes suggests the influence of both mechanisms [161]. Statistical adjustment for measured or estimated cell composition is one possibility; I explore these methods in **Chapter 3** and **Chapter 4**. An experimental approach would be *in vivo* stimulation of **PBMCs** with vaccine, ruling out cell migration, but not shifts in cell subtype composition [243].

The overall patterns of expression over time were consistent between array and **RNA-seq**, with the meta-analysis identifying genes with outlying effect in both platforms. In contrast, I was not able to replicate the 58 single gene-level associations between day 7 expression and antibody response reported by Sobolev *et al.* [161] that were assessable in my meta-analysis. The difference was not wholly due to response definitions, as within the array data alone, switching to **TRI** still replicated the majority of associations reported, but using either **TRI** or binary response status in the **RNA-seq** data alone found no significant associations. Initially, 15/58 signals replicated using frequentist random-effects meta-analysis to combine per-platform estimates. I do not consider these hits as robust, as the estimated between-platform heterogeneity was zero for all 15 of these signals. None of these signals replicated in the Bayesian random-effects meta-analysis, where prior information about  $\tau$  is incorporated, discouraging unrealistic estimates of zero heterogeneity. The Bayesian meta-analysis was in general more conservative, calling fewer differentially expressed genes compared to the frequentist analysis for all contrasts (Fig. 2.19). Most of the 58 genes also had larger effects in the array dataset than in the **RNA-seq** dataset, possibly because the array data contains more extreme **TRIs**. At a single-gene level, significant associations with timepoint are robustly detectable, but associations with **TRI** have effects too modest relative to the noise introduced by platform-dependent technical effects and dataset-dependent phenotype distributions.

I think the best place for 'lessons learnt' is in the discussion chapter, since similar conclusions are relevant to pants

Expression associations with antibody response were, however, observed at the gene set level, for modules associated with **TRI** as a whole. The strongest effects were observed at day 7, where expression of modules suggesting of cell types involved in adaptive immunity (cell cycle, stimulated CD4<sup>+</sup> cells, plasma cells) were positively associated with **TRI**. These are the same modules observed to be upregulated at day 7 compared to baseline; it seems that those individuals with the greatest antibody response to vaccination are most able to induce these cell types by day 7 post-vaccination.

if they don't have the signature until day 8,9,10 or ever, then it will probably add unexplained variation to **TRI**, more noise

Module associations were also observed pre-vaccination with both positive (e.g. chemokines, proinflammatory **DCs**, B cells, platelet activation) and negative (e.g monocytes), suggesting baseline immune state has influence on long-term antibody response to Pandemrix. Some of the positive associations have been previously reported for unadjuvanted seasonal influenza vaccines in multiple independent cohorts. The same B cell modules were reported by Nakaya *et al.* [156], and similar **DC**, inflammatory, and platelet activation modules were found to be predictive of

it doesn't compare, sobolev did not find any baseline associations

antibody response in young adults [158]. The negative association of monocyte modules with antibody response was also reported by Nakaya *et al.* [156]. Interestingly, I detected the same negative associations at day 1 and day 7. Monocyte modules were one of the most upregulated modules at day 1, and although the module annotations do not separate monocyte subsets, abundance of CD16<sup>+</sup> inflammatory monocytes were particularly increased at day 1 in the **FACS** data [161]. This lends some support to the hypothesis that chronic baseline inflammation or excessive/prolonged post-vaccination inflammation—specifically driven by monocytes—can be detrimental to the humoral response [156, 244, 245].

There are several caveats to consider when drawing comparisons to the systems vaccinology literature. Most studies are of unadjuvanted multivalent seasonal vaccines; **HIRD** used an adjuvanted monovalent pandemic vaccine. Most studies measure post-vaccination antibody response around the expected peak of day 28; **HIRD** measured later at day 63, which may attenuate the signal. The specific genes within modules driving associations may also differ. Nevertheless, the ability to observe module-level associations with **TRI** also reported in previous studies with diverse populations, measurement platforms, influenza seasons, and analysis pipelines, is a stark contrast to difficulty of replicating single-gene associations even within the **HIRD** cohort. When the effect of individual genes on phenotype is expected to be subtle, module-level analyses are not only more sensitive, but appear to be more generalisable.

The next step is to explore the utility of the associations I identified for prediction. Although I have identified highly significant associations between expression modules and antibody response, that does not imply the ability to accurately predict response from expression [160]—the existence of molecular signatures. Some exploration can be done within **HIRD** using cross-validation, or by setting aside a subset (e.g. the array data) as a test set, but having an independent test set is especially important for prediction to guard against overfitting. Matched expression and antibody data are rare for adjuvanted and pandemic vaccines, so an initial effort would likely use published seasonal vaccine datasets (e.g. [156, 158]), with the aim of identifying shared molecular signatures.

The fundamental question of why gene expression and antibody responses vary between **HIRD** individuals also remains. Which genes, if their expression was to be modulated, would lead to a change in antibody response? This a critical question in the move from identifying correlates of protection and molecular signatures, towards targeted interventions to improve vaccine outcomes [145]. The descriptive design of the **HIRD** study does not lend itself to exploring causation between expression and antibody titres without a causal anchor. Interindividual genetic variation could play such a role; **Chapter 3** will examine the impact of common host genetic variant on expression response in the **HIRD** cohort.



## Chapter 3

# Genetic architecture of transcriptomic response to Pandemrix vaccine

### 3.1 Introduction

#### 3.1.1 Host genetic factors affecting influenza vaccine response

Many human traits are heritable and complex—response to vaccination is no exception. Twin studies have demonstrated approximately 30–90 % heritability of antibody responses to many vaccines, including smallpox, hepatitis A and B, anthrax, pneumococcal, *Haemophilus influenzae* type b (Hib), diphtheria-tetanus-pertussis (DTP), Bacillus Calmette–Guérin (BCG) [246–249]. Candidate gene studies and genome-wide association studies (GWASs) have identified multiple genetic associations with antibody response [246, 247, 250, 251], including replicated associations for hepatitis B vaccine in a haplotype block in the human leukocyte antigen (HLA) region encompassing *HLA-DR* and *BTNL2*, and for measles vaccine in an intron of a receptor known to interact with measles virus, *CD46*.

In contrast, Brodin *et al.* [249] found anti-haemagglutinin (HA) antibody responses to seasonal influenza vaccine in 105 adult twin pairs (median age, 44 yr) had no detectable heritability, alongside a general decrease in heritability of most immune parameters with age. They posited that the genetic contribution to response was overshadowed by environmental factors such as previous influenza vaccination or infection in adults, whereas the estimated heritability of the aforementioned vaccines was substantial because they are vaccines against non-circulating pathogens, or are childhood vaccines for which heritability was assessed in young children with shorter immune history.

Nevertheless, a small number of candidate gene studies have identified genetic variants associated with antibody response to influenza vaccines [251]. Gelder *et al.* [252] ( $n = 73$ ) identified associations between HLA alleles in *HLA-DRB1* and *HLA-DQB1* with haemagglutination inhibition (HAI) seroconversion after trivalent inactivated influenza vaccine (TIV); Moss *et al.* [253] ( $n = 185$ ) also found associations between HLA class II alleles (*HLA-DRB1\*04:01* and *HLA-DPB1\*04:01*) and HAI seroconversion after seasonal influenza vaccination. Poland *et al.* [254] ( $n = 184$ ) tested HLA alleles, and single nucleotide polymorphisms (SNPs) in coding and regulatory regions of cytokine or cytokine receptor genes, for association with post-TIV HAI

titres specific to H1 and H3 subtypes (two of the components in the trivalent vaccine). They reported nominally significant associations for two *HLA-A* alleles with H1-specific titres, six SNPs associations with H1-specific titres and ten SNPs associations with H3-specific titres. Egli *et al.* [255] ( $n = 196$ ) identified a SNP upstream of *IFNL3* (rs8099917) to be associated with seroconversion post-TIV, and also found the SNP to be an expression quantitative trait locus (eQTL) for *IFNL3* expression in H1N1-stimulated peripheral blood mononuclear cells (PBMCs) in a second cohort ( $n = 49$ ). Lastly, Avnir *et al.* [256] focused on a coding variant (rs55891010) in the part of *IGHV1-69* that encodes the complementarity-determining region (CDR) of broadly neutralising antibodies that bind influenza HA. One month after H5N1 avian influenza vaccination ( $n = 85$ ), associations were detected with usage of *IGHV1-69* in the antibody repertoire, and serum antibody binding efficiency to H5N1 HA. The associations listed above have all been found in small cohorts and have not been validated by subsequent studies, so it remains unknown whether robust genetic associations with antibody response to influenza vaccines exist.

no gwas studies that i can find

### 3.1.2 Response expression quantitative trait loci (reQTLs) following influenza vaccination

Host genetic variation could play a causal role in influenza vaccine response by altering the expression of genes as eQTLs. As mentioned in Section 1.2.3 and Section 1.2.4, the effect sizes of eQTLs can be highly context-dependent, and many eQTLs in the immune system are response expression quantitative trait loci (reQTLs) only detectable after stimulation, not at baseline.

hopefully sufficient background is covered in the intro for this to be understandable

ReQTLs can be mapped considering a vaccination as an *in vivo* immune stimulation. This usually involves measuring the transcriptome of immune cells before and after vaccination in genotyped individuals, then testing for genotype-dependent changes in expression. As expression is a key molecular intermediate between genotype and phenotype, a genotype-dependent change in expression after vaccination may be a mechanism mediating genotype-dependent vaccine antibody responses.

As reviewed in Section 1.2.4, few *in vivo* reQTL studies have been conducted, and even fewer studies have been conducted where the *in vivo* stimulation is vaccination, despite the potential for learning about genetic regulation of vaccine-induced expression responses. To my knowledge, there is only one such study: by Franco *et al.* [92] on response to seasonal inactivated TIV. Franco *et al.* [92] enrolled healthy Europeans adults into discovery ( $n = 119$  males) and validation ( $n = 128$  females) cohorts in two consecutive influenza seasons\*. In each cohort, peripheral blood gene expression was measured by expression array on day 0 (baseline); and on days 1, 3, and 14 post-vaccination. Serum HAI and microneutralisation (MN) titres were measured at days 0, 14, and 28 against each of the three vaccine components. The titre response index (TRI) [152] was computed from these titres as a single measure of antibody response adjusted for baseline titres. Genotyping was done by genotyping array.

*Cis*-eQTL were mapped using a linear mixed model jointly over all four days, with day, genotype, day-genotype interaction, and a random intercept for individual as predictors; and gene expression the response variable. This resulted in 467 eQTL for 78 genes replicated in both cohorts, with a significant day effect (indicating the gene was differentially expressed

\*Sex-dependence of effects was not addressed.

post-vaccination) and a significant genotype effect (indicating the eQTL effect). To call reQTLs, eQTLs were also mapped separately for each day with a linear model including only genotype as a predictor, from which the model  $R^2$  was computed as a rough measure of the variance in expression explained by the eQTL at each day. Franco *et al.* [92] then computed delta- $R^2$ : the maximum absolute deviation of the three post-vaccination  $R^2$ s from the day 0  $R^2$ . Out of the eQTLs that replicated in both cohorts, 146 eQTLs for 34 genes ranked above the 99th percentile of the delta- $R^2$  distribution were defined as reQTLs. The union of the 78 and 34 genes from the above analyses (98 genes with differential gene expression (DGE) and an eQTL; or a reQTL) was enriched for pathways and gene sets related to antigen processing and presentation, CD8<sup>+</sup> T cell-mediated apoptosis, dendritic cell (DC) maturation and function, and membrane trafficking.

Lastly, integrating antibody titre data, they filtered down 20 gene with expression correlated to TRI at any day, with an eQTL, and with either post-vaccination differential expression *or* a reQTL effect. Seven genes out of these 20 were antigen transport, processing, or presentation in antigen-presenting cells (APCs): *NAPSA*, *C1orf85*, *GM2A*, *SNX29*, *FGD2*, *TAP2*, and *DYNLT1*.

Critically, Franco *et al.* [92] recognised that just assessing overlap of multiple filtering criteria does not allow them to infer the direction of causal relationships between genetic variation, expression and TRI. They attempted a model comparison with the causal inference test (CIT) [257] to resolve the directionality of association between expression and TRI, but unfortunately concluded there was only ~60% power at the total sample size of  $n = 247$ . Nevertheless, the study is proof of concept that integration of genotype, expression and antibody response data in an *in vivo* reQTL framework can be of suggestive genes under genetic regulation likely to be involved in vaccine response.

### 3.1.3 Chapter summary

The Human Immune Response Dynamics (HIRD) cohort represents a unique opportunity for detecting genetic contributions to influenza vaccine response. Similar to Franco *et al.* [92], expression, antibody response, and genotypes are all available for the same individuals. As Pandemrix is against a pandemic strain that had not been in seasonal circulation for decades at the time of cohort recruitment, responses will be less driven by individual immune history, so power to detect genetic associations is expected to be greater. In Chapter 2, I characterised differential gene expression induced by Pandemrix, as well as expression associations with antibody titres. In this chapter, I apply the *in vivo* reQTL framework to HIRD data, aiming to characterise the association of common genetic variants with expression across multiple timepoints, and pinpoint genes important to Pandemrix response.

## 3.2 Methods

### 3.2.1 Genotype phasing and imputation

Genotyping and pre-imputation processing are described in Section 2.2.3 and Section 2.2.4. Prior to imputation, 213 277 monomorphic variants that provide no information for imputation were removed. Variant alleles were aligned such that the reference allele matches the GRCh37

reference, and 358 indels were removed, leaving only SNPs. Imputation for the autosomes and X chromosome was conducted using the Sanger Imputation Service\*, which involved pre-phasing (separate estimation of haplotypes before imputation to improve imputation speed) with EAGLE2 [258] (v2.4) and imputation with PBWT [259] (v3.1) against the Haplotype Reference Consortium (r1.1) panel [260]. Imputed SNPs were lifted-over from GRCh37 to GRCh38 coordinates using CrossMap [261]. Poorly-imputed SNPs with imputation information score INFO < 0.4 were removed, leaving 40 290 981 SNPs measured for the 169 genotyped individuals.

### 3.2.2 Overall strategy for mapping reQTLs

A myriad of approaches to mapping reQTLs with linear models exist; each with its own advantages, disadvantages, and assumptions.

Since the aim of this chapter is to identify genetic variation that affects expression response to vaccination, it may seem most direct to model the change in each individual's expression after vaccination as the response variable. This approach has been applied for identification of condition-specific eQTL, typically with the response taking units of log fold change between conditions (e.g. [262–264]). Although potentially powerful if eQTL effects are small and opposite between conditions[263], it is analogous to the “change score” approach, which can suffer from regression to the mean (??), and increased uncertainty from the variance sum law if effects between conditions have positive covariance[169, 265].

Instead, I map eQTLs within each of three timepoint conditions (day 0 pre-vaccination, day 1, and day 7), and find reQTLs by looking for eQTLs that have different effects between conditions. Unlike a test for difference implemented using a genotype-condition interaction term in a joint regression model, homoscedasticity of errors is not assumed for all conditions[266]

Within each timepoint, recall the the HIRD dataset includes expression measured by both array and RNA-sequencing (RNA-seq). As discussed in Section 2.2.9.3, it is difficult to directly estimate the between-studies heterogeneity when the number of studies is small, and Bayesian meta-analysis was preferred for combining array and RNA-seq DGE estimates. That method does not scale to eQTL analysis, where the number of tests is large, in the order of thousands of tests per gene, versus the handful DGE contrasts per gene performed in Chapter 2. Instead, I perform a mega-analysis within each timepoint, first merging array and RNA-seq expression estimates into a single matrix with ComBat[205]. For comparison purposes, analyses were also run using in the array and RNA-seq samples separately.

Defining whether an eQTL is shared between conditions can be a tricky business. Naively, one can map eQTLs separately in each condition, then assess the overlap of significant associations between conditions. This underestimates sharing due to the difficulty of distinguishing true lack of sharing from missed discoveries from incomplete power within each condition [66, 267]. Condition-by-condition analysis also cannot borrow information across conditions for mapping shared associations[267–269]. Counterintuitively, a joint multivariate analysis may be more powerful even when associations are not shared across all conditions[270].

A variety of models have been employed for joint eQTL mapping, including the use of classical multivariate methods such as multivariate analysis of variance (MANOVA)[78], frequentist

upend change score bit,  
here expression is a y  
variable. compare all the  
options as glms etc.

Can this really demon-  
strate genotype-  
dependent change in gene  
expression between time-  
points? i.e. need under-  
stand how the change  
score/ANCOVA ap-  
proaches differ from re-  
peated measures ANOVA  
differ from the interac-  
tion/stratified approach I  
take?

why I didn't just do a  
mega-analysis in chapter  
2 then, given I haven't  
any evidence if it's better  
or worse than Bayesian  
meta-analysis in that  
context.

add -7 note as with ch2

\*<https://www.sanger.ac.uk/tool/sanger-imputation-service/>

meta-analyses (e.g. Meta-Tissue[271], METASOFT), and Bayesian models (e.g. eQtlBma[267], MT-HESS, MT-eQTL). Joint mapping has been repeatedly demonstrated to be more powerful than condition-by-condition analysis, and recent methods are now computationally efficient when scaling to large numbers of conditions and variants tested (e.g. RECOV[272], mashr[268], HT-eQTL[269]). In this chapter, I apply `mashr`[268] for the estimation of eQTL effects across my three timepoints. `mashr` learns patterns of correlation among multiple conditions empirically from condition-by-condition summary statistics, then applies shrinkage to provide improved posterior effect size estimates, and compute measures of significance per condition.

### 3.2.3 Controlling for population structure with linear mixed models

As shown in Table 2.1, the HIRD cohort is multi-ethnic, hence there is potential for confounding by population structure (sample structure due to genetic background) in genetic association studies [180, 273].

There is population structure due to ancestry in the HIRD cohort, which was incorporated in DGE analyses by treating the top principal components (PCs) of the genotype matrix as continuous covariates for large-scale population structure (Section 2.2.5). In the context of eQTL mapping (and genetic association studies in general), where the aim is to assess the marginal effect of a single genetic variant on expression, population structure can be correlated with both expression (e.g. through polygenic effects) and the tested variant (e.g. through ancestry-dependent frequency differences). This leads to omitted-variable bias (OVB) from confounding, which if not controlled for, leads to genome-wide inflation of test statistics [274]. An useful approach is the linear mixed model (LMM) with a random effect that incorporates genetic correlation between individuals, usually in the form of a kinship matrix, into the covariance of that random effect[273–275] The LMM approach has the advantage of not only modelling large-scale population structure, but also cryptic relatedness (the presence of closely related individuals in a sample assumed to consist of unrelated individuals[276]) due to finer-scale effects such as family structure[275].

add some indication of how much inflation can be reduced by LMMs

#### 3.2.3.1 Estimation of kinship matrices

When testing a variant for association using LMMs, to avoid loss of power from “proximal contamination”, the kinship matrix used should not include that variant[277]. A simple way to avoid this is to compute a leave-one-chromosome-out (LOCO) kinship matrix using all variants on chromosomes other than the tested variant’s chromosome[278].

I estimated kinship in the HIRD data from common autosomal variants, using LDAK (5.0), which computes kinship matrices adjusted for bias caused by linkage disequilibrium (LD)[279]. Filtered, pre-imputation sample genotypes from Section 3.2.1 were pruned to MAF > 0.05. A kinship matrix was computed for each autosome, then combined into a single genome-wide matrix using LDAK --join-kins. To obtain a LOCO kinship matrix for each autosome, each autosome’s kinship matrix was then subtracted from this genome-wide matrix (LDAK --sub-grm).

add chr1 loco kinship matrix as example, note the estimates for self-relatedness on the diagonals are not constrained to be 1

### 3.2.4 Additional eQTL-specific expression preprocessing

There are a number of transformations often applied to expression data before eQTL mapping, such as the rank-based inverse normal transformation (INT) (e.g. GTEx v8[52]), which conforms often non-normal expression data to an approximately normal distribution, and reduces the impact of expression outliers. In the context of genetic association studies, the practice of applying rank-based INT to phenotypes has been criticised for only guaranteeing approximate normality of residuals when effect sizes are small, and potential inflation of type I error, especially in linear models that include interactions[280]. In multi-condition datasets, these transformations are also typically applied within conditions (e.g. within each tissue individually in GTEx v8[52]). Another common transform is standardising (centering and scaling to zero mean and unit variance) (e.g. eQTLGen Consortium[56]), often done so that effects across genes and studies can be comparably interpreted in units of standard deviation expression[281].

helps with coloc

emph here that the sims  
match what my def of  
reqlt is for rest of chapter

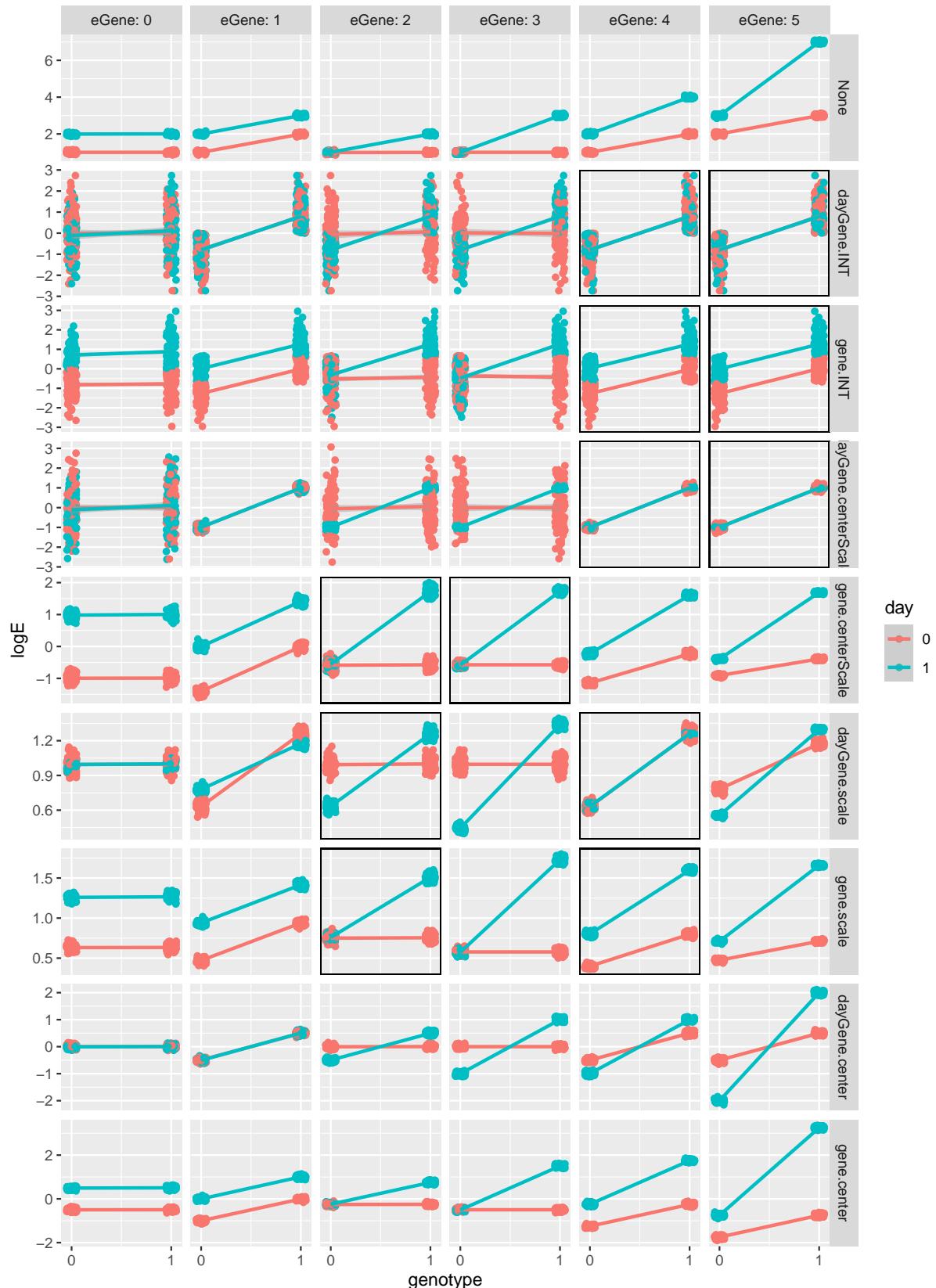
log scale: as interactions  
depend on the scale at  
which departure from ad-  
ditivity is detected

I performed simulations to evaluate the effect of these transformations on reQTL detection between a hypothetical baseline and day 1 post-vaccination condition. Expression values on the log scale were simulated with the eQTL slope (beta) set to specific values corresponding to six scenarios for six gene-variant pairs (Fig. 3.1). The simulated scenarios were subjected to rank-based INT (Blom method[280]), standardisation (both centering and scaling), scaling-only, and centering-only transformations. Transformations were applied both within each condition and without separating conditions.

The boxed facets in Fig. 3.1 represent undesirable effects of transformations on reQTL calls. For example, rank-based INT induces false shared eQTL effects in scenarios 4 and 5. In general, transformations that scale within condition are not appropriate, as different variance between conditions can be what drives a reQTL effect. Scaling without separating conditions can also be problematic, since the total variance also contributes to the reQTL effect size. For example, scenarios 2 and 4 have the same 1 unit increase in slope pre-transformation (the same fold-change between conditions), but after scaling-only the beta increases are  $0.75 - 0 = 0.75$  and  $0.8 - 0.4 = 0.4$  respectively—eQTL 4 now looks like a weaker effect.

In light of these simulations, I decided that neither rank-based INT nor standardisation were appropriate given my intent of detecting reQTLs between conditions. Only the centering-only transformation avoided both false shared effects and preserves relative reQTL effect sizes between genes. The simple inclusion of an intercept term in the eQTL model already achieves this. Not performing any rank-based transform does lose the advantage of reining in outliers. The expression data have already been preprocessed to remove low-expression outliers in Section 2.2.7, but automatic outlier exclusion based on standard deviation thresholds at the eQTL mapping step could be considered in future implementations[56]. Note that many preprocessing steps done prior to this stage in the pipeline (e.g. variance-stabilisation, ComBat batch effect correction) are also expression transformations, but I only consider the preservation of reQTL effects defined from expression values post-adjustment for those technical effects to be important.

add sample sizes and  
model for expression sim



**Figure 3.1:** Simulated log scale expression in two conditions for six genes (columns) representing six different scenarios: Scenario 0 has no eQTL, scenario 1 is a shared eQTL ( $\beta = 1$ ), scenario 2 is a reQTL where  $\beta$  increases from 0 to 1, scenario 3 is a reQTL where  $\beta$  increases from 0 to 2, scenario 4 is a reQTL where  $\beta$  increases from 1 to 2, and scenario 6 is a reQTL where  $\beta$  increases from 1 to 4. Rows represent the effect of different expression transformations across samples, conducted both within condition, and including both conditions.

### 3.2.5 Estimation of cell type abundance from expression

PBMC samples are a mixture of immune cells, and a fixed input of RNA extracted from that mixture is used to estimate expression, so estimates for genes that have cell type-specific expression depend on the relative proportions of each cell type in each sample. These proportions shift after Pandemrix vaccination[161], and eQTL effects can also be cell type-specific. As genotype can be assumed to stay constant, it is valid to compare the effect of genotype on expression between multiple timepoints to call reQTLs, but changes in cell type abundance influence this by both expression and the effect of genotype on expression. Immune cell abundance also varies naturally between healthy individuals[108, 249], so it is important to model these effects even at baseline.

Cell type abundance directly measured via fluorescence-activated cell sorting (FACS) are only available for a small subset of HIRD individuals (Section 2.2.1), so I derived cell type abundance estimates from the expression data as an alternative. Such estimates have previously been used in eQTL analyses from bulk samples where cell type-specific effects are expected[69, 70, 72, 94]. As the estimates are based on the expression of multiple genes, is not entirely circular to use them as covariates in this way for genewise eQTL models. I selected xCell[282], which previously been shown to outperform other deconvolution methods for cell type-specific eQTL mapping in blood[72]. xCell computes enrichment scores based on the expression ranks of approximately 10000 signature genes derived from purified cell types, works for both array and RNA-seq expression data, and implements “spillover compensation” to reduce dependency of estimates between related cell types[282]. xCell was originally developed for tumor samples, so many of the built-in cell types are not expected in PBMC. Reviewing the literature to find which broad classes of peripheral blood cell types are commonly-expected in the PBMC compartment[94, 283, 284], I selected 7/64 of the built-in cell types: CD4<sup>+</sup> T cells, CD8<sup>+</sup> T cells, B cells, plasma cells, natural killer (NK) cells, monocytes, and DCs. Array and RNA-seq data from Section 2.2.8 and Section 2.2.7 were processed through xCell separately. The large batch effect present in the array expression was first removed using ComBat. Finally, enrichment scores were standardised, so that a score of zero estimates the average abundance of that cell type across all timepoints (Fig. 3.2 and Fig. 3.3).

As with actual cell type abundances, the enrichment scores are correlated. Multicollinearity will be a problem for interpreting effect size estimates when these scores are used as independent variables in regression downstream.\* To prune the number of scores, I performed a principal component analysis (PCA) of the cell type scores across samples, determined the number of principal components that exceed the eigenvalues-greater-than-one rule of thumb[286], then selected only the one cell type with the highest contribution for each of those components. In both array and RNA-seq datasets, the number of components retained was three, and the selected cell types were monocytes, NK cells, and plasma cells (Fig. 3.4). The choice to use the actual cell type scores over principal components directly as covariates is a sacrifice of orthogonality for interpretability.

Scores were validated against FACS measurements in the subset of individuals that had them. Depending on each panel’s gating strategy for each cell subset, the FACS data were in units of

\*high intercorrelation is not necessary nor sufficient by itself to induce multicollinearity, but multiple correlation does have an inverse relationship with the standard error of coefficient estimates [285]

determine appropriate citations from existing refs in intro

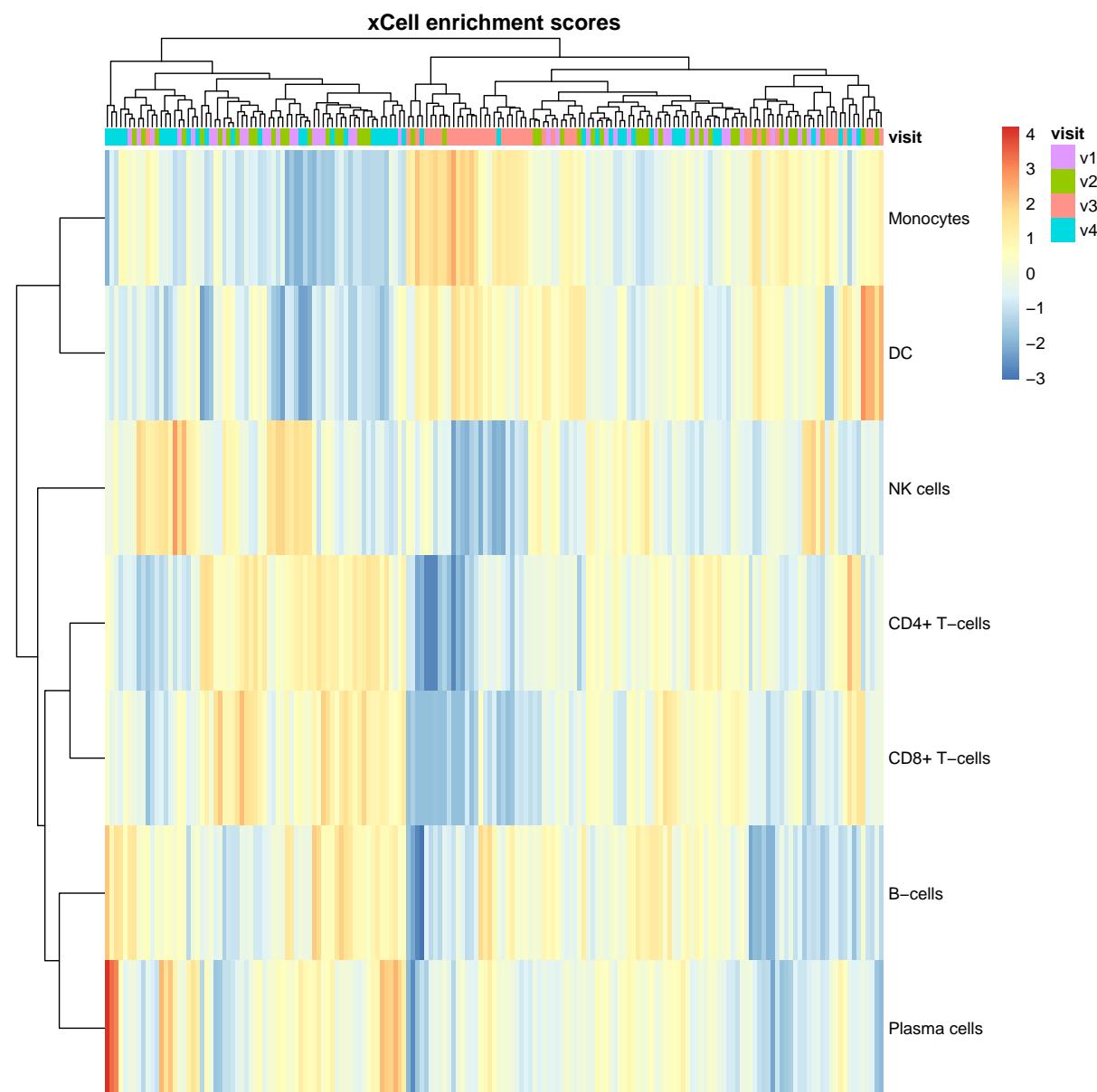
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add comment on existence of chosen cell types in samples, and clustering by visit

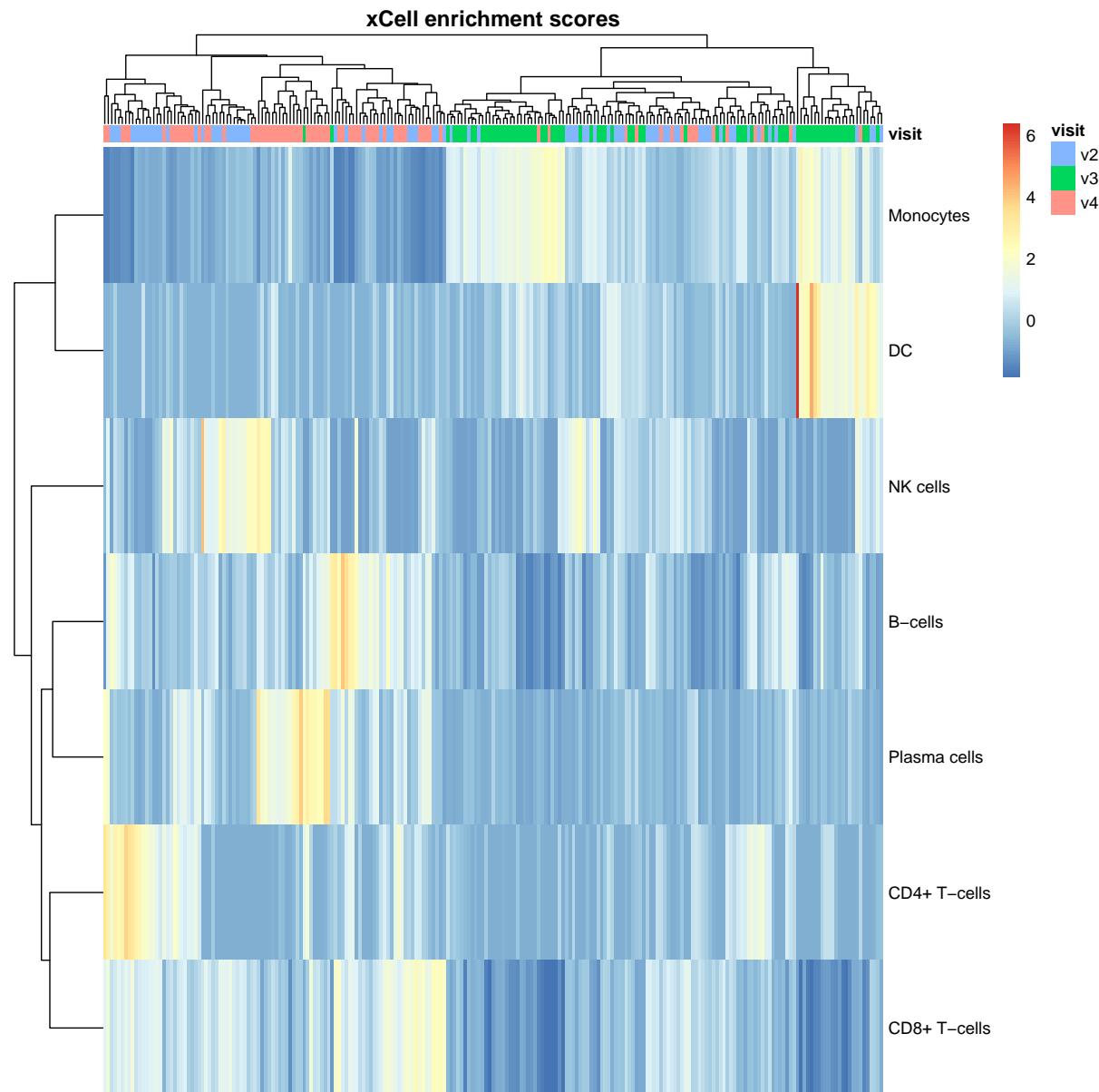
does not bias least squares regression, but unstable (vary sample to sample) to changes in data due to sampling var, and more std error of estimates will be high (tending to inf if perfect multi)

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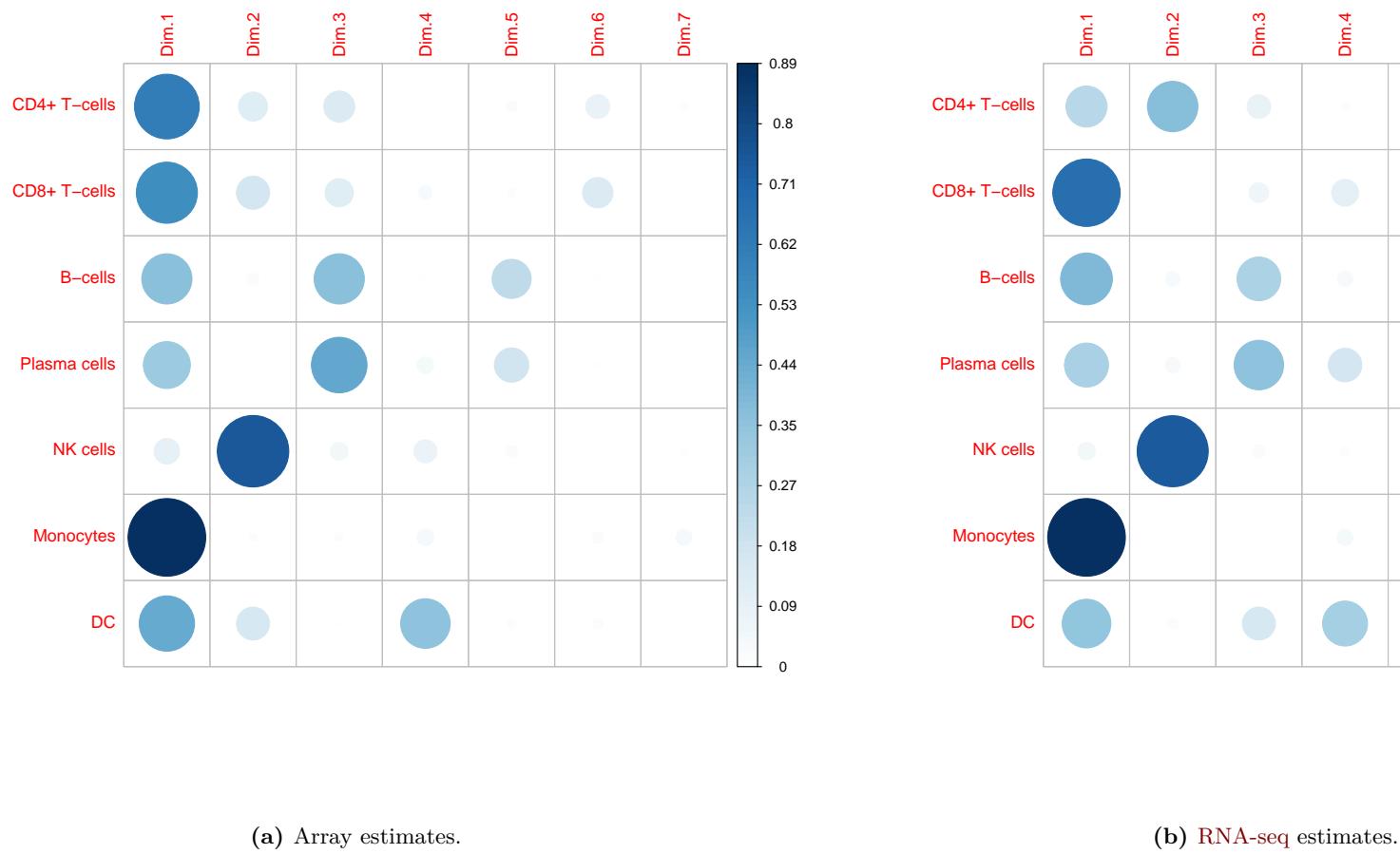
add info on the markers used for the chosen FACS counterparts



**Figure 3.2:** Standardised xCell enrichment scores for seven **PBMC** cell types in array samples.



**Figure 3.3:** Standardised xCell enrichment scores for seven **PBMC** cell types in **RNA-seq** samples.



**Figure 3.4:** Quality of representation ( $\cos^2$ ) for each input variable in each PC dimension after PCA of xCell scores. Higher  $\cos^2$  represents higher contribution of that variable to that dimension.

either absolute counts, or percentage of the previously gated population. A rank-based INT was applied within each panel and cell subset, so that the transformed measure could be compared between individuals for each subset ([287] takes a similar approach for cell abundance data using a quantile-based INT). Missing values were imputed with `missForest`, a random forest imputation method suitable for high-dimensional data where  $p \gg n$ . Although the increase in xCell score for monocytes at day 1 and plasma cells at day 7 reflect the increases in these cell types observed by [161], overall correlation between xCell and FACS was weak (Fig. 3.5). Weighing the downside of having imperfect estimates of cell type abundance against the downsides of not accounting for abundance, or excluding samples without FACS measures, I chose to continue the analysis using the xCell scores.

get subset size

change corr scatterplots  
to corr matrix

### 3.2.6 Finding hidden covariates using factor analysis

Apart from cell type abundance, a myriad of other unmeasured variables contribute to expression variation. Hidden determinants of expression variation were learnt using PEER[177]. As suggested by [177], between-sample normalisation and variance stabilisation on RNA-seq count data was performed using `DESeq2::vst`. ComBat was applied to first merge array and RNA-seq data into a single log scale expression matrix per timepoint, treating the largest global effects on expression—the two array batches and three RNA-seq library prep pools (Fig. 2.13)—as known batch effects. Given selected known covariates (intercept, sex, four genotype PCs from Section 2.2.5 representing ancestry, and the three xCell scores estimated above), PEER was used to estimate additional hidden factors that explain variation in expression matrix. Factors are assumed to be unmeasured covariates that have global effects on a large fraction of genes, whereas a cis-eQTL will typically only have local effects, so including factors as covariates should not introduce dependence with the genotype term, but should soak up some of residual variation, improving power to detect cis-eQTLs. The analysis was run per timepoint, otherwise global changes in expression between timepoints induced by the vaccine would be recapitulated as factors.

Correlating the estimated factors to a larger set of known covariates reveals many correlations with xCell estimates, indicating that cell type abundance does indeed have substantial global effects on the expression matrix. There is little correlation with known array or RNA-seq batch effects, indicating ComBat did an adequate job of removing batch- and platform-dependent global effects on expression (Fig. 3.6). Note that I did not leave this adjustment for PEER to perform, as ComBat estimates centering and scaling factors per gene to adjust for batch effects, whereas the use of PEER factors represent a mean-only adjustment. Given the severity of the batch effect in this dataset, especially between platforms, mean-only adjustment may be insufficient[208].

remake this with only top  
k factors, and prune the  
possible covariates

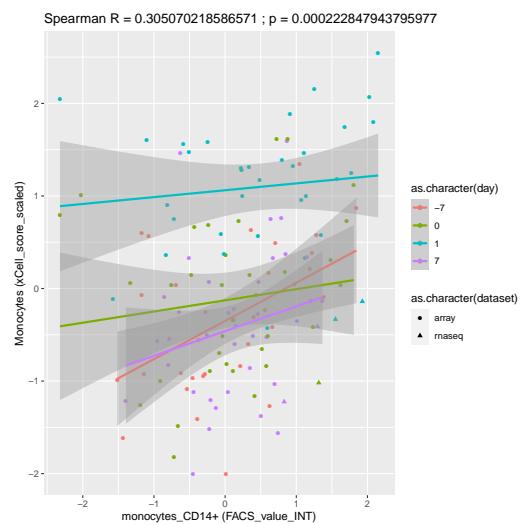
### 3.2.7 eQTL mapping per timepoint

The performance of various software implementations of LMMs specialised for genetic association studies are highly comparable; the specific choice of implementation can usually be made on the basis of computational efficiency[273]. I map eQTLs within each timepoint using LIMIX[288], which implements univariate and multivariate LMMs with one or more random effects.

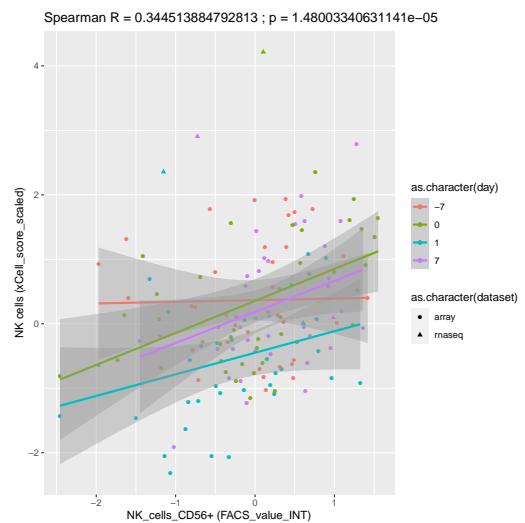
Imputed genotype probabilities were converted to continuous alternate allele dosages using bcftools (1.7-1-ge07034a). Variants with sample AC < 15 within each timepoint were excluded.

add approximate MAFs,  
then cite hierarch paper

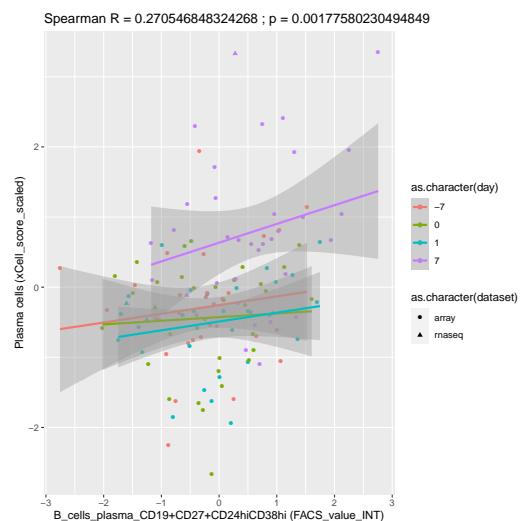
add note on treating x  
chrom variants with cau-  
tion



(a) Monocytes.

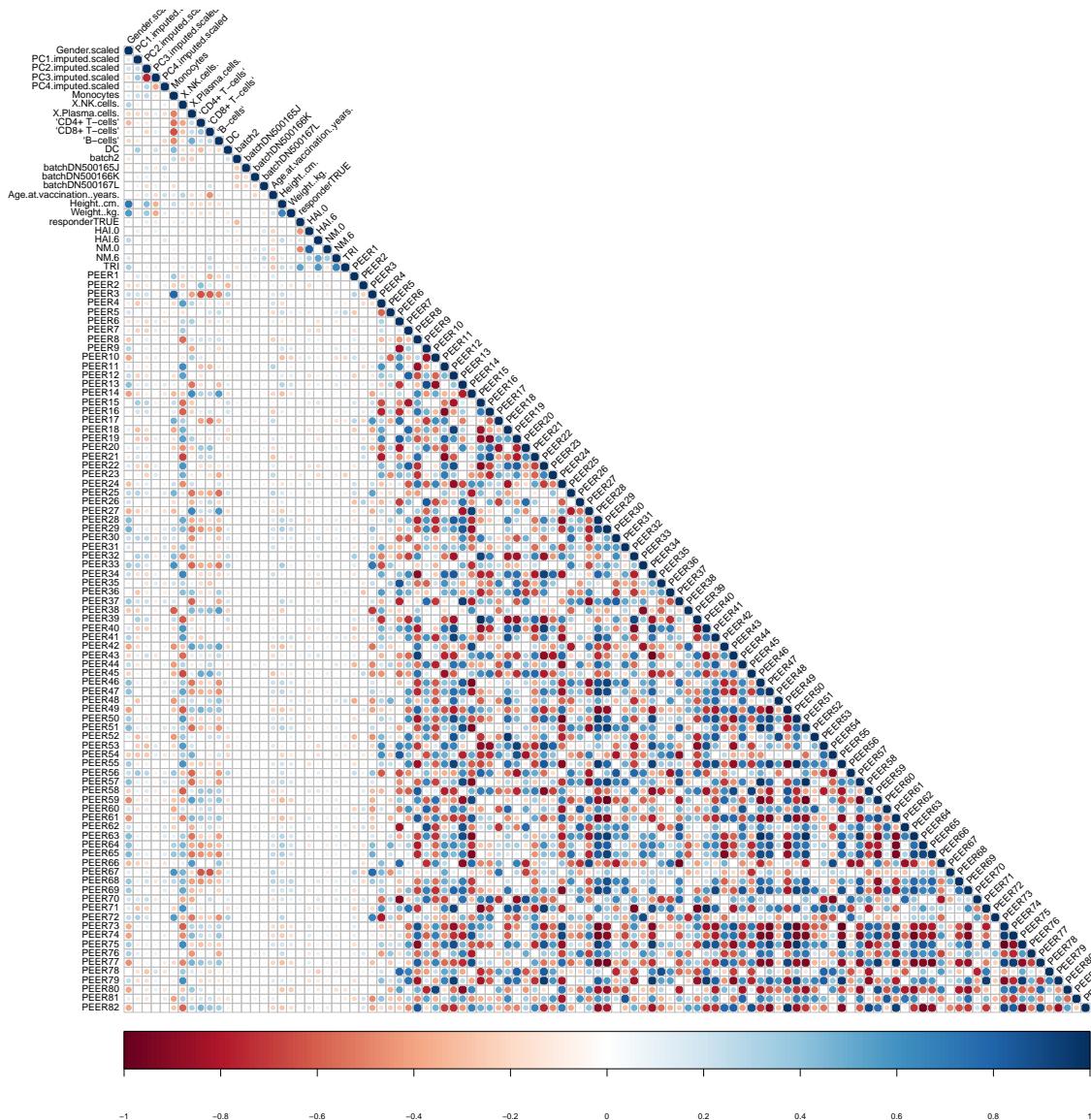


(b) NK cells.



(c) Plasma cells.

**Figure 3.5:** Correlation between standarised xCell scores and normalised FACS measurements for a similar immune subset, in the subset of individuals with FACS data.



**Figure 3.6:** Correlation of PEER factors to known factors and other possible covariates. Note that PEER factors are not constrained to be orthogonal, so correlations to known factors are expected.

At each of 13570 genes, at all cis-variants within within  $\pm 1$  Mbp of the gene transcription start site (TSS), I fit the following model to map eQTL:

$$Y = 1 + sex + \sum_{i=1}^4 PC_i + \sum_{i=1}^3 xCell + \sum_{i=1}^k PC_i + \beta G + \mathbf{u} + \epsilon \quad (3.1)$$

where the eQTL effect size of interest is the slope of the genotype fixed effect  $\beta$ , the average additive effect of the alternate allele [13]; and  $\mathbf{u}$  is a random effect with zero mean and covariance matrix proportional to the LOCO kinship matrix\*.

lift proper vector notation from limix, then redo this with a timepoint subscript

PEER factors are automatically weighted such that the variance of factors tends to zero as more factors are estimated, hence continuing to add more and more factors as covariates will not continue to improve eQTL detection power, and eventually the model degrees of freedom will be depleted. To optimise  $k$ , the number of factors to include as covariates<sup>†</sup>, Per-timepoint eQTL mapping was performed in chromosome 1, iteratively increasing the number of factors until the number of eQTLs detected plateaus. I settled on a final choice of  $k = 10$  factors for pre-vaccination, 5 factors for day 1, and 5 factors for day 7 (Fig. 3.7).

add formulation of the 0-mean random effect to show exactly how the kinship matrix is used [289]

note stacking of kinship for day -7 repeated measures

i leave the pcs in to guard against unusually differentiated between pop markers, where random effect alone may not be enough [274],  
<https://www.nature.com/articles/srep06874>

### 3.2.8 Joint eQTL analysis across timepoints

Joint analysis was conducted with `mashr`[268], at 40197618 gene-variant pairs (mean of 2962 tests per gene) for which summary statistics from within timepoint mapping were available in all three timepoint conditions. The `mashr` model incorporates multiple canonical (the identity matrix etc.) and data-driven covariance matrices to represent patterns of effects across conditions (in this case,  $3 \times 3$  matrices). Data-driven covariance matrices are derived by dimension reduction of a strong subset of tests likely to have an effect in at least one condition. I took the most significant variant per gene per condition, which ensures strong condition-specific effects are included (Fig. 3.8), then further filtered to only nominally significant tests, resulting in a strong subset of 45962 tests.

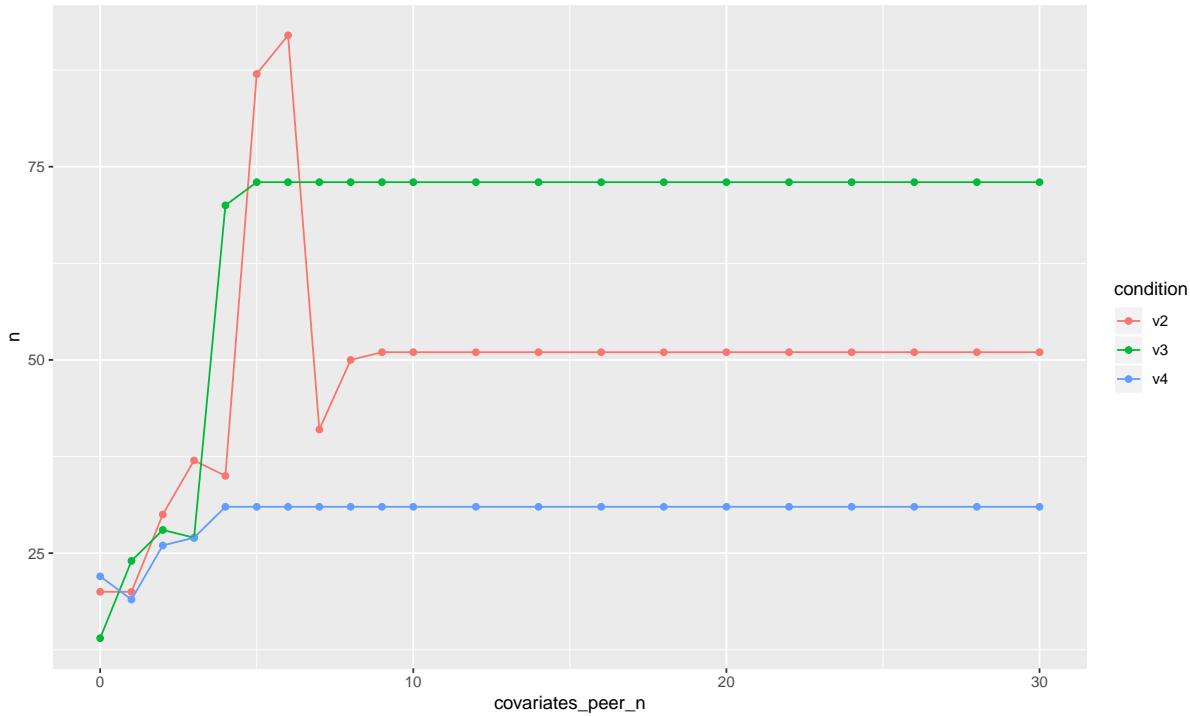
recheck if did I do a SNPs only filter

The `mashr` model was trained on a random subset of 200000 tests, using the Exchangeable Z-scores model[268]. The correlation of null tests between conditions, critical to account for due to the repeated measures structure of the data, was estimated using `mashr::estimate_null_correlation`. The fitted model was used as a prior to compute posterior effects and standard errors for all tests through shrinkage. A condition-specific Bayesian measure of significance local false sign rate (lfsr) is returned, the probability that the declared sign of the effect is incorrect [232]. Note that `mashr` is the multiple-condition extension of `ashr`, previously used in Section 2.2.9.7 for computing posterior effects and their significance in DGE analyses.

note this is critical, since we know a priori not independent due to eqtl sharing

\*For chromosome X variants, no LOCO matrix is available from LDAK, so the matrix for chromosome 1 is used.

<sup>†</sup>I avoid the commonly-performed two-stage approach of treating PEER residuals as expression phenotypes, as the degrees of freedom seen downstream will be incorrect, which can have a substantial effect on estimates at this modest sample size.



**Figure 3.7:** Number of significant eGenes detected on chromosome 1 (hierarchical Bonferroni-Benjamini-Hochberg (BH)[290] FDR < 0.05) as a function of the number of PEER factors included as covariates k.

### 3.2.9 Defining shared and response eQTLs

Many of the tested variants for each gene will be in high LD. To unambiguously select a lead eQTL variant per gene, I selected the variant with the lowest lfsr in any condition, breaking ties by highest imputation INFO, highest MAF, most upstream of the TSS, and genomic coordinate. Sharing was then evaluated for that gene-variant pair across all three conditions.

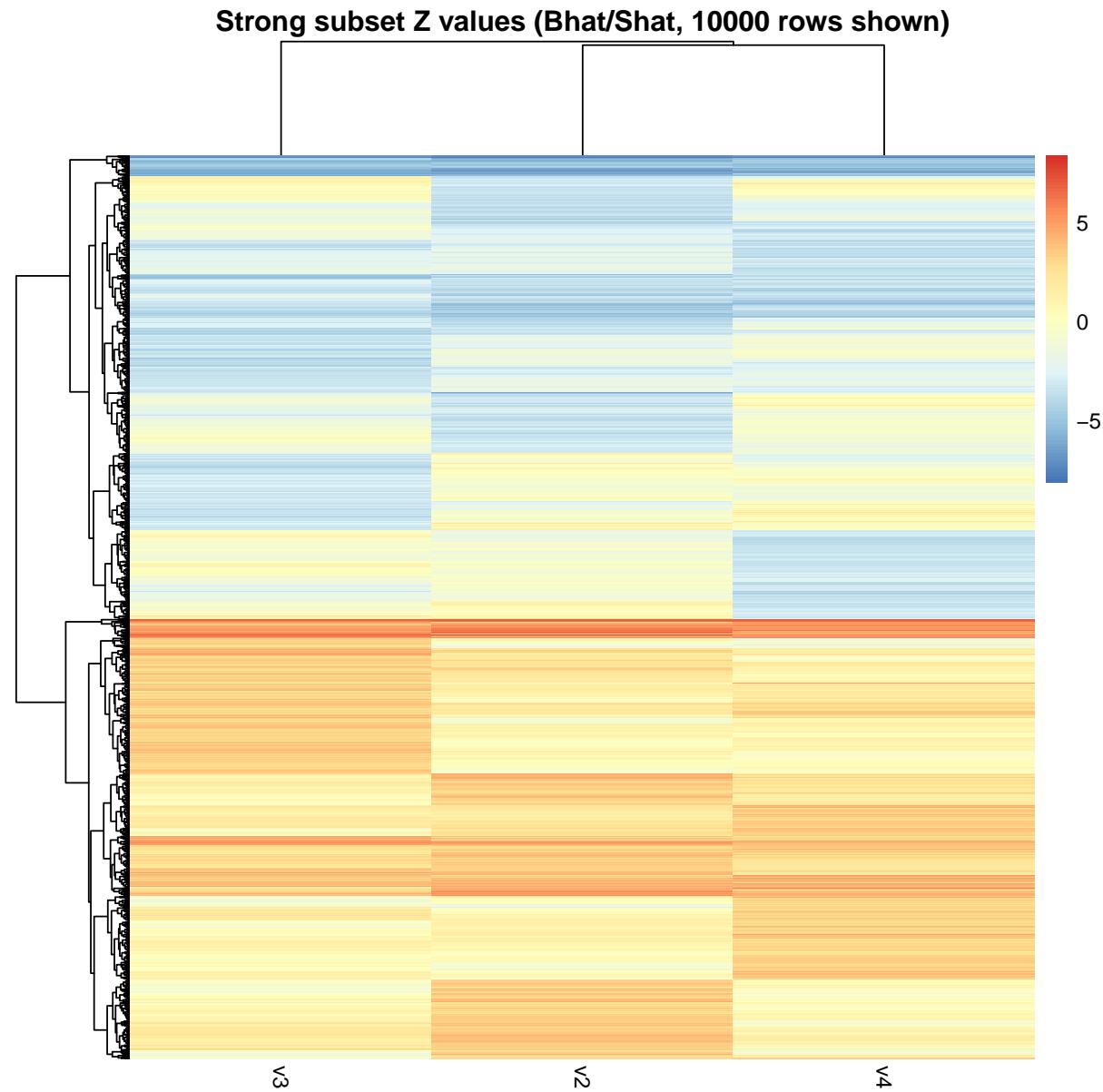
Thresholding on the lfsr is not appropriate for determining sharing, as the difference between significant and non-significant effect estimates in two conditions is not necessarily significant[291, 292]. [268] provides a heuristic that two effects are shared by magnitude if they have the same sign, and are also within a factor of 2 of one another, but this does not consider the posterior standard error of the estimates. Between a pair of effects in two conditions, I compute a *z*-statistic for the difference in effects [266, 291]:

$$z = \frac{\beta_x - \beta_y}{\sqrt{\sigma_x^2 + \sigma_y^2 - 2\sigma^2(x, y)}} \quad (3.2)$$

This strategy has been applied to call reQTLs by [83], assuming posterior pairwise covariance of effects is zero  $\sigma^2(x, y)$ . A Wald test *p*-value for the difference can be computed, as under the null hypothesis of zero difference, asymptotically  $z \sim \mathcal{N}(0, 1)$ . I use nominal *p*-value < 0.05 as a heuristic threshold (like the mashr recommended 2-fold threshold) to define reQTL effects that are strong, rather than a formal measure of significance. Effects are only compared if at least one of the two effects has lfsr < 0.05, to avoid sharing being driven by null effects.

not sure whether this  
is conservative or anti-  
conservative

mashr does not provide  
by default



**Figure 3.8:** Clustering of within-timepoint Z scores in the strong mashr subset (random sample of 10000/45962 tests), confirming the presence of strong condition-specific effects.

### 3.2.10 Replication of eQTLs in a reference dataset

To validate the **eQTL** mapping approach, I estimate the replication of significant eQTLs in a large independent reference. Due to the lack of large sample size **eQTL** maps specific to **PBMC**, I use the GTEx v8 whole blood dataset as my reference dataset ( $n=670$ , 51.2% eGene rate). For lead variants called as significant in the **HIRD** dataset at a given **lfsr** threshold, I lookup the nominal  $p$ -value for that variant in GTEx (where the variant exists in both datasets). I applied `qvalue::qvalue_truncp` to estimate the proportion of those GTEx nominal  $p$ -values that are null ( $\pi_0$ ), then compute a measure of replication  $\pi_1 = 1 - \pi_0$ .

The mega-analysis has comparable replication rate to **RNA-seq**-only analysis for shared **eQTLs** at moderately stringent **lfsr** thresholds up to  $10^{-5}$  (Fig. 3.9). Past this, as the  $\pi_1$  procedure assumes a well-behaved  $p$ -value distribution in  $[0, 1]$ , reliability declines due to the number of  $p$ -values being too small\*, or the maximum  $p$ -value being too far from 1. The numbers of **reQTLs** were too low to assess replication using this method, and one might not expect them to replicate in a baseline dataset such as GTEx whole blood, especially for those **reQTLs** significant only at post-vaccination timepoints. As the mega-analysis has a higher eGene rate (50.8% vs. 29.9%) compared to the **RNA-seq**-only analysis, with similar replication, I assume this represents a power advantage from having larger a sample size, rather than technical effects from merging the expression data.

RNAseq does test about  
7000 more genes though...

be more specific: "moderator", 'modify'?????

point is, doesn't make  
sense to assume the geno-  
type effect is the same  
at all levels of cell type  
abundance

### 3.2.11 Genotype interactions with cell type abundance

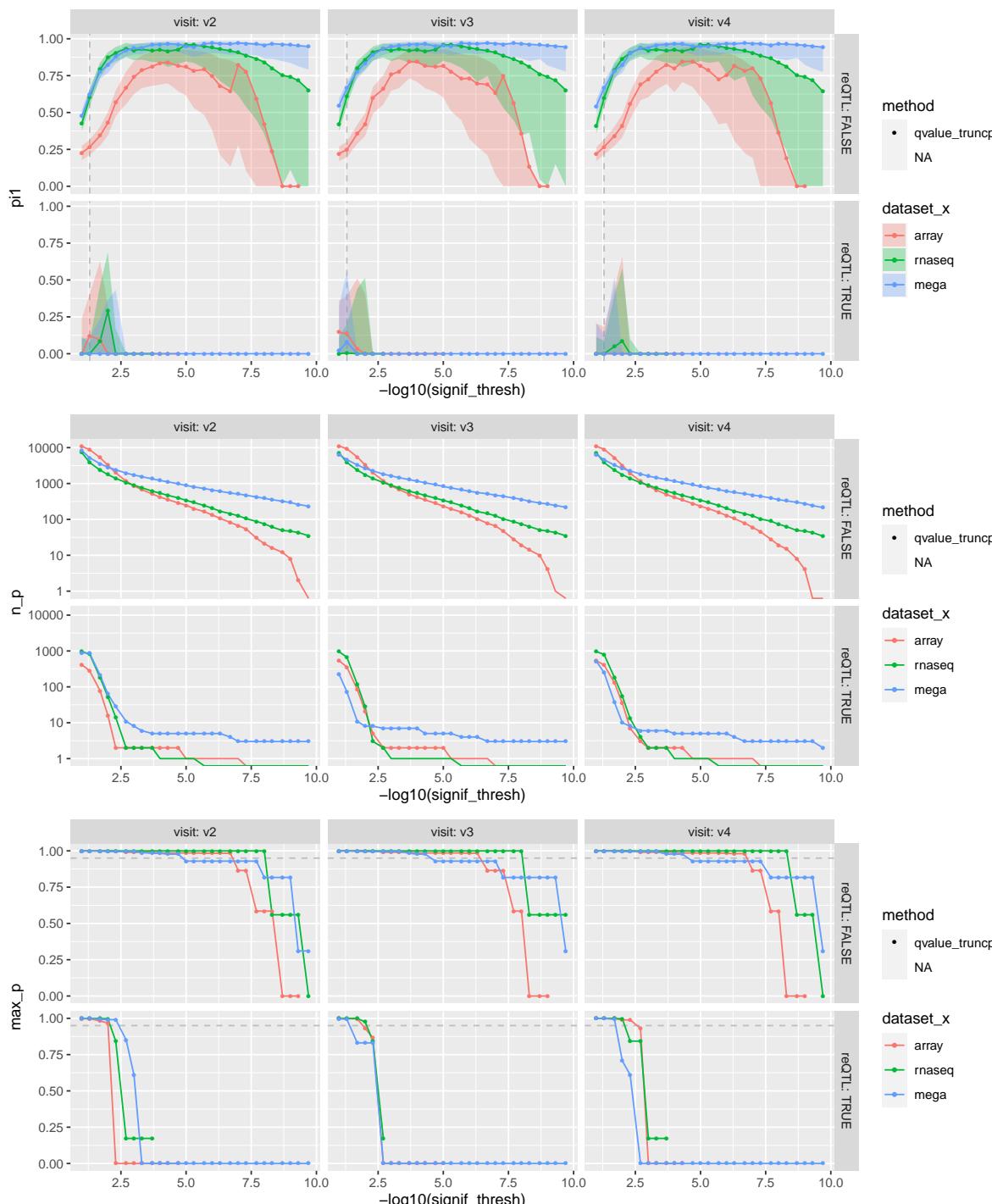
If the abundance of a particular cell type does truly modify the **eQTL** effect, then an interaction term between genotype and cell type abundance is required, otherwise the regression slope of the **eQTL** term will be biased; one cannot adjust for this modification just by including the main effect for cell type abundance. Given the modest sample size, I use the two-step approach used by others[66, 69, 83, 94], where tests for interaction are only performed at a subset of tests, often the lead **eQTL** variant for each gene. The key to the two-stage approach is that if the estimates for the interaction effect are sufficiently independent from the estimates of the main effect from main-effect only models, the type I error can be controlled based on the number of interactions that are actually tested, rather than the number of interactions that could have been tested for[66, 293]. It is unclear whether this assumption holds, as the size of the main effect may contribute to power for detecting interaction effects. As the main purpose of the interaction analyses is scanning for cell type effects at detected **reQTLs**, I chose to test for interactions only at the lead **eQTL** variant for each gene with a significant main **eQTL**, then apply the **BH** false discovery rate (FDR), as used by others[66, 83].

Models in interactions between genotype and other predictors were fit using `lme4qt1`. The model specification identical to Eq. (3.1), with the addition of three interaction terms between genotype and each `xCell` score. Significance is assessed using the likelihood-ratio test versus the nested model with no interaction terms.

can we interpret with  
peer in? add note of  
CLAIM here that al-  
though peer is correlated  
with `xcell`, interactions  
are only formed with  
`xcell`, so the interaction  
term can be interpreted  
per unit of genotype in-  
crease when `xcell=0`

### 3.2.12 TODO Statistical colocalisation

\*<https://github.com/StoreyLab/qvalue/pull/6#commitcomment-26277751>



**Figure 3.9:** Effect of HIRD lfsr threshold on GTeX whole blood replication rate ( $\pi_1$ ), number of  $p$ -values used to compute  $\pi_1$ , and maximum  $p$ -value among those  $p$ -values; for shared and reQTL called from the array-only, RNA-seq-only and mega-analysis pipelines. Shaded region for  $\pi_1$  represents the 5th-95th percentile range of 1000 bootstraps.

- if adding coloc analysis, add <https://github.com/jrs95/hyprecoloc> methods here - cannot deal with multiple causal within each group

### 3.3 Results

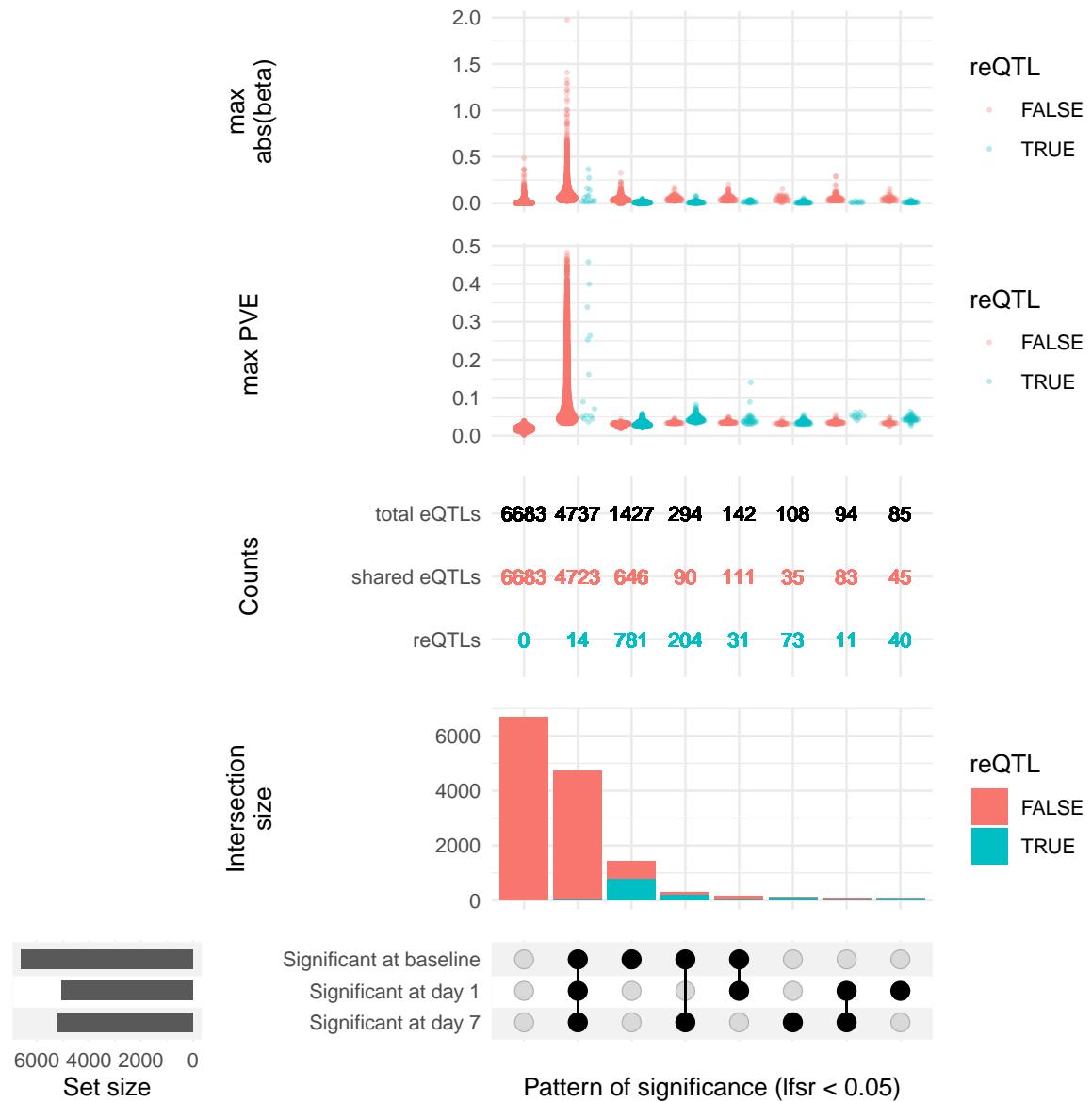
#### 3.3.1 Mapping reQTLs to Pandemix vaccination

To characterise the effect of common host genetic variation on expression response to Pandemrix, I mapped **cis-eQTLs** for each gene ( $\pm 1$  Mbp of the **TSS**) within each timepoint condition (baseline, day 1, and day 7), then conducted joint analysis of all three timepoints with **mashr** [268] to obtain per-timepoint posterior effect sizes, posterior standard errors, and measures of significance (**lfsr**). At  $lfsr < 0.05$ , 6887/13 570 genes (50.8 %) were eGenes (genes with a significant **eQTL**) in at least one timepoint. The most significant tested variant over all timepoints was selected as the lead variant for each gene, then **ReQTLs** were defined by comparing the effect size of this lead variant between each pair of timepoints. This guards against differences in effect size from differential tagging efficiency (of an assumed single causal variant), which might occur if different variants were compared across timepoints. **Fig. 3.10** shows patterns of sharing over timepoints for the lead variant for each of the 13 570 genes, illustrating the difference between calling **reQTL** using a significance threshold versus the difference in betas approach. For example, there were 85 **eQTL**-eGene pairs significant only at day 1 post-vaccination ( $lfsr < 0.05$ ); of these only 40/85 are **reQTLs** by the difference in betas method. The difference in betas method is more strict because calling by significance alone would call a **reQTL** for an **eQTL** with  $lfsr = 0.049$  at baseline and  $lfsr = 0.051$  at day 1, even if the effect sizes are similar.

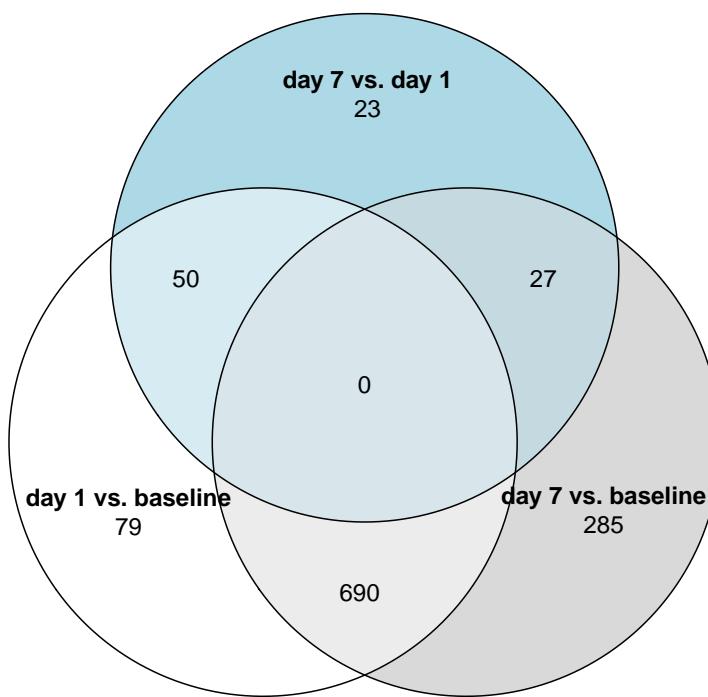
The largest number of eGenes was detected at baseline, reflecting the larger sample size compared to other timepoints. Most **eQTLs** were shared across timepoints; these were also the strongest **eQTLs** in terms of both maximum absolute beta and **proportion of variance explained (PVE)** across timepoints, highlighting the power advantage for mapping shared effects granted by joint analysis. 1154/6887 (16.8 %) **eQTLs** were classified as **reQTLs** based on difference in effect size (beta) between any pair of timepoints (nominal  $p < 0.05$ ). Of these, 690/1154 were **reQTLs** in both baseline- day 1 vs. baseline and day 7 vs. baseline, and only 23/1154 were unique to the day 7 vs. day 1 comparison, indicating most **reQTL** effects were differences between pre- and post- vaccination (**Fig. 3.11**).

#### 3.3.2 Characterising reQTLs post-vaccination

To characterise the eGenes associated with post-vaccination **reQTLs**, I ranked eGenes by the increase in **PVE** for their associated **reQTLs** from baseline to day 1 and baseline to day 7, then performed ranked gene set enrichments with **tmod::tmodCERN0test**. The same four modules were significant at both post-vaccination timepoints: “immune activation - generic cluster” (LI.M37.0, day 1 **FDR** =  $1.28 \times 10^{-6}$ , day 7 **FDR** =  $3.39 \times 10^{-6}$ ), “enriched in monocytes (II)” (LI.M11.0, day 1 **FDR** =  $4.69 \times 10^{-3}$ , day 7 **FDR** =  $1.88 \times 10^{-2}$ ), “cytoskeleton/actin (SRF transcription targets)” (LI.M145.0, day 1 **FDR** =  $2.07 \times 10^{-2}$ , day 7 **FDR** =  $2.04 \times 10^{-2}$ ), and “MHC-TLR7-TLR8 cluster” (LI.M146, day 1 **FDR** =  $2.07 \times 10^{-2}$ , day 7 **FDR** =  $2.04 \times 10^{-2}$ ). The enrichments



**Figure 3.10:** Summary of eQTL mapping results at 13570 genes-lead eQTL pairs, with intersections based on significance ( $\text{lfsr} < 0.05$ ). Counts of shared eQTLs and reQTLs; and distribution of INFO score, min MAF across timepoints, and max PVE across timepoints for those lead variants are shown above each intersection.

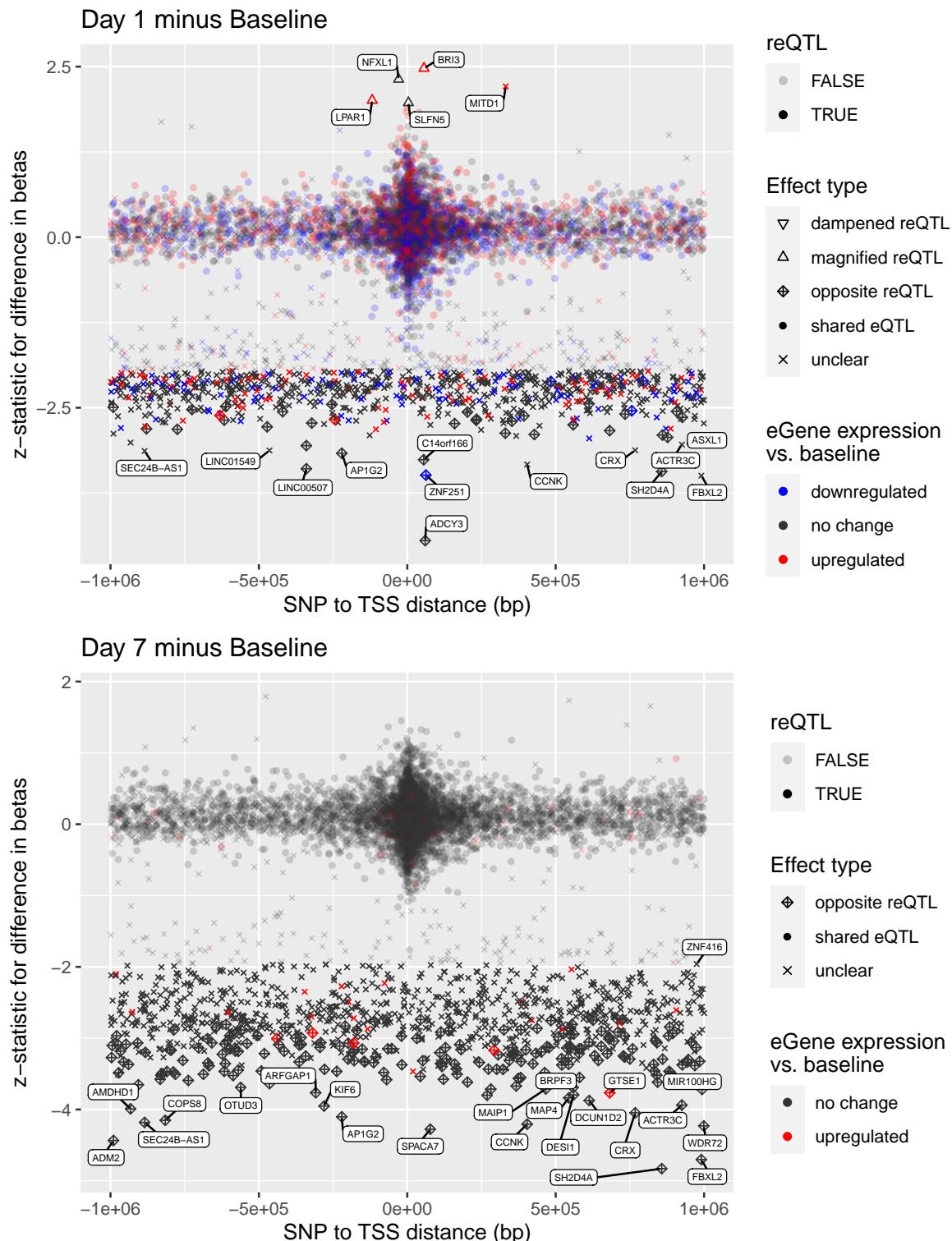


**Figure 3.11:** **reQTLs** were observed for 1154 unique eGenes, where the lead **eQTLs** had a significant difference in beta between pairs of timepoints (nominal  $p < 0.05$ ).

are weak but consistent with immune activation driving post-vaccination **reQTLs**. Given that TLR7 and TLR8 are primarily expressed in monocytes, macrophages and **DCs** [294], and *SRF* is a regulator of the cytoskeleton in macrophages [295], there is suggestive evidence **reQTLs** may be enriched in genes specific to these phagocytic **APCs**.

Changes in **PVE** do not capture changes in allelic direction. I classified post-vaccination **reQTLs** into one of three effect types: magnified, where the beta increases after vaccination but remains the same sign; dampened, where the beta decreases after vaccination but remains the same sign; and opposite, where the allelic direction changes after vaccination. As **lfsr** quantifies uncertainty in the sign of the effect, I do not make this classification for **reQTLs** that are not significant both at baseline and post-vaccination—the effect type for these are unclear. The classifications are shown in Fig. 3.12, plotting all 6887 shared or **reQTL** by their distance relative to the eGene **TSS**. Shared **eQTLs** have  $z$ -statistics for difference in betas close to  $z$ , and are concentrated close to the **TSS** as expected, **reQTL** had a distribution of mostly negative  $z$ -statistics clearly separated from the shared **eQTLs** at both day 1 and 7, and these were mostly unclear or opposite rather than dampened effect types. Many of these unclear effects may actually be dampening, but as the sample size is greatest at baseline, dampening effects are hard to distinguish from drops in power at post-vaccination timepoints, whereas an opposite effect significant in both timepoints is unambiguous.

**reQTLs** also tended to be distributed evenly across the entire *cis*- window, raising the question or whether they are enriched in false positives. A nominal  $p < 0.05$  threshold may be too lax for calling **reQTLs**, so I applied a stronger **BH FDR** threshold of 0.2. At this threshold, the only remaining **reQTL** was at day 1 was for *ADCY3* (nominal  $p = 8.68 \times 10^{-6}$ , FDR = 0.12)—the next smallest FDR value was 0.6490604. At day 7, 676 significant **reQTL** had **FDR** < 0.2, of which 221



**Figure 3.12:** *z*-statistic for difference in beta post-vaccination versus baseline for shared and reQTLs, stratified by distance from the eGene TSS. For each plot, all eQTLs significant in either timepoint are shown. Shared eQTLs can only have shared effect type. An unclear effect type indicates the eQTL in question was not significant in both timepoints. Allelic direction of effect is aligned so that the beta at baseline is positive.

were opposite effects. Gene set over-representation analysis on the set of 221 eGenes was relatively uninformative, and revealed only one enrichment for genes *PRKACB*, *PRKACA*, *SAR1B* and *APOE* in “Plasma lipoprotein assembly” (Reactome pathway identifier R-HSA-8963898, set size = 11, adj. p = 0.01).

### 3.3.3 Exploring possible mechanisms generating reQTLs

#### 3.3.3.1 Genotype by cell type interaction effects

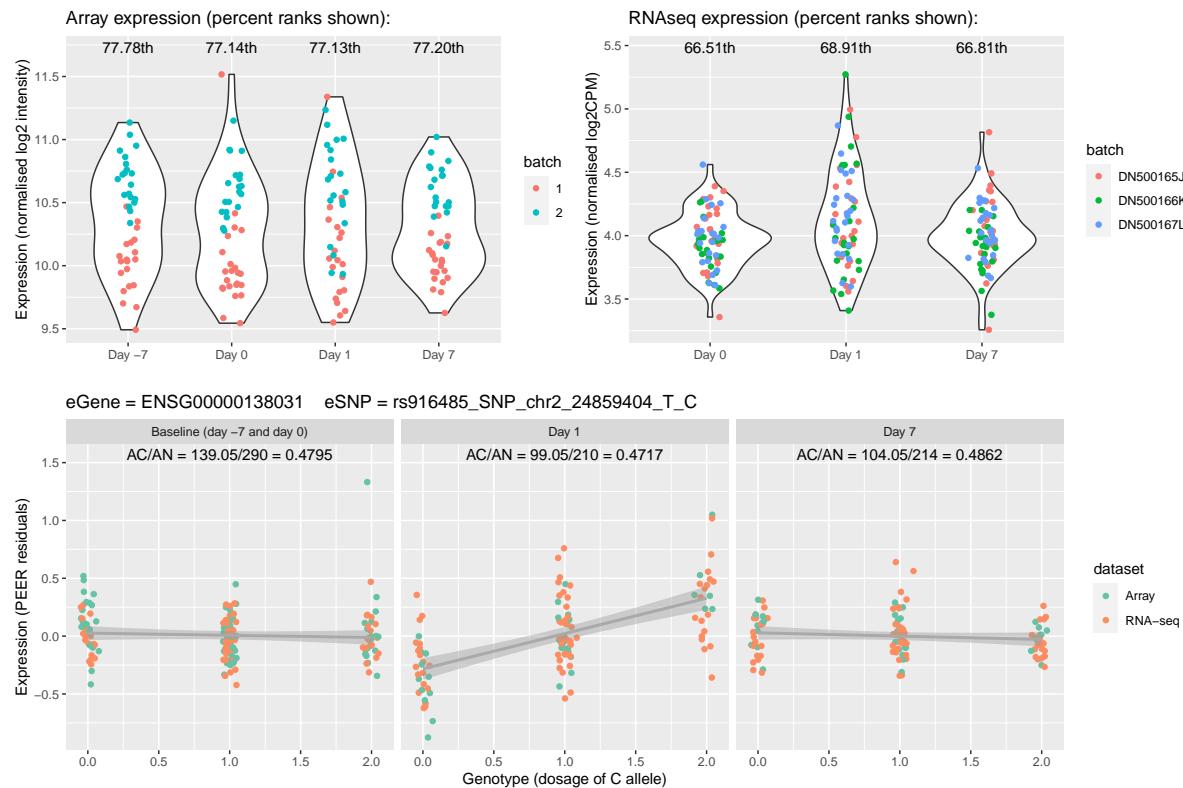
As gene set analyses based on the effect sizes of **reQTLs** at different timepoints had been largely uninformative, I considered whether **reQTL** could be characterised by shared mechanisms. One mechanism that could generate **reQTLs** effects is differential expression, where an **eQTL** is not detected at baseline because the eGene is not expressed, and vaccine-stimulated upregulation reveals the effect post-vaccination. Fig. 3.12 also shows whether each eGene was up or downregulated at the timepoint based on the **DGE** analyses in Chapter 2. Visually, a large number of **reQTL** occur without corresponding differential expression. Statistically, compared to genes without **reQTL**, genes with **reQTLs** were less likely be differentially expressed post-vaccination at day 1 (26.5 % for genes with **reQTL**, 42.3 % for genes without **reQTL**, Fisher’s test  $p < 2.20 \times 10^{-16}$ ). This was also the case when restricting the scope to only eGenes (26.5 % for genes with **reQTL**, 47.9 % for genes with **shared eQTL**, Fisher’s test  $p < 2.20 \times 10^{-16}$ ).

At day 7, no significant difference was observed comparing to genes without a **reQTL** (2.2 % for genes with **reQTL**, 1.4 % for genes without **reQTL**, Fisher’s test  $p = 0.05$ ), but compared to genes with **shared eQTL**, genes with **reQTL** were more likely to be upregulated (2.2 % for genes with **reQTL**, 1.1 % for genes with **shared eQTLs**, Fisher’s test  $p < 0.01$ ). Twenty-two genes with both day 7 **reQTL** and upregulated expression were strongly enriched within gene sets related to the cell cycle (e.g. “mitotic cell cycle”, Gene Ontology biological process term GO:0000278, term size = 914, intersection size = 12, adj. p = 0.00). However, these 22 genes previously appeared in Fig. 3.12, all having **reQTL** with decreased or opposite effect at day 7 versus baseline, making it implausible the generating mechanism is increased detection power due to upregulation. The enrichment for cell cycle is likely driven by the **DGE** signal alone, especially as cell cycle gene modules were detected to be strongly upregulated at day 7 in Section 2.3.1.2.

The presence of **reQTL** without **DGE** is exemplified at the strongest and only significant **reQTL** at day 1 at FDR < 0.2 (Fig. 3.13). At day 1, the **PVE** for this **reQTL** associated with *ADCY3* explained 1.9 % of expression variation at day 0, increasing to 14.1 % at day 1, yet the gene was not differentially expressed from baseline to day 1 (lfsr = 0.26). There is strong evidence that many post-vaccination **reQTLs** are generated by mechanisms unrelated to **DGE**.

#### 3.3.3.2 Genotype by cell type interaction effects

The presence of cell type-specific **eQTL** effects was considered as an alternate explanation. Even if an eGene is not differentially expressed on average in bulk expression data, the composition of cell types that are the source of that gene’s transcripts can change. **xCell** enrichment scores were used to approximate abundance of seven **PBMC** cell types from the expression data. After pruning highly correlated cell types to avoid multicollinearity, standardised scores for monocytes,



**Figure 3.13: Expression and lead eQTL of *ADCY3* over study timepoints.** Normalised array (top-left) and RNA-seq (top-right) expression before batch effect correction with ComBat and eQTL mapping. Bottom: eQTL effects at each timepoint condition in the mega-analysis of array and RNA-seq data.

NK cells and plasma cells were tested for genotype interactions. Within each timepoint, full eQTL models including the genotype main effect, the three cell type abundance main effects, and three cell type-genotype interaction terms, were fit using `lme4qtl`, then compared to a nested model excluding the three interaction terms with a likelihood ratio test (LRT).

For *ADCY3* at day 1 (full vs. nested FDR =  $9.54 \times 10^{-5}$ ), although the genotype effect was 0.26 (SE = 0.03) in the nested model, the estimate in the full model was  $-0.01$  (0.07); with the three cell type-genotype interaction term estimates being 0.21 (0.05) for monocytes,  $-0.01$  (0.04) for NK cells, and 0.02 (0.07) for plasma cells. The small magnitude of the genotype main effect in the full model compared to the nested model suggests the eQTL effect is driven largely by the monocyte score (or a cell type that is highly correlated with monocyte score in Fig. 3.4). In the case where the monocyte score is zero (representing an average abundance across samples, as scores are standardised), the effect of increasing genotype dosage on *ADCY3* expression is minimal. Fig. 3.14 and 3.15 illustrate this effect. Monocyte abundance has no effect on expression at baseline, increases after vaccination, and modifies the effect of genotype on expression at day 1.

Significant cell type interactions were detected at 16/1154 reQTLs-gene pairs in at least one timepoint (BH FDR < 0.05). Fifteen were significant in only one timepoint: baseline (*SLAMF8*, *CSE1L*, *MAST1*, *DLGAP1*), day 1 (*ZNF519*, *LPAR1*, *ADCY3*, *NAA20*, *EPB41L5*), or day 7 (*APOL6*, *ADAR*, *ADAM17*, *UHRF2*, *MST1*, *CUL1*). It is feasible that the mechanism generating reQTL at the remainder of these genes involves cell type-specific eQTL effects, although I have

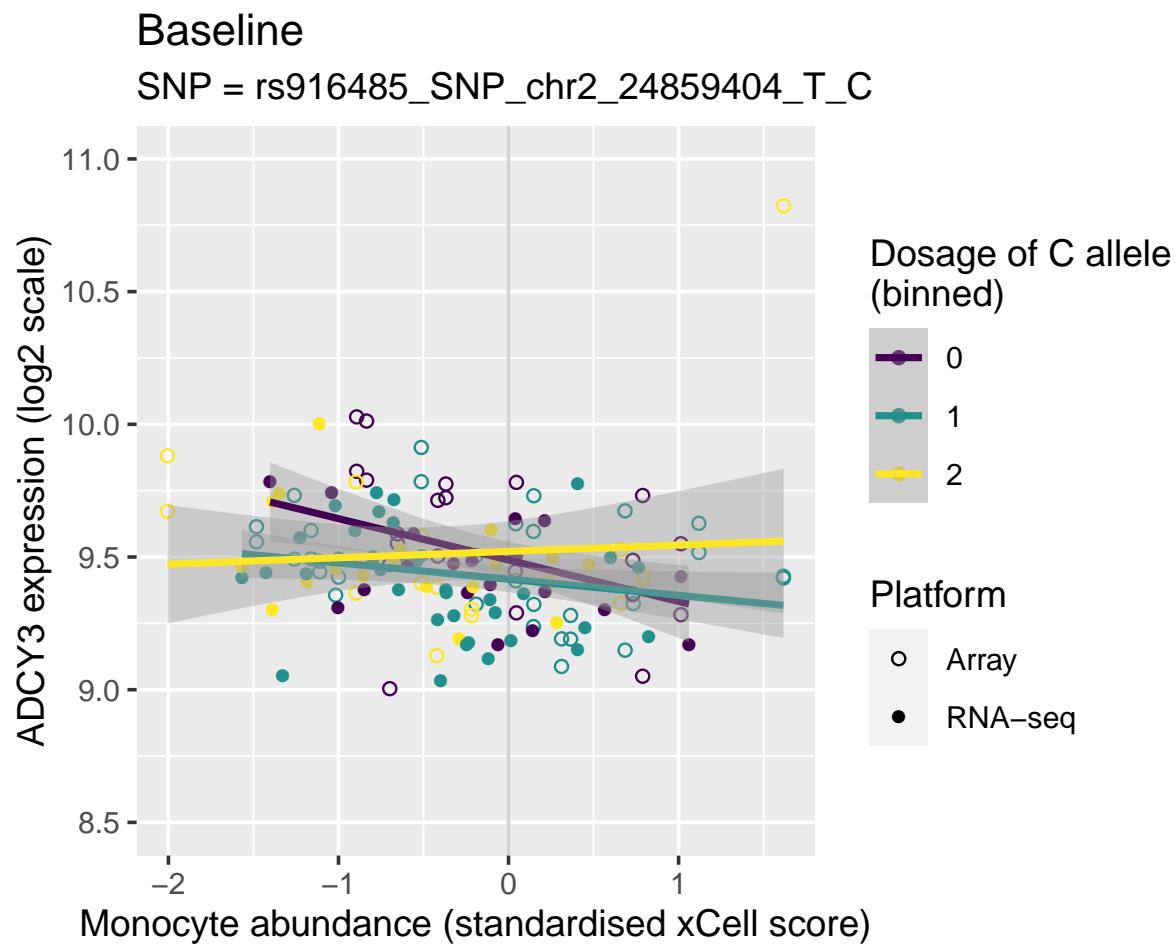


Figure 3.14: Effect of estimated monocyte abundance on *ADCY3* expression at baseline, stratified by genotype at a day 1 *ADCY3* reQTL.

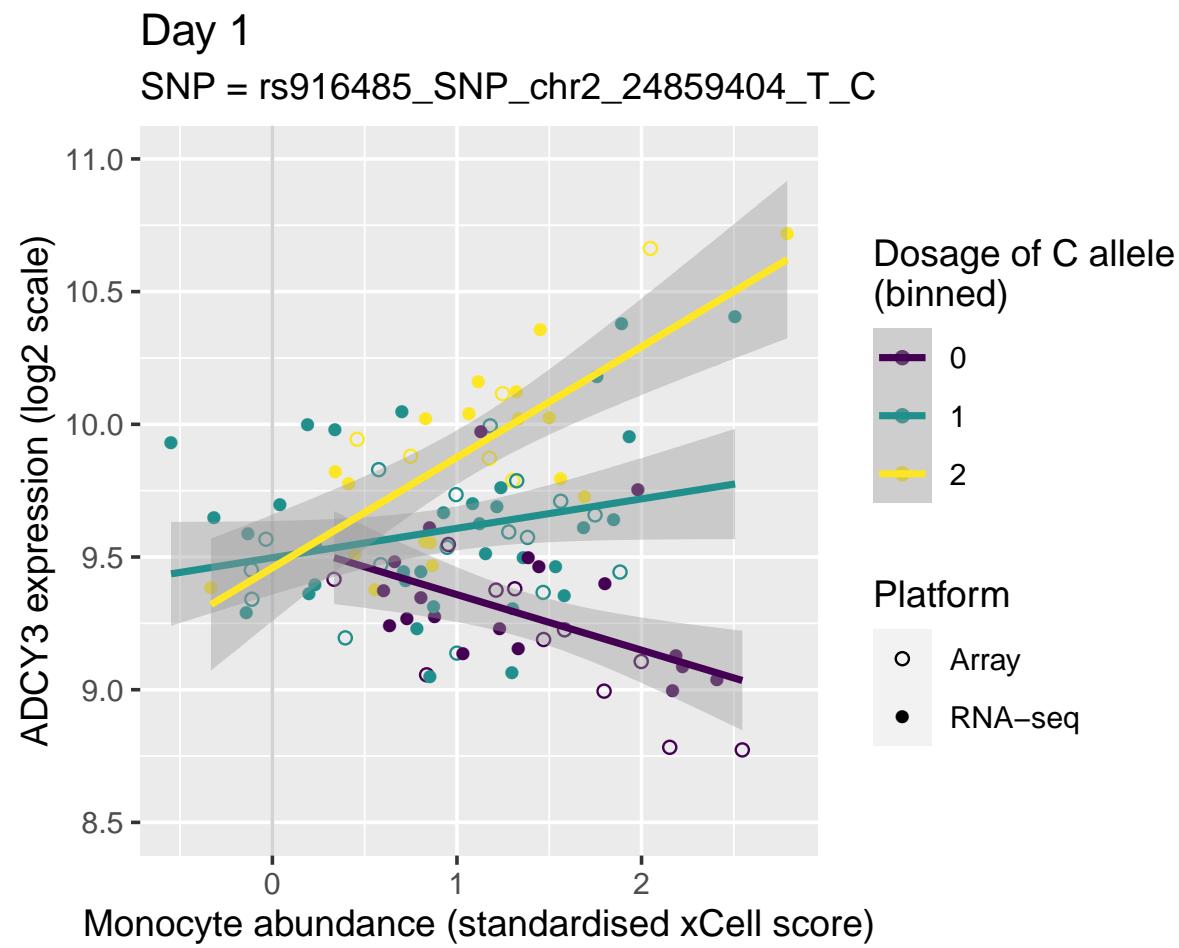


Figure 3.15: Effect of estimated monocyte abundance on *ADCY3* expression at day 1, stratified by genotype at a day 1 *ADCY3* reQTL.

not yet determined the likely cell types at genes other than *ADCY3*.

### 3.3.4 TODO Colocalisation of reQTLs with known *in vitro* condition-specific immune eQTLs

Aside from monocytes, *ADCY3* is also expressed a wide range of immune cells: CD4<sup>+</sup> T cells, CD8<sup>+</sup> T cells, B cells, and NK cells (Fig. 3.16).

The *ADCY3* locus has not only but implicated in disease risk for **immune-mediated inflammatory diseases (IMIDs)**

The genotype by cell type interaction model cannot distinguish between cell types with highly correlated abundances [72], and the high contributions to the same PC monocyte, CD4<sup>+</sup> T cell, and CD8<sup>+</sup> T cell xCell scores indicate these abundances are correlated in HIRD (Fig. 3.4).

this analysis is incomplete, and is one of the things I would suggest to round off this chapter

To try and resolve cell type and see shared cell type contexts with IMID coloc

- Colocalisation is used to understand the molecular basis of GWAS associations (of a variety of human disease traits) (Giambartolome, 2014)
- Here the inverse: coloc is used to understand the biological relevance of observed reQTL by coloc with known immune QTL
- In a 500 Mb window around the lead *ADCY3* variant rs916485, HyPrColoc to colocalise with existing datasets and fine map.
- Day 1 HIRD colocs with BLUEPRINT and Fairfax monocytes (both stim and non stim), but not with Quach or Schmiedel monocytes (Fig. 3.17)
  - Biases from ethnicity-derived differences in LD?
  - Also, priors need tuning?
- HyPrColoc fine maps the signal to rs13407913 (credible set size=1, PP = 1), an intronic variant 45064 bp downstream of the TSS.

FYI the IBD/T cell coloc fine maps to chr2:24935139 T C (rs713586) with PP=1

add obesity GWAS

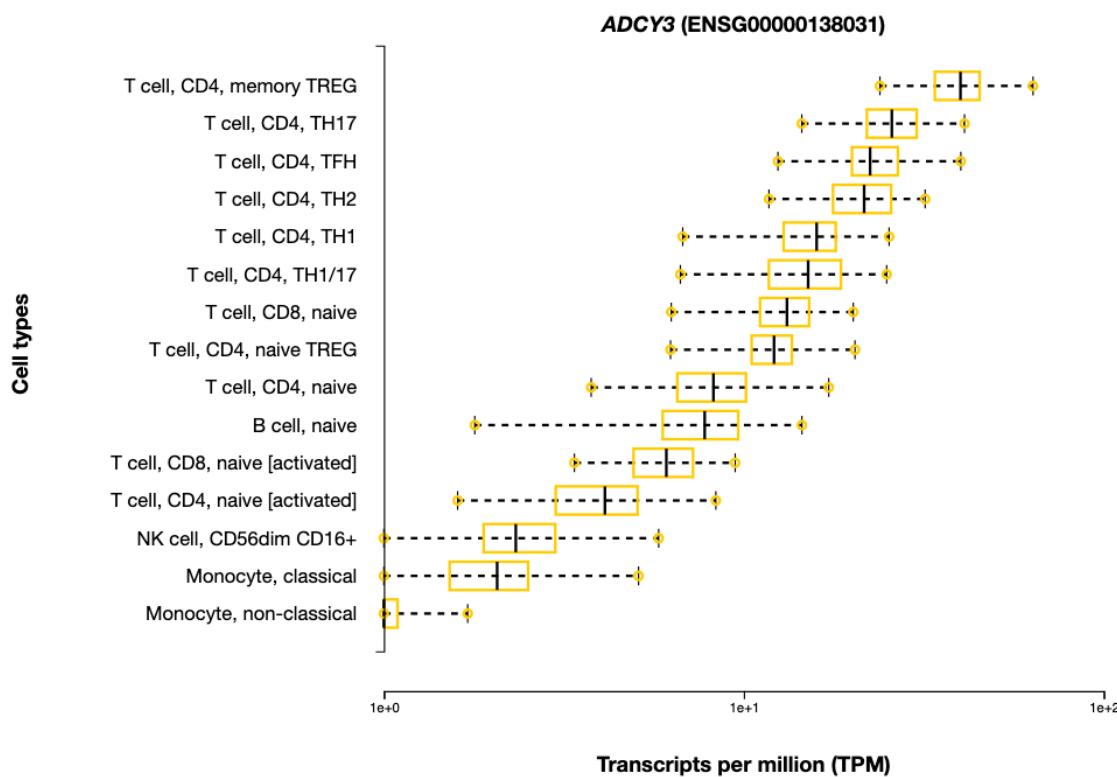
– note not accurate due to MAF issues

## 3.4 Discussion

In the HIRD cohort, **eQTL** were detected for 50.8 % of genes in at least one timepoint, day 0, day 1, or day 7. Even in a joint mapping framework, defining **reQTL** by set significance thresholds, or change in the amount of expression variation explained, will miss classifying equal but opposite effect sizes. I account for the direction and magnitude of effect sizes, defining reQTL strength as the difference in effect size between timepoints. Most **eQTL** are shared between conditions and replicate well in GTEx whole blood; 16.8 % of lead **eQTL** for each eGene were **reQTL** that differed in effect size between timepoints.

compare sharing with mashr and on gen2017EstimatingCausalTissues

Multiple independent eQTLs are present for a large fraction of eGenes[296]. As the lead variant for reQTL assessment for each eGene was chosen based on significance across all conditions, I can



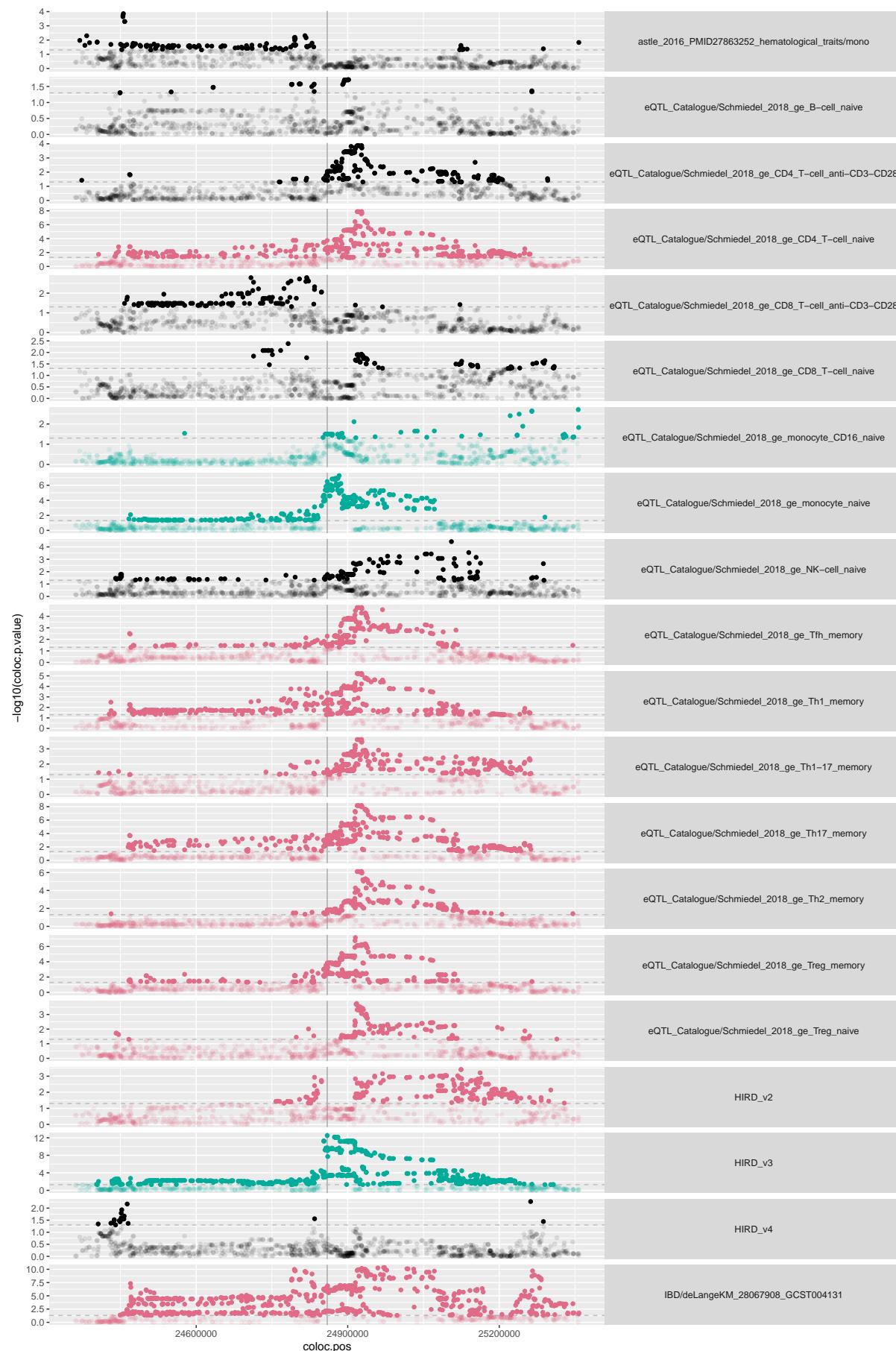
**Figure 3.16:** Expression of *ADCY3* in immune cell types from the DICE database (Schmiedel *et al.* [86]).

not detect reQTL that are masked by a stronger shared eQTL at that gene. This is not expected to be uncommon, as the effective sample size for shared eQTLs is usually large due to borrowing of information across conditions. Secondary eQTL signals tend to be weaker, more distal to the TSS, more likely to be enriched in enhancers rather than promoters, and importantly, more context-specific[53, 297, 298]. The proportion of genes with reQTL I detect based on only the lead signal likely represents a lower bound.

Given the larger global changes in expression vs. baseline at day 1 compared to day 7 described in Chapter 2, the larger number of reQTLs detected at day 7 was unexpected (819 vs. 1002). Opposite sign effects among reQTL post-vaccination were common. Prevalance of opposite sign effects between pairs of conditions has been previously described in multi-tissue studies. In [299], the proportion of opposite sign effects as a percentage of all eGenes was 7.4 % (48 tissues); in HIRD, I find 39/6887 (0.6 %) at day 1, and 211/6887 (3.1 %) at day 7. In [74], the proportion of opposite sign effects as percentage of all reQTLs was 4.4 % (5 tissues); in HIRD, I find 39/819 (4.8 %) at day 1, and 211/1002 (21.1 %) at day 7. The enrichment of opposite sign effects in HIRD is also apparent at day 7. The strongest reQTL at day 7 is one such opposite sign effect; *SH2D4A* has constitutive expression in T cells, B cells, macrophages, and DCs, encoding a adapter protein involved in intracellular signal transduction\*. An approach for validating these opposite sign reQTL using the existing HIRD RNA-seq data is allele-specific expression (ASE) (e.g. [300]), where one would expect true opposite sign reQTL effects would also be recapitulated as opposite

I'm not exactly sure why at the moment. Enrichment analyses so far have not turned up much. Up regulation of cell cycle TFs is a possibility.

\*<https://doi.org/10.1111/j.1600-065X.2009.00829.x>



**Figure 3.17:** Multi-trait colocalisation of HIRD reQTL signal at ADCY3 (500 Kb window), with QTL studies from IHEC, BLUEPRINT, eQTL Catalogue, and GWAS Catalogue. Plots are colored by colocalised cluster. Black indicates non-colocalised datasets.

directions of expression imbalance.

The strongest reQTL detected at day 1 was *ADCY3*, a membrane-bound enzyme that catalyses the conversion of ATP to the second messenger cAMP[301]. GWASs have identified *ADCY3* as a candidate gene for diseases such as obesity[301] and IBD[302]. *ADCY3* has been identified as a target for reQTLs in multiple studies involving stimulated blood immune cells: in PBMC 24h post-infection with rhinovirus[81], in whole blood *in vivo* day 1 after vaccination with seasonal TIV[92], and in whole blood after stimulation with *M. leprae* antigen for 26-32 h[90]. Given the diversity of stimulations and tissue types, the effect is likely a consequence of general immune activation, rather than a Pandemrix-specific response.

replace mcgov-  
ern2015GeneticsInflammatoryBowe  
with more recent

Statistical colocalisation suggests that the day 1 reQTL signal identified here is likely to be a monocyte-specific effect—and independent to the IBD signal, which colocalises with T cell and macrophage datasets. The proportion of monocytes in the PBMC increase at day 1, supported by both FACS[161] measurements, and an increase in monocyte xCell score. Expression of *ADCY3* is not monocyte-specific, as despite the increase in monocyte proportion, no upregulation is observed at day 1. Colocalisation is also not restricted to stimulated monocytes, hence the signal could be hypothesised to result simply from the increased proportion of the bulk sample taken up by monocytes, rather than a upregulation-driven increase in detection power, or a vaccine-induced activation of the locus at day 1.

add lfsr.dge

Changes in relative abundances for many cell types occur in the bulk PBMC samples after vaccination. I accounted for the effect of abundance on mean expression including xCell scores and PEER factors as fixed effects in the model, and also considered the effect of abundance on the genotype effect using interaction terms between xCell scores and genotype. Due to the modest sample size, and computational requirements for `lme4qt1`, I focused only whether reQTLs that have a detectable main effect may be driven by cell type interactions, testing only for interactions at significant lead reQTL. Compared to FACS measurements in a cohort subset, the xCell scores used above were only weakly correlated. Some discrepancy is expected, as the cell types as defined in the xCell signatures do not directly correspond to the combinations of surface markers used for FACS. The FACS gating strategy also meant that for some cell populations, the only available FACS measure was a proportion of the previously gated population, whereas xCell attempts to estimate scores that represent proportions of the whole mixture. The accuracy of the built-in signatures is lower when applied to the expression matrix for a stimulated state, likely because the enrichment-based method can not distinguish differential expression of signature genes due to stimulation from actual changes in cell abundance. Nevertheless, as assuming a single genotype where cell type-specific slopes are likely is inappropriate, so xCell scores were used as a best approximation. At 16/1154 reQTLs, the genotype effect was detected to interact with abundance of one or more of the tested cell types (or a correlated cell type). At the day 1 *ADCY3* reQTL, the genetic effect can be mainly attributed to the monocyte score-genotype interaction term, further supporting the hypothesis that it is monocyte-specific.

need to consider: if this kind of thing is what bulk *in vivo* reQTL can find, they what is the additional value over FACS?

A pressing question remains: what molecular mechanisms underlie the *ADCY3* reQTL, and indeed the remainder of the reQTLs? Power differences due to condition-specific expression are unlikely to explain a large proportion of reQTLs. As in [83, 94], the overlap between differentially expressed genes and genes with reQTL was poor, and reQTL were not more likely

dge is coupled to reql, if you do an enrichment of dge+reqtl overlap genes, likely their enrichment is driven by DGE signal

to be differentially expressed compared to genes without reQTL. One mechanism by which cis-eQTL affect expression is through their impact on **transcription factor (TF)** binding affinity to motifs in promoters and enhancers[303]. Immune cells, including monocytes, are regulated by **cell type-specific TFs**[304]. **cell type-specific expression of different TFs** have been proposed as a model for explaining **magnifying, dampening and opposite reQTL effects**; for example, opposite effects can result from **TFs** regulating the same gene, that are activating in one cell type and suppressive in another[74]. There is evidence that **TF** activity is important for *in vivo* immune reQTL: [81] found rhinovirus reQTLs in **PBMCs** were enriched in ENCODE ChIP-seq peaks for the **TFs STAT1 and STAT2**, and [94] found interferon and anti-IL6 drug reQTLs likely disrupt **ISRE** and **IRF4** binding motifs. Rather than condition-specific expression of the eGene, what may be condition-specific is the expression of **TFs** whose activity is affected by the reQTL\*.

Finally, I address the prospect that common genetic variation may explain some variation in antibody response to Pandemrix. I have indirectly demonstrated genotype-dependent effects on expression response by identifying reQTLs with differing effect size between timepoints, but have not yet determined resulting genotype-dependent differences in antibody phenotypes. Some of the identified reQTLs will undoubtedly affect genes whose expression or post-vaccination expression change correlates with antibody response, but correlation is not transitive[305], and a formal tests such as the **CIT**[257] are required to distinguish mediation of genotype-antibody associations through gene expression from competing models. [92] realised this, but concluded that they had insufficient power with a greater sample size and comparable study design to **HIRD**. The **HIRD** cohort is also too small for a direct **GWAS** of Pandemrix antibody response. A suitable approach for prioritising reQTL that contribute to the antibody response to Pandemrix will be to leverage external genetic associations to similar phenotypes, for example, colocalisation with existing GWAS summary statistics for antibody response to a similar type of adjuvanted, inactivated vaccine.

harmonise terminology  
for 'opposite'

check "rs2223286 is associated with profound directional effects in the expression of SELL dependent upon genotype, with the minor C allele associated with increased expression of SELL in B-cells and reduced expression of SELL in monocytes "

note coloc doesn't distinguish pleiotropy from mediation?

add 1 concluding line

Overall I feel like the chapter is too descriptive, and falls short of making biological insights into Pandemrix response. Any additional analyses would hope to address that.

\*A cursory scan of **TF** motifs disrupted by the location of the fine-mapped *ADCY3* reQTL intronic variant rs13407913 on <https://ccg.epfl.ch/snp2tfbs/snpviewer.php>, does indeed show several motifs (for NR2C2, HNF4A, HNF4G, NR2F1) where the PWM score is higher for the ALT allele, consistent with the direction of effect for the day 1 reQTL.

## Chapter 4

# Transcriptomic associations with anti-TNF drug response in Crohn's disease patients

### 4.1 Introduction

#### 4.1.1 Crohn's disease and inflammatory bowel disease

Crohn's disease (CD) is a chronic, inflammatory disease of the gastrointestinal tract. It is characterised by patchy inflammation, where lesions are interspersed with regions of normal mucosa. The lesions can be distributed anywhere in the gastrointestinal tract, and tend to be transmural, affecting all layers of the gut wall.

difficult to separate out CD from IBD in literature, section probably needs to decide to focus on CD only or IBD.

CD is one of the two main forms of inflammatory bowel disease (IBD). The second form, ulcerative colitis (UC), is characterised by continuous inflammation, with lesions that are superficial rather than transmural, and restricted to the colon [306]. Whilst the two are distinct forms of IBD, similarities in clinical presentation, available therapies, and genetic architecture mean CD and UC have often been studied together. Both are immune-mediated inflammatory diseases (IMIDs), a group of related diseases involving immune dysregulation of common inflammatory pathways. Other IMIDs include type 1 diabetes (T1D), systemic lupus erythematosus (SLE), rheumatoid arthritis (RA), multiple sclerosis (MS), and psoriasis [307, 308].

Pathogenesis of CD is not completely understood, but involves interaction of the immune system, environmental factors (e.g. smoking, stress, diet [306, 309]), and gut microbial factors in a genetically-susceptible individual [310]. Since the seminal discovery by linkage analysis in 2001 that genetic variation in *NOD2* was linked to CD risk [311], much progress has been made in establishing the disease's genetic architecture. The most recent genome-wide association study (GWAS) studies catalogue over 240 risk loci for IBD [176]. Most associations are shared between CD and UC, with some heterogeneity of effects, such as *NOD2* being more strongly linked to CD risk [312, 313].

CD has historically been considered a disease of the Western world. The highest prevalence and incidence of new cases of CD are in North America and western Europe [306], although disease burden is now rising in newly industrialised countries in Asia, Africa and South America

[314, 315]. The modal age of onset is typically between late adolescence and early adulthood. The disease is progressive: within 20 years of diagnosis, 50% of patients with CD will develop gastrointestinal tract complications and approximately 15% require surgical intervention [306]. Given the rising prevalence and large impact on quality of life, there is active research into developing treatment regimes with the goal of inducing complete mucosal healing [306, 316].

#### 4.1.2 Anti-TNF therapies for Crohn's disease

the subsection on anti-TNFs in the intro chapter may be merged here

Tumour necrosis factor (TNF), also known by the archaic name TNF- $\alpha$ , is a proinflammatory cytokine produced mainly by immune cells such as monocytes, macrophages, natural killer (NK) cells, T cells, and B cells. It is synthesised in transmembrane form, then enzymatically cleaved into its soluble form. TNF binds to receptors TNFR1 and TNFR2; most cells in the body express one receptor or the other. Binding triggers a signalling cascade that in different contexts, regulates inflammation, apoptosis, cell proliferation, and cell survival [317–319]. In the context of IBD pathogenesis, current models suggest high TNF levels promote apoptosis of monocytes, macrophages, and gut epithelial cells via TNFR1, while inhibiting apoptosis of mucosal CD4 $^{+}$  T cells via TNFR2 [316, 319, 320], contributing to maintained gut inflammation.

The development of anti-TNF biologic therapy has revolutionised CD patient care in the last two decades. Infliximab and adalimumab are the two major drugs approved for treatment of CD, UC, and a number of other IMIDs. Both are IgG1 monoclonal antibodies that bind soluble and transmembrane TNF to inhibit interactions with its receptors [320, 321]. Two main mechanisms for their action have been proposed: induction of CD4 $^{+}$  cell apoptosis in the gut mucosa by inhibiting the TNF-TNFR2 interaction; and binding of the antibody tail (Fc) region of the antibody to Fc receptors on monocytes, inducing their differentiation into wound-healing M2 macrophages [316].

Adalimumab is a human antibody, typically administered subcutaneously via auto-injector pen, with two initial doses aimed to induce remission, then a dose every two weeks to maintain remission. Infliximab is a chimeric mouse-human antibody administered via intravenous infusion, with a three-dose induction and a dose every eight weeks for maintenance [320]. Anti-TNF biologics are among the drugs with the highest global spendings; adalimumab and infliximab ranked first and fourth respectively in 2017, with an estimated combined spending of 29 billion USD [322].

I assume dosing follows the induction and maintenance schedule from [320]. Can't find anything about it in the PANTS protocol, although Sim confirmed the 2w/8w frequencies.

#### 4.1.3 Anti-TNF treatment failure

Despite the expense, anti-TNF therapy is not always effective at treating CD. Various types of treatment failure can occur: primary non-response (PNR) within the induction period (the first 12–14 weeks for adalimumab and infliximab), developing secondary loss of response (LOR) during maintenance after an initial response, failure to achieve remission after the treatment course, and adverse events that lead to treatment stoppage [323]. For IBD patients, the incidence of PNR is 10–40%, and the incidence of secondary LOR is 24–46% in the first year of treatment [324–326]. Another factor affecting treatment outcome is immunogenicity, the generation of antibodies against the drug, thought to increase the probability of treatment failure by increasing drug clearance rate [321, 326]. As a chimeric antibody, infliximab is more immunogenic than

adalimumab [326, 327]. Although remission with complete mucosal healing is the gold standard for successful treatment [306], PNR and LOR can be defined much earlier in the treatment course, and help guide changes in treatment such as dose intensification or switching to a drug class with a different mechanism of action [321, 324].

Anti-TNF biologics are near the top of the therapeutic pyramid for CD, among the treatment options with the highest toxicity and costs [328]. The traditional approach to disease management is “step-up”, beginning at the bottom of the pyramid with steroids [320]. This may undertreat patients that require more aggressive therapy, allowing the disease time to progress. An inverted approach begins at biologic therapies, then steps-down the pyramid if possible. This risks exposing patients to aggressive therapies they may not have needed [325]. The best approach would be to predict whether a particular treatment will be required and effective for a patient, especially given the costliness and patient risks associated with therapies near the top of the pyramid. Baseline prediction would be especially valuable for stratifying patients to specific therapies.

#### 4.1.4 Predicting response to anti-TNFs

Clinical variables reported to have association to anti-TNF response include age, disease duration, body mass index (BMI), smoking, C-reactive protein (CRP), faecal calprotectin, serum drug concentrations, and anti-drug antibody concentrations. These have mostly been found in small retrospective cohorts, and have rarely been independently validated [319, 325, 329–332]. In the Personalised Anti-TNF Therapy in Crohn’s Disease (PANTS) study, the largest study of infliximab and adalimumab response in CD patients to date (n=1610), baseline obesity, smoking, and greater disease activity were associated with low serum drug concentration after induction. Low drug concentration was in turn associated with PNR and non-remission, suggesting immunogenicity may be mediating treatment failure [326].

Studies have looked for transcriptomic predictors for anti-TNF response [319, 332]. In gut biopsies, expression of sets of “signature” genes were found to be predictive of mucosal healing after infliximab treatment in cohorts of UC (*TNFRSF11B*, *STC1*, *PTGS2*, *IL13RA2*, *IL11*; n=46 [333]) and CD patients (*TNFAIP6*, *S100A8*, *IL11*, *G0S2*, *S100A9*; n=19 [334]). Expression of *OSM* was associated with anti-TNF response defined by improved Mayo score, a multiparameter clinical score of UC activity (n=227) [335]. Most recently, single-cell RNA-sequencing (RNA-seq) identified a module of IgG plasma cells, inflammatory mononuclear phagocytes, activated T cells, and stromal cells associated with clinical remission after anti-TNF therapy in two separate CD cohorts (total n=340) [336].

As obtaining blood samples is non-invasive, there has been great interest in finding transcriptomic predictors of response in blood. While blood is not the disease-relevant tissue for CD, many genes in gut biopsy signatures have high expression in infiltrating immune cells, and blood gene expression may capture the precursors of those cells [337]. Blood *TREM1* expression has been identified as a marker of anti-TNF response in two studies with inconsistent directions of effect. Gaujoux *et al.* [337] defined response based on “clinical and/or endoscopic improvement”. *TREM1* expression was lower in infliximab responders in gut biopsies (total n=72), but higher in responders in a separate cohort measuring whole blood expression (n=22). Verstockt *et al.* [338]

defined response based on endoscopic remission, reporting *TREM1* to be a marker of response with lower expression in responders to infliximab and adalimumab in both gut biopsies and blood. Proposed reasons for the discrepancy include small sample sizes, patient ethnicity, and different definitions of response <https://pubmed.ncbi.nlm.nih.gov/30007919/> [319].

Attempts have been made to find genetic markers for response, as they are baseline by definition, and may also help form mechanistic hypotheses of treatment response. Anti-TNF response does not necessarily share the same genetic architecture as disease risk. Variants in TNF-regulated genes that are also associated with IBD risk (*NOD2*, *TNFR1*, *TNFR2*) are not associated with response to infliximab [319, 332]. A number of candidate gene studies found single nucleotide polymorphism (SNP) associations with response in genes such as apoptosis-related Fas ligand and caspase-9 that have yet to be validated [325, 339]. Recently, larger cohorts have enabled GWASs of anti-TNF response in IBD. In PANTS, although no associations to PNR were genome-wide significant\*, HLA-DQA1\*05 carriage was associated with higher anti-drug antibody levels [340], which may mediate related phenotypes such as LOR.

Overall, small sample sizes and variation in analysis methods, anti-TNF drug, response definition, tissues sampled, and disease among studies make a consensus hard to establish. No algorithms using clinical, transcriptomic, or genetic markers for predicting IBD patient response to anti-TNF therapy have yet been translated to clinical practice, although several are currently undergoing validation [332].

#### 4.1.5 Chapter summary

This chapter focuses on identifying novel transcriptomic associations with anti-TNF primary response in a subset of the PANTS cohort with longitudinal RNA-seq data from the first year of follow-up. I model differential gene expression (DGE) between primary responders and non-responders at the gene and module-level at baseline (week 0), post-induction (week 14), and during maintenance (week 30 and week 54). As this is one of the largest datasets currently available for assessing transcriptomic associations with anti-TNF response in IBD, I attempt to validate and resolve conflicts in the literature for previously identified transcriptomic markers such as *TREM1*. Finally, I integrate existing genotype data to map response expression quantitative trait locus (reQTL) between timepoints, with the aim of identifying common genetic variants controlling expression response to anti-TNF drugs.

trying not to 'spoil' any results in the intro, I guess

## 4.2 Methods

### 4.2.1 The PANTS cohort

PANTS is a prospective, observational, UK-wide, cohort study of response to anti-TNF therapy in CD patients, described in detail by Kennedy *et al.* [326]. The study was registered with ClinicalTrials.gov identifier NCT03088449, and the protocol is available at <https://www.ibdresearch.co.uk/pants/>. Total enrollment was 1610 patients, who were at least 6 years old, had

\*

active luminal CD, and were naive to anti-TNF therapy. Patients were invited to attend up to ten major study visits over a maximum follow-up period of three years, or until drug withdrawal.

The anti-TNF drugs evaluated were adalimumab and infliximab. The study also evaluated infliximab biosimilars; data from patients who received a biosimilar is not included in this chapter. All major visits were scheduled immediately prior to a drug dose. Adalimumab and infliximab have 2-week and 8-week dosing intervals respectively, so the timing of major visits was chosen such that the same visit structure could be used for patients on either drug. Additional visits were scheduled in case of secondary LOR, or premature exit due to drug withdrawal, usually replacing the next scheduled major visit.

The overall rate of primary non-response by week 14 was 21.9% for infliximab, and 26.8% for adalimumab. The rate of secondary LOR by week 54 among primary responders was 36.9% for infliximab and 34.1% for adalimumab. Remission rate by week 54 was 39.1% for infliximab and 33.1% for adalimumab.

#### 4.2.2 Definition of timepoints

The RNA-seq data for this chapter comes from a subset of the cohort sampled around four timepoints: week 0, week 14, week 30, and week 54. These are the target timings for four major visits in the first year of follow-up. Whole blood samples were taken prior to the scheduled drug dose and preserved for RNA-seq in Tempus Blood RNA Tubes. The study day that sampling occurred relative to the first drug dose was recorded.

To measure the transcriptome at trough drug levels, I mapped samples from major and additional visits to four timepoints centered around the four major visits. As it could not be guaranteed that visits occurred on the exact day specified in the protocol, I considered the visit windows defined by Kennedy *et al.* [326]: week 0 (week -4–0), week 14 (week 10–20), week 30 (week 22–38), and week 54 (week 42–66). Samples were mapped according to the following criteria:

- Major visit samples were mapped to the corresponding timepoint, regardless of whether they fell within the corresponding window i.e. an available week 0 sample is always mapped to the week 0 timepoint.
- Samples taken at additional LOR or exit visits falling within one of the windows were mapped to that timepoint, unless the patient also had a major visit sample inside that window.

Only a small minority of major visit samples fell outside their corresponding windows. Inclusion of samples from additional visits was important as they often replaced major visits for patients with primary non-response or LOR. Samples included under both criteria should be representative of trough drug levels, as major visits and LOR visits were always scheduled prior to a drug dose, and exit visits were scheduled for when the next drug dose would have been.

compute maximum deviation?

Still discussing with Sim on the exact def of LOR and exit visits to decide whether this is sensible.

#### 4.2.3 Definition of primary response and non-response

The definition of primary response and non-response was based on the clinical decision tree from Kennedy *et al.* [326]. Primary response status was assessed at week 12, prior to the scheduled

week 14 visit. The criteria for primary non-response was *either* of the following:

- exit for treatment failure before week 14 (e.g. as decided by physician global assessment), *or* corticosteroid use at week 14 (a continuing or new prescription);
- compared to week 0, a decrease in **CRP** by less than 50% or to  $>3 \text{ mg l}^{-1}$ , *and* a decrease in **Harvey Bradshaw index (HBI)** by less than 3 points or to  $>4$ .

As **PANTS** was an observational study that continued until drug withdrawal, a patient's clinician may have decided to continue anti-**TNF** therapy even if a patient had primary non-response, so it was possible for non-responders to be sampled past week 14.

The criteria for primary response was *all* of the following:

- not classified as a primary non-responder;
- **CRP**  $\leq 3 \text{ mg l}^{-1}$  by week 14;
- **HBI**  $< 4$  by week 14.

Grey zone patients that only met a subset of criteria for either primary response or non-response were excluded.

There were additional inclusion criteria applicable to just the **RNA-seq** subcohort. Patients were required to be at least 16 years old, and have an available baseline serum sample. Primary non-responders were filtered to exclude patients in remission at week 54.

#### 4.2.4 Library preparation and RNA-seq

Total RNA was extracted following the Qiagen QIAsymphony instrument protocol (RNA Isolation PAX RNA CR22332 ID 2915). RNA was quantified with the ThermoFisher QuBit BR RNA (Q10211), and RNA integrity assessed with the Agilent RNA ScreenTape assay (5067-5579, 5067-5577, 5067-5576) on the Agilent 4200 TapeStation.

Library preparation was done using the Kapa mRNA HyperPrep Kit, including enrichment for mRNA using magnetic oligo-dT beads, depletion of rRNA and globin mRNA using the QIAseq FastSelect RNA Removal Kit, and adapter ligation with IDT xGEN Dual Index UMI adapters. Libraries were sequenced on the Illumina HiSeq 4000 with 75bp paired-end reads.

#### 4.2.5 RNaseq quantification and preprocessing

A total of 1141 samples were initially sequenced. Sequencing data was demultiplexed with Picard. Reads were mapped to GRCh38 using STAR (2.6.1d) and deduplicated to unique reads using UMI-tools. Gene expression was quantified against the Ensembl 96 gene annotation with featureCounts (1.6.4).

Total number of read pairs, sequence quality, overrepresented sequences, adapter content and sequence duplication rates were checked using FastQC. Samples were filtered to remove outliers ( $>2$  standard deviations from the mean) according to percentage of aligned reads in coding regions reported by Picard, percentage of unique reads, and number of unique reads. Samples that could not be mapped to a timepoint according to subsection 4.2.2 were removed.

Samples that came from patients with sex mismatch grey zone primary response, or missing data for variables considered in the variable selection process (subsubsection 4.2.6.1), were removed. A total of 814 samples remained after filtering.

The Ensembl 96 gene annotation contains 58 884 genes, many of which are not expressed in whole blood. Effective library sizes were computed using `edgeR::calcNormFactors(method='TMM')`. Between-sample normalisation for library size was done using `edgeR::cpm`, converting counts to **counts per million (CPM)**. Genes with low expression were filtered, requiring >1.25 CPM in >10% of samples (1.25 CPM was approximately 10 counts at the median library size of 8 million assigned read pairs), and non-zero expression in >90% of samples. Globin genes and short ncRNAs were removed. A total of 15511 genes remained after filtering. Finally, **CPMs** were converted to the  $\log_2$  scale, and precision weights to account for the expression mean-variance relationship were computed for each gene and sample using `limma::voomWithDreamWeights`.

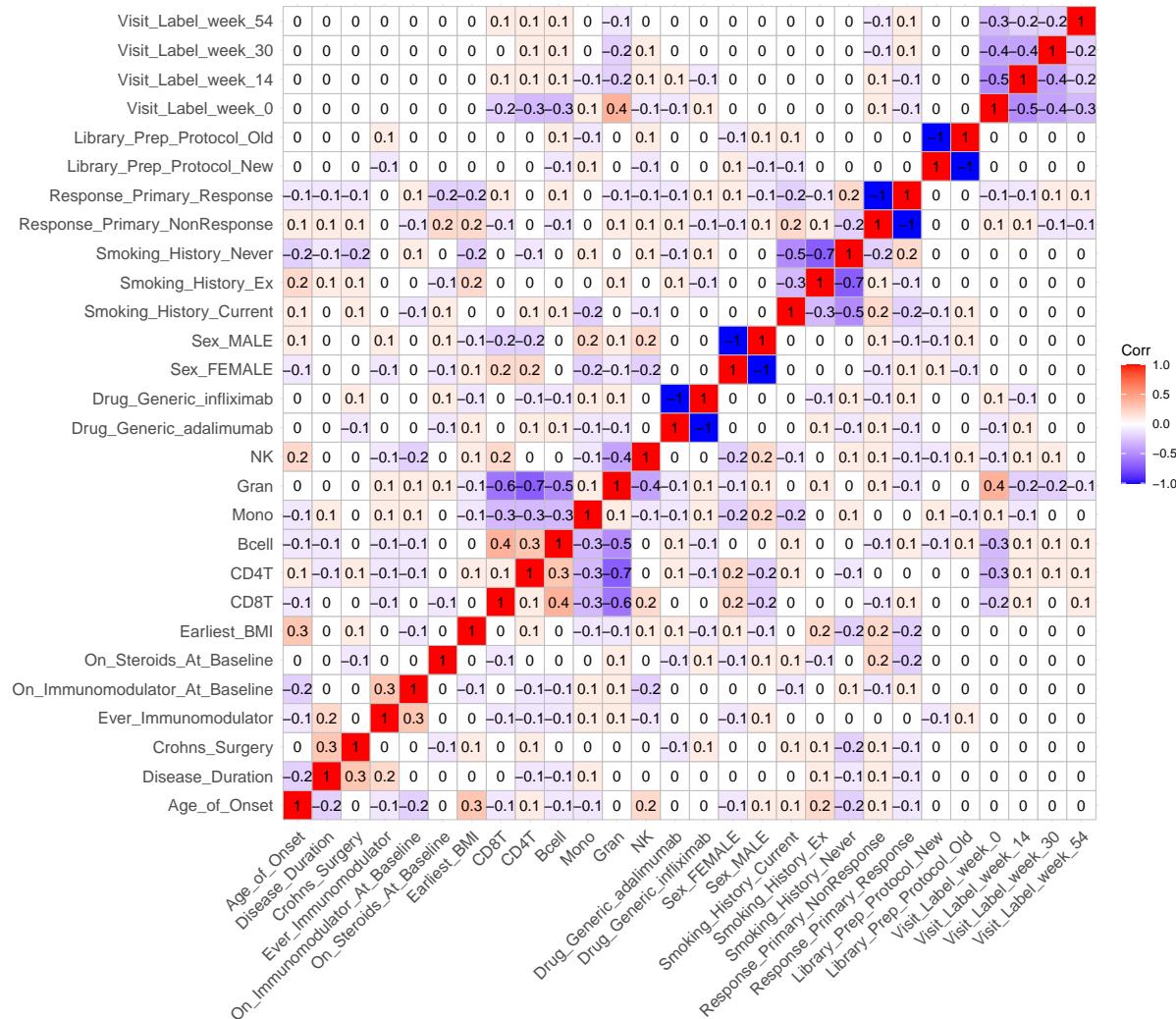
## 4.2.6 Differential gene expression

### 4.2.6.1 Variable selection by variance components analysis

For each gene, the **DGE** model was a regression expressing the response variable, gene expression, as a linear function of predictor variables of interest (primary response status, drug, timepoint), and other selected predictor variables. In estimating the association  $X \rightarrow Y$ , of predictor X to response Y by regression, adjustment for a third variable Z can increase, decrease, or even reverse the effect estimate (the regression coefficient). I aimed to select third variables for inclusion into the **DGE** model that were covariates, defined here as a Z that is associated with Y, but not with X. Such variables are also known as neutral controls [341], precision variables, or prognostic variables. At the cost of 1 **degree of freedom (df)**, Z explains variation in Y that would otherwise be considered residual, so conditioning on Z increases the efficiency of estimating  $X \rightarrow Y$ , but does not change the effect estimate.

Many variables were available for selection; Figure 4.1 shows their correlation matrix. These included three variables associated with primary response in Kennedy *et al.* [326]: baseline immunomodulator use, smoking and **BMI**. Also available were proportions of six common cell types in whole blood ( $CD4^+$  T cells,  $CD8^+$  T cells, B cells, **NK** cells, monocytes, granulocytes), estimated using the Houseman method (`minfi::estimateCellCounts` <https://academic.oup.com/bioinformatics/article/30/10/1363/267584>) from whole blood Illumina MethylationEPIC data collected from the same patients and timepoints. The Houseman method uses differentially methylated regions between immune cell types as cell type markers <https://bmcbioinformatics.biomedcentral.com/articles/10.1186/1471-2105-13-86>.

A variance components analysis was done to quantify the proportion of expression variance explained by each variable for each gene using `variancePartition` [342]. Variables that do not explain much variation in the response are unlikely to improve efficiency if conditioned on. The model was a mixed effects regression model with variables in Figure 4.1 included as predictors. Additional categorical variables were included for patient and **RNA-seq** library preparation plate. An additional continuous variable consisting of random numbers drawn from the standard normal distribution was also included as a null. Granulocyte proportion estimates were dropped



**Figure 4.1:** Correlation matrix of variables measured in PANTS that were considered as potential independent variables.

to relieve perfect multicollinearity. Categorical variables were coded as random intercepts, and continuous variables as fixed effects. Surprisingly, simulations from Hoffman *et al.* [342] showed variance proportion estimates were unbiased even when coding categorical variables with as few as two categories as random, as long as model parameters were estimated using **maximum likelihood (ML)** rather than **restricted maximum likelihood (REML)**, which is commonly used for variance components analysis. It was also shown this approach avoids overestimates of variance proportions that occur if categorical variables with many levels are treated as fixed.

As downstream **DGE** methods require the same set of predictors for all genes, the aim was to select variables that explain a lot of variance for many genes. Variables were ordered by the median of gene-wise variance proportion estimates ([Figure 4.2](#)). Variables that explained the most variance on average were patient, cell proportions and **RNA-seq** plate. Some variables that did not explain more variance on average than the null nevertheless had high maximum values, indicating their importance for a relatively small number of genes. These included sex, library preparation protocol version, and smoking status, but also primary response status, a variable of interest, so it was difficult to justify excluding all variables with lower median variance explained than the null. Thus all non-null variables in [Figure 4.2](#) were selected as predictors in downstream models apart from “Ever\_Immunomodulator” (whether the patient had ever had immunomodulator treatment), as that had both low median variance explained and was correlated with baseline immunomodulator use. This is a crude approach, but the sample size is large compared to number of **df** lost by including predictors that may not be relevant for some genes.

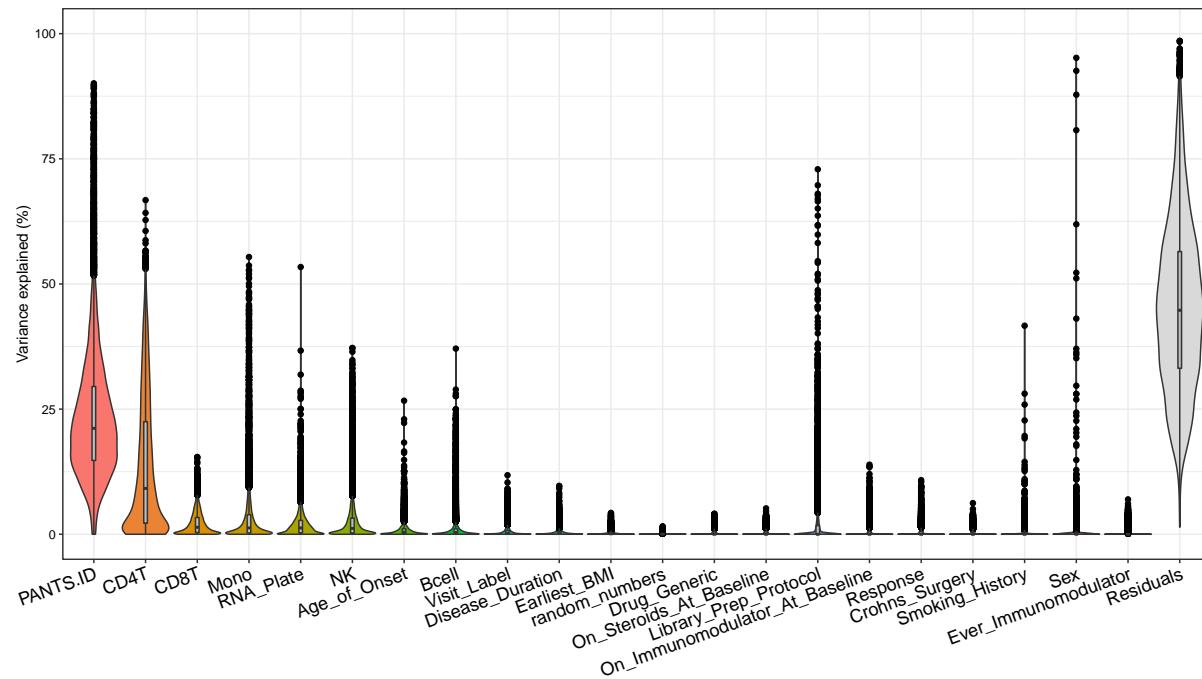
How are interpretations of effect sizes of interest be affected by including this suite of other variables, all of which can be considered as third variables? If a third variable Z is not a precision variable, but is also associated with X, conditioning changes the effect estimate. The regression model is mathematically agnostic to causal relationships between variables, but distinct types of third variable can be distinguished conceptually by assuming the direction of causal relationships <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2819361/>. Conditioning on a confounder ( $X \leftarrow Z \rightarrow Y$ ) reduces bias of the effect estimate, conditioning on a collider ( $X \rightarrow Z \leftarrow Y$ ) induces bias, and conditioning on a mediator in the causal path ( $X \rightarrow Z \rightarrow Y$ ) changes the effect estimated by removing the indirect effect mediated by Z, usually biasing the effect estimate towards zero\*. The major influence I consider in this chapter is adjusting for cell proportions. From the variance partition analysis ([Figure 4.2](#)), cell proportions were among the biological factors that explained the most variance on average. I have not systematically assessed what types of third variable other selected predictors may act as.

The assumed causal relationship is response → cell proportion → expression, where cell proportion mediates the association between response and expression †. I fit separate **DGE** models including and excluding cell proportions as predictors, but otherwise identical. These have complementary interpretations. In models without cell proportions, the effect size of response status could represent up or downregulation on a per cell basis, but could also come from

The observational study design does not allow straightforward estimation of causal effects, so this is only assumed

\*It is not easy to determine the direction of bias (positive or negative) for any of these cases in general <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7064555/>.

†The assumption in the **DGE** model that response status is an intrinsic property of a patient that is causally upstream will be discussed in [chapter 5](#).



**Figure 4.2:** Variance partition analysis showing distribution of gene-wise percentage of variance in expression explained by each variable. “PANTS.ID” is patient ID.

differences in cell proportions in the bulk samples associated with response. The estimates from models adjusted for cell proportions are more likely to reflect up or downregulation on a per cell basis.

Could cell proportions act as colliders?

#### 4.2.6.2 Contrasts for pairwise group comparisons

gene-wise DGE models were fit in `dream` [343]. Like the variance partition model models were linear mixed models:

Expression ~  
 $0 +$   
`concat(Visit, Response, Drug) +`  
`Sex + Age_of_Onset + Disease_Duration +`  
`Smoking_History + Crohns_Surgery +`  
`On_Immunomodulator_At_Baseline +`  
`On_Steroids_At_Baseline + Earliest_BMI +`  
`[CD8T + CD4T + Bcell + Mono + NK] +`  
`Library_Prep_Proto +`  
`(1 | RNA_Plate) +`  
`(1 | Patient)`

where the response variable is expression at a particular visit; 0 indicates there is no intercept term; and `concat(Visit, Response, Drug)` is experimental group defined by combinations of the predictors of interest: visit (week 0, 14, 30, 54), response (responder, non-responder), and drug (infliximab, adalimumab). This is equivalent to a model with an intercept term and a

Alter and move this to ch2

three-way interaction between visit, response, and drug, including all lower order terms ( $1 + \text{Visit} * \text{Response} * \text{Drug}$ ), but is more convenient for testing pairwise expression differences between groups, as the coefficient for each term is the estimate of mean expression for that group. As the interest was in estimating a single coefficient for each predictor's effect size on expression (rather than estimating variance components), most predictors are modelled as fixed effects. RNA\_Plate and Patient are nuisance variables with a large number of levels, so they are modelled as random intercepts. To avoid small-sample bias in estimates of fixed effect standard errors, estimation was done with **REML** [344].

Two sets of gene-wise models were fit with and without the cell proportion terms in square brackets. Two more sets of gene-wise models were fit with drugs pooled (i.e.  $\text{concat}(\text{Visit}, \text{Response}, \text{Drug})$  replaced with  $\text{concat}(\text{Visit}, \text{Response}) + \text{Drug}$ ), but otherwise identical to the first two sets.

Specific hypotheses were tested using sum-to-zero contrasts, which are linear combinations of the model coefficients with weights summing to zero. For example, to test for **DGE** between responders and non-responders to infliximab at baseline in the non-pooled model, I used a contrast where the weight for the (week 0, responder, infliximab) group coefficient was 1, the weight for the (week 0, non-responder, infliximab) group coefficient was -1, and all other coefficient weights were 0.

To get  $p$ -values, the contrast divided by its standard error was compared to the t distribution using the Satterthwaite approximation for **df**. **False discovery rate (FDR)** control was done with the **Benjamini-Hochberg (BH)** method, computed separately for each contrast\*.

#### 4.2.6.3 Spline model of expression over time

The aim was to use expression data from all four timepoints to find genes associated with response, while avoiding a large number of pairwise comparisons. I fit a natural cubic spline (**splines::ns**) to the study day to allow for non-linear trajectories of expression over time. The natural cubic spline is a continuous function defined piecewise in each successive interval between a set of  $k$  knots in the range of the input variable. The  $k - 1$  pieces between knots are polynomials of degree 3. As a natural spline, the function is constrained to be linear outside of the boundary (first and last) knots to avoid unpredictable behaviour at the boundaries. The model form used was:

```
Expression ~
  1 +
  Primary_Response * ns(Study_Day, knots=7*c(14, 30)) +
  Drug_Generic +
  Sex + Age_of_Onset + Disease_Duration +
  Smoking_History + Crohns_Surgery +
  On_Immunomodulator_At_Baseline +
  On_Steroids_At_Baseline + Earliest_BMI +
  [CD8T + CD4T + Bcell + Mono + NK] +
  Library_Prep_Proto
```

---

\*It could also have been computed globally over all contrasts if it were necessary to have the same t-statistic threshold for statistical significance in all contrasts.

```
(1 | RNA_Plate) +
(1 | PANTS.ID)
```

Two inner knots set at week 14 and week 30, as expression is expected to change after each drug dose. To include all data to within the boundaries, the two boundary knots were set at the minimum and maximum values of study day rather than week 0 and week 54. The function `ns(Study_Day, knots=7*c(14, 30))` returns a basis matrix for the spline with 3 `df` (columns). The basis used by `ns()` is a B-spline basis which transforms the input [TODO...] [345]. Separate sets of gene-wise models were again fit with and without cell proportions.

trying to understand how exactly the B-spline basis for the natural spline works will take a few more youtube lectures...

To test for response-associated differences in the spline parameters, the predictors of interest are the three second-order interaction terms between response and the basis matrix columns. The three terms are tested jointly by F-test, and **FDR** correction was done with the **BH** method separately for each test. A significant result indicates a significant difference in the trajectory of expression over study day between responders and non-responders.

#### 4.2.6.4 Clustering expression over all timepoints

To aid in interpretation of significant spline hits from the cell proportion adjusted model, I clustered genes by their expression trajectories.

Expression data was converted to the **CPM** scale using **trimmed mean of M-values (TMM)** normalisation factors, then regressed against cell proportions. Residuals were centered and scaled per gene. A distance matrix was computed using 1 - Pearson correlation as the distance metric. Hierarchical clustering was done with complete agglomeration for inter-cluster distance (`fastcluster::hclust(method='complete')`). The optimal number of clusters was determined using the gap statistic (`factoextra::fviz_nbclust(method='gap_stat', nboot=500)`), which determines when the change in within-cluster dispersions are no longer significantly improved by increasing the number of clusters <https://rss.onlinelibrary.wiley.com/doi/epdf/10.1111/1467-9868.00293>. The hierarchical clustering tree was then cut into that number of clusters.

move this to ch2, then refer to it

#### 4.2.6.5 Rank-based gene set enrichment on gene modules

Rank-based gene set enrichment analyses were done using `tmod::tmodCERN0test` [235] and **blood transcription modules (BTMs)**, as described in [Section 2.2.10](#). For each contrast, as the t-statistics are not comparable between genes due to the use of approximate `df`, I ranked genes by the signed Z score reported by `dream`, which is a monotonic transformation of the *p*-value. Similarly, moderated F-statistics from the spline are not comparable between genes, so I used the signed F-statistic from the transformation of the *p*-value.

collab note: QC done by Alex

#### 4.2.7 Genotyping and genotype data preprocessing

Genotype data were subsetted from the post-quality control **PANTS** cohort genotypes used in Sazonovs *et al.* [340], where the preprocessing pipeline is described in full detail. These data are from whole blood samples collected into EDTA tubes at week 0 and genotyped on the Illumina CoreExome genotyping array. Pre-imputation quality control was performed as described in de Lange *et al.* [176]. Imputation was done using the Sanger Imputation Service with

the Haplotype Reference Consortium panel. Post-imputation, samples that were non-European, related (proportion identity-by-descent  $> 0.1875$ ), or were outliers in genotype missingness or heterozygosity rate were removed; SNPs that poorly imputed (INFO score  $< 0.4$ ), deviated from Hardy-Weinberg equilibrium (HWE) ( $p < 1e-10$ ), had high missingness ( $> 5\%$ ), or low minor allele frequency (MAF) ( $< 1\%$  before subsetting) were removed. 7 503 762 SNPs remained after filtering. Genotypes were converted to dosages of the non-reference allele.

I've collected the QC details here from Alex's thesis

precision for integers

#### 4.2.8 Response expression quantitative trait locus mapping

The overall strategy and methods used were largely identical to chapter 3. For each timepoint, covariates for the expression quantitative trait locus (eQTL) models were computed, eQTLs were mapped separately for each timepoint, followed by joint mapping using summary statistics from all timepoints to call reQTLs.

much of this section is brief, since the same pipeline as ch3

##### 4.2.8.1 Computing genotype PCs

Samples were projected onto principal components (PCs) defined by 1000 Genomes Project samples using SNP weights from akt, confirming that samples were of European ancestry (Figure 4.3). The first four PCs in the 1000G genotype data were found to be significant according to the Tracy-Widom test in subsection 2.2.5. Here I chose the first five PCs for use downstream; the specific number is not important, as long as a sufficient number of PCs are included to capture large-scale population structure [180]. PCs were centered and scaled before downstream use to improve model convergence.

##### 4.2.8.2 Finding hidden confounders in expression data

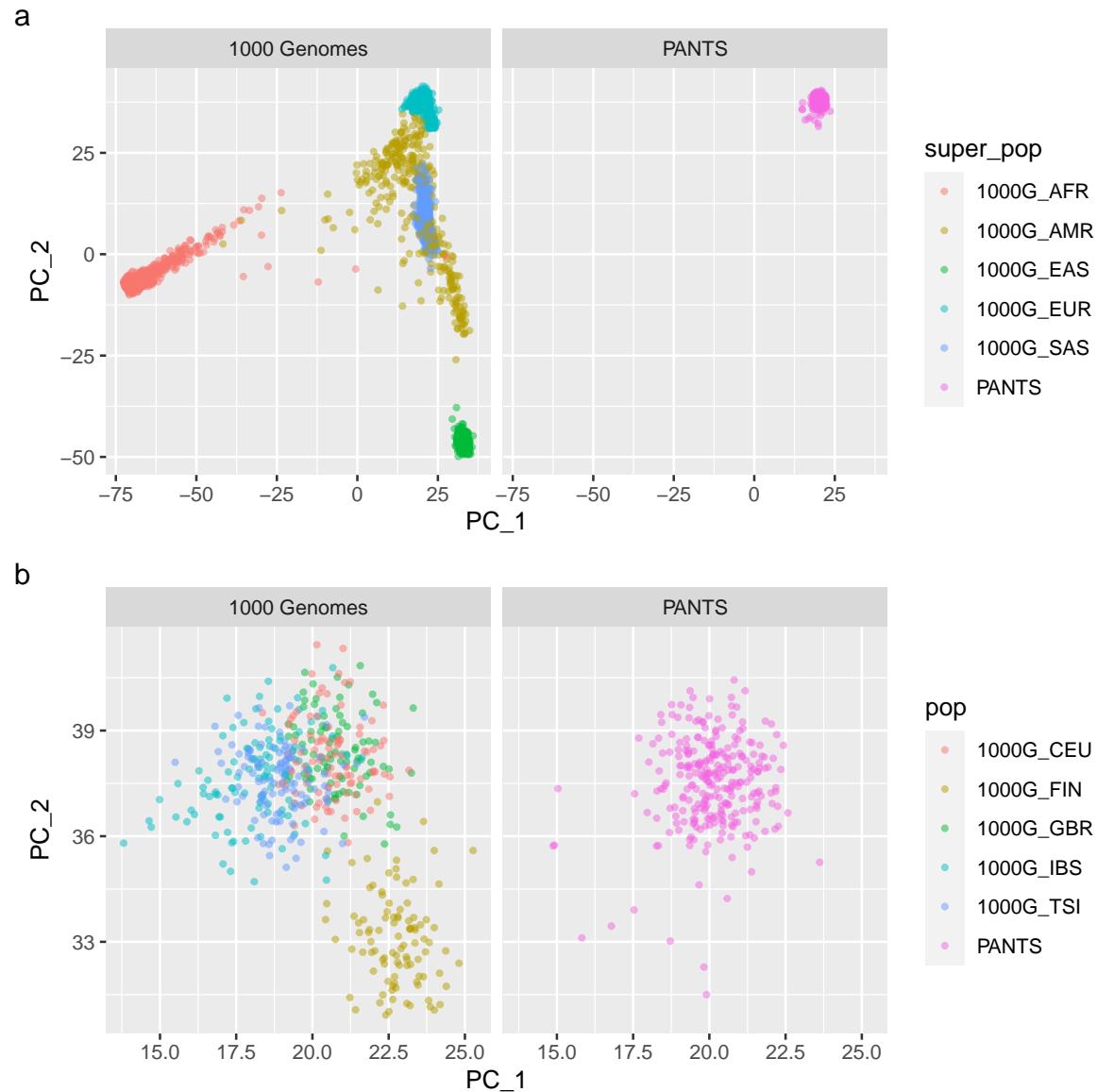
Between-sample normalisation and variance stabilisation was applied to the counts matrix (DESeq2::vst), resulting in log2 scale expression estimates. Given known factors (response, drug, five scaled genotype PCs, cell proportions), PEER was used to find additional hidden factors that explain variance in the expression matrix for a large fraction of genes. This is similar to the process undertaken in subsubsection 4.2.6.1, but these hidden factors can be unmeasured. To maximise efficiency for cis-eQTL mapping, the number of PEER factors retained for each timepoint was selected to maximise the number of genes with at least one significant eQTL detected on chromosome 1 (Figure 4.4). The selected numbers were 25, 20, 15, and 5 for weeks 0, 14, 30, and 54.

##### 4.2.8.3 Computing kinship matrices

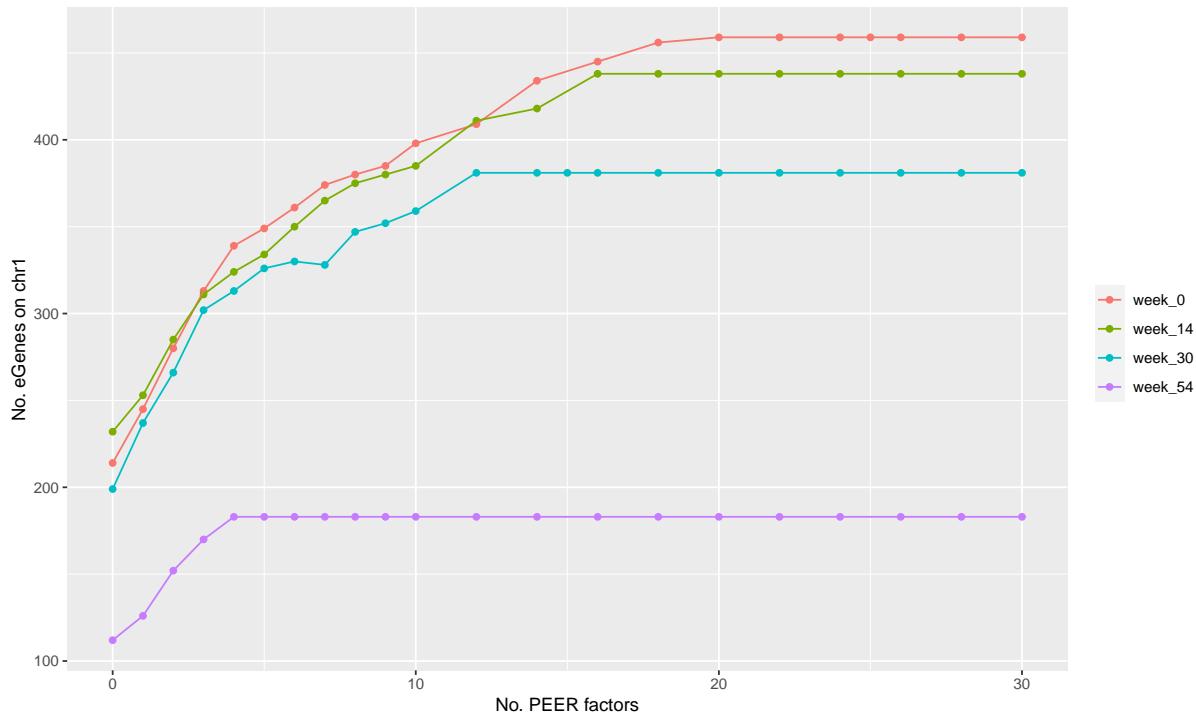
Leave-one-chromosome-out (LOCO) kinship matrices were computed on typed SNPs for each chromosome using LDAK as described in subsubsection 3.2.3.1. The kinship matrix will be incorporated into the eQTL model to adjust for fine-scale population structure.

##### 4.2.8.4 Mapping cis-eQTLs in each timepoint separately

eQTLs were mapped in each timepoint using a linear mixed model in limix. Within each timepoint, patients with multiple samples (taken on different study days) had the non-major



**Figure 4.3:** 1000G samples and PANTS samples projected onto 1000G genotype PC1 and PC2 axes, colored by superpopulation (a) and population (b).



**Figure 4.4:** Number of eGenes on chr1 vs number of PEER factors included in eQTL mapping. The number of PEER factors for each timepoint is chosen after the plateaus.

visit sample removed. Although the eQTL model form does not prohibit duplicate samples, it led to strange behaviour in limix where eQTL betas and standard errors were comparable to the deduplicated results, but log-likelihood estimates were abnormally high. The deduplicated sample sizes at weeks 0, 14, 30 and 54 were 223, 205, 167, and 84.

For each autosomal gene, cis-SNPs within 1 Mb of the Ensembl gene start (gene end on the minus strand), were filtered to keep SNPs where the number of samples in the smallest dosage group was at least 5. Small group numbers lead to data points with high leverage that may be unduly influential on the genotype beta. This is done in place of a per-timepoint MAF or minor allele count filters.

The limix model for each SNP-gene pair had log2 expression as the response variable and genotype dosage as the predictor of interest. Other fixed effect predictors were the intercept, known factors (response, drug, five scaled genotype PCs, cell proportions), and PEER hidden factors (timepoint-specific number selected above). A random intercept term was also included with mean zero and covariance matrix proportional to the LOCO kinship matrix for the SNP's chromosome.

#### 4.2.8.5 Joint reQTLs mapping over all timepoints

Summary statistics from per-timepoint mapping were input to `mashr` [268]. A total of 25 908 527 SNPs were tested in all timepoints. The null correlation structure of the timepoints was estimated using null tests within a random subset of 200 000. Data-driven covariance matrices representing patterns of effects across timepoints were estimated using a strong subset of 129 002 eQTLs. The strong subset should contain eQTL that are likely to have an effect in at least

as with most of this section, this is more explained in ch3

one timepoint. For each gene and timepoint, I selected the **eQTL** with the smallest *p*-value, if that *p*-value was  $< 0.05$ . The mash model was fit on the full random subset, accounting for the computed null correlation and covariance matrices, in exchangeable Z-scores mode. Finally, posterior betas and standard errors were computed for all tests using the fitted model parameters. A corresponding **local false sign rate (lfsr)** is also returned, controlling for multiple testing.

The lead **eQTL** for each gene was chosen as the **eQTL** with the lowest **lfsr** in any condition, breaking ties by highest INFO, highest **MAF**, shortest dist to gene start (or end), and smallest genomic coordinate. Each lead **eQTL** was assessed for being a significant **reQTL** by a Z test for whether the difference in betas was zero, between the week 0 beta and each of the other three weeks. Multiple testing for the number of genes was controlled using the **BH FDR** for each of the three comparisons separately.

## 4.3 Results

what to put in results vs discussion. going with the pattern of providing enough info for the reader to interpret the data in the results, then doing a summary and my own interpretation in the discussion

Some primary non-responders have loss of response samples. Not sure why.

add caption and label after finalising table data

### 4.3.1 Longitudinal RNA-seq data from the PANTS cohort

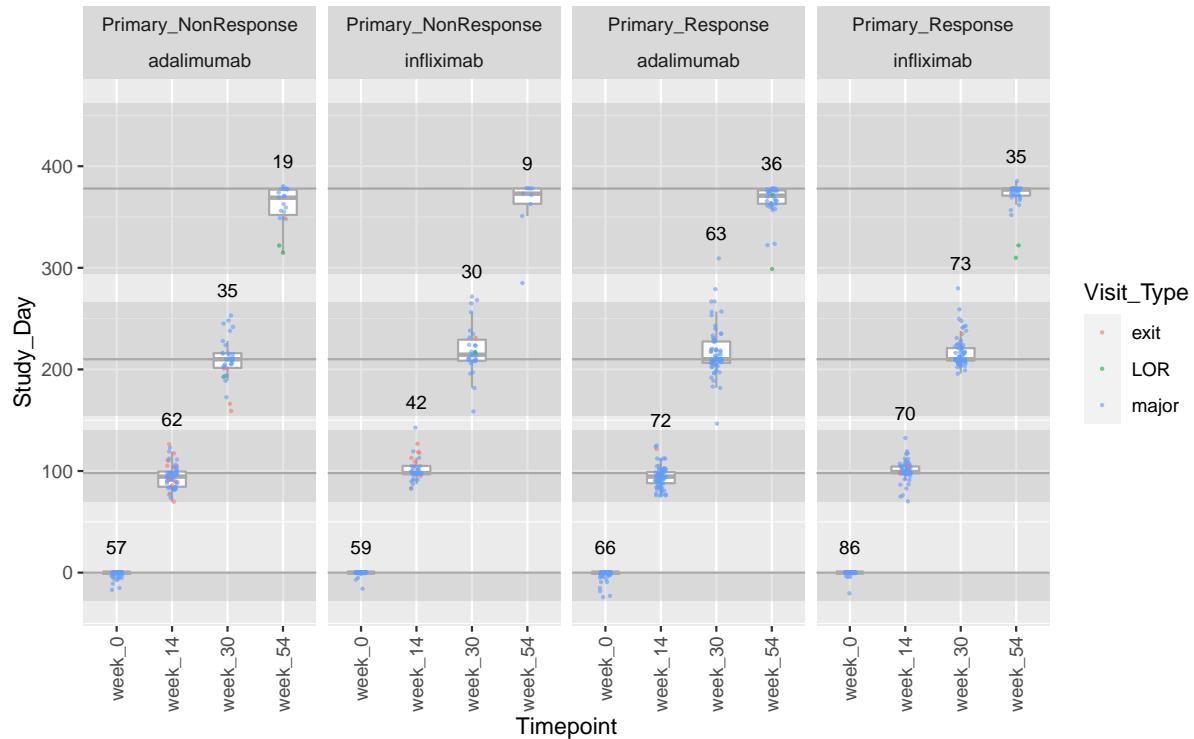
To define transcriptomic differences between primary responders and non-responders to anti-TNF therapy in the **PANTS** cohort, I analysed whole blood **RNA-seq** gene expression measured at up to four timepoints per patient: week 0 baseline before commencing anti-TNF therapy, and weeks 14, 30 and 54 after commencing anti-TNF therapy. After quality control, expression data was available for 15584 genes and 814 samples (Figure 4.5). These samples came from 324 patients, with a median of three samples per patient (Figure 4.6).

Patient characteristics are shown in Table 4.1. The proportion of primary non-responders is high (43.8%) compared to the overall proportion in the **PANTS** cohort (23.8%, [326]). This is due to sample selection for **RNA-seq** to balance the sample size for each combination of drug and primary response status.

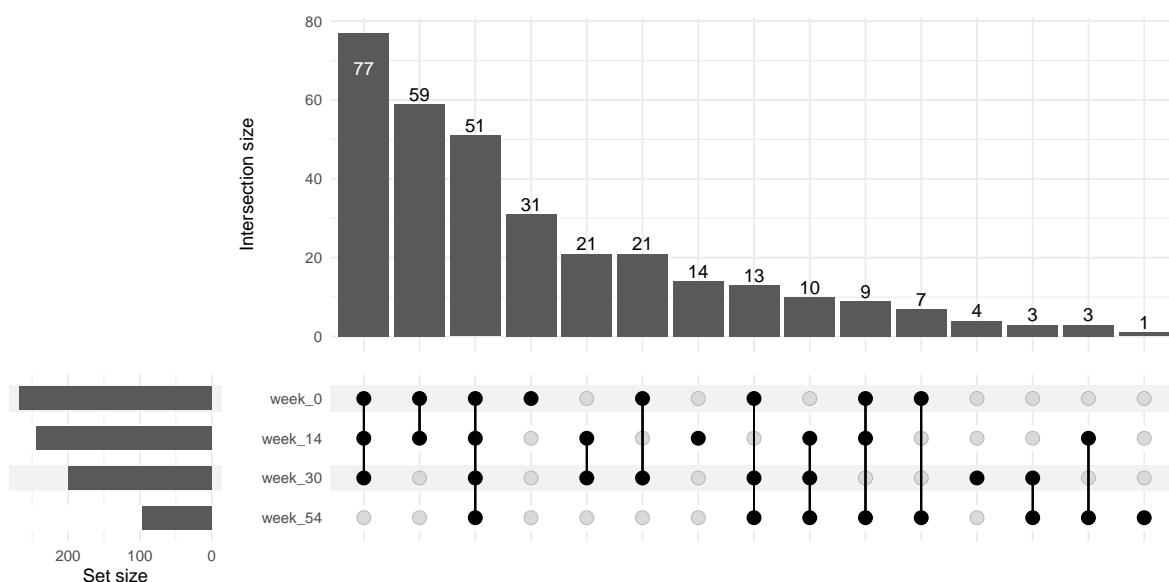
### 4.3.2 Baseline gene expression associated with primary response

Patient primary response to anti-TNF was defined after the induction period (week 12–14) according to the clinical decision algorithm from Kennedy *et al.* [326] described in subsection 4.2.3, which integrates clinician assessment with change in **CRP** level and **HBI** score. To identify differences in baseline gene expression associated with future primary response, I fit gene-wise linear models at 15511 genes, comparing week 0 gene expression in primary responders with primary non-responders. Comparisons were performed both within infliximab-only and adalimumab-only subgroups, and with both drugs pooled. Models were run both adjusting for cell composition estimates of six immune cell types, and without adjustment. Throughout this section, the significance threshold was set at  $FDR < 0.05$  for each comparison, and positive logFCs indicate increased expression in responders versus non-responders.

Without adjusting for cell composition, the largest effects were infliximab-only, with 859 genes differentially expressed. Only *KCNN3* ( $\log_2 FC = -0.84$ ) was significant for the adalimumab-only comparison, and only *SIGLEC10* ( $\log_2 FC = 0.35$ ) was significant in the pooled analysis (Figure 4.7).



**Figure 4.5:** Number and distribution of RNA-seq samples in experimental groups over time. Windows for the four major visits are colored in grey. Samples mostly come from major visits, but a small number of LOR and exit visit samples were included according to subsection 4.2.2.



**Figure 4.6:** Distribution of RNA-seq samples from each patient among timepoints.

After adjustment for cell composition, there were no longer any significant genes in the infliximab-only analysis, with 856/859 genes that were significant before the comparison having a dampened effect size after correction (smaller absolute effect and same sign), suggesting many effects may be mediated by cell composition. *SIGLEC10* in the combined analysis was also non-significant after adjustment (adjusted log<sub>2</sub>FC=0.31, FDR=0.05). Conversely, at three genes downregulated in the adalimumab-only analysis that were the only significant genes post-adjustment, I observed increased significance: *PDIA5* (unadjusted log<sub>2</sub>FC=−0.33, adjusted log<sub>2</sub>FC=−0.35), *KCNN3* (−0.84, −0.88), and *IGKV1-9* (−1.15, −1.22).

To identify coordinately up and downregulated gene sets and increase sensitivity for detecting differences between responders and non-responders, I performed rank-based gene set analysis in on the gene-wise z-statistics using blood transcriptomic modules: annotated sets of coexpressed genes in peripheral whole blood from Li *et al.* [234] (prefixed “LI”). This module-level analysis was also run unadjusted (Figure 4.8) and adjusted for cell composition (Figure 4.9).

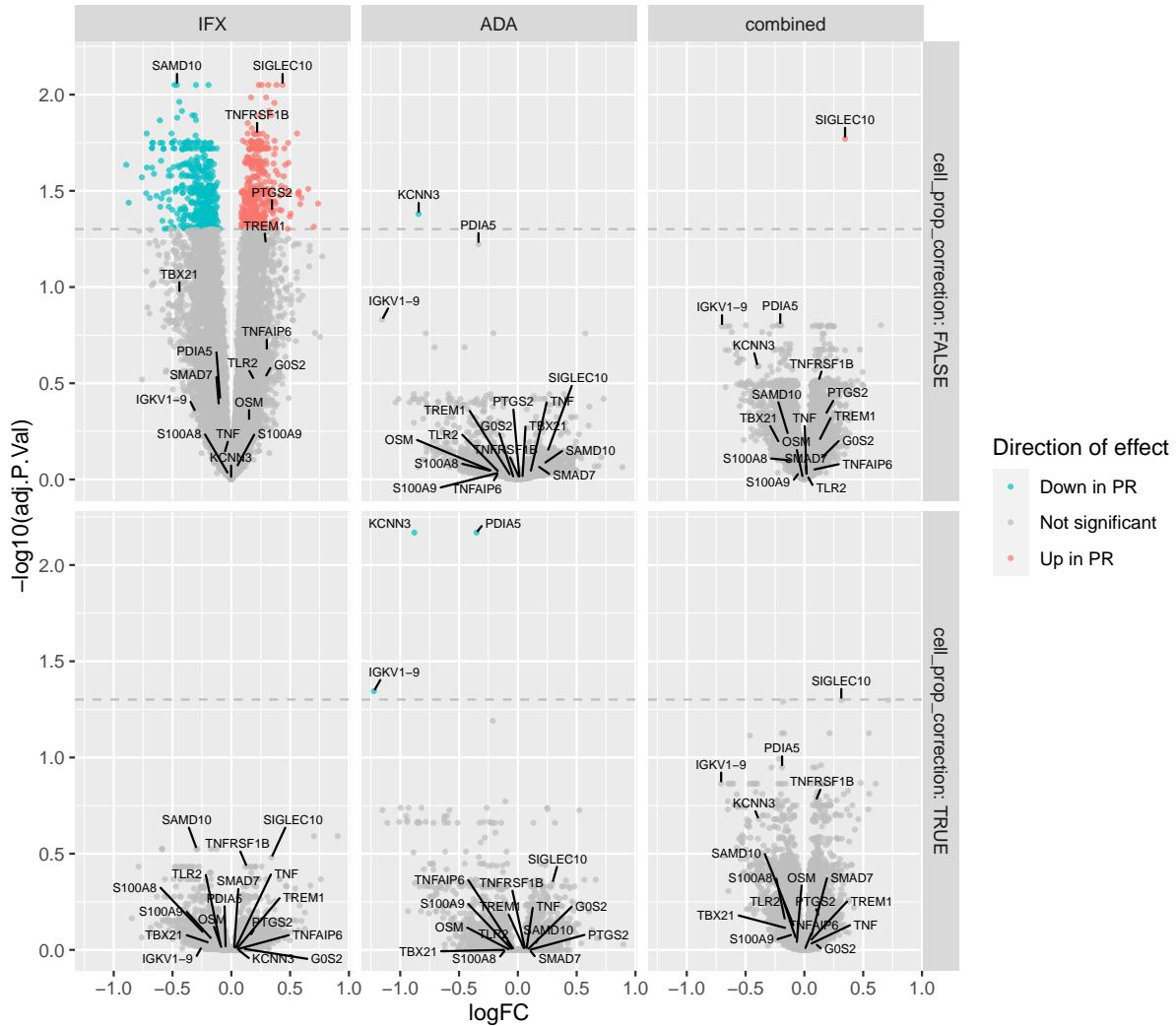
Despite only *SAMD10* having a significantly different effect between drugs at the gene-level (a significant interaction between drug and response at week 0), the large global differences observable in Figure 4.7 were detected in the module-level analysis\*. Without adjusting for cell composition, many of the most significantly upregulated modules in the pooled analysis, including upregulation of monocyte (LI.M11.0, LI.S4), neutrophil (LI.M37.1, LI.M11.2), and dendritic cell (LI.M165, LI.S11), appear to be driven by infliximab. These modules have heavily reduced significance after adjusting for cell composition. The new modules that are most upregulated in the pooled analysis after adjustment have more consistent effects between drugs, such as MHC-TLR7-TLR8 cluster (LI.M146), antigen presentation (LI.M71, LI.M95.0), and myeloid cell enriched receptors and transporters (LI.M4.3).

For downregulated modules before adjustment, I observed infliximab-specific effects for NK cell (LI.M7.2) and T cell (LI.M7.0, LI.M7.1) modules. Adalimumab-specific effects were observed for plasma cell, B cell and immunoglobulin modules (LI.M156.0, LI.M156.0, LI.S3); and cell cycle and transcription modules (LI.M4.0, LI.M4.1). After adjustment, the significance of infliximab-specific modules was reduced, but the significance of adalimumab-specific modules and the corresponding interaction effects was increased. In both gene-level and module-level results, there is striking heterogeneity between infliximab and adalimumab that is only partially reduced by cell proportion adjustment.

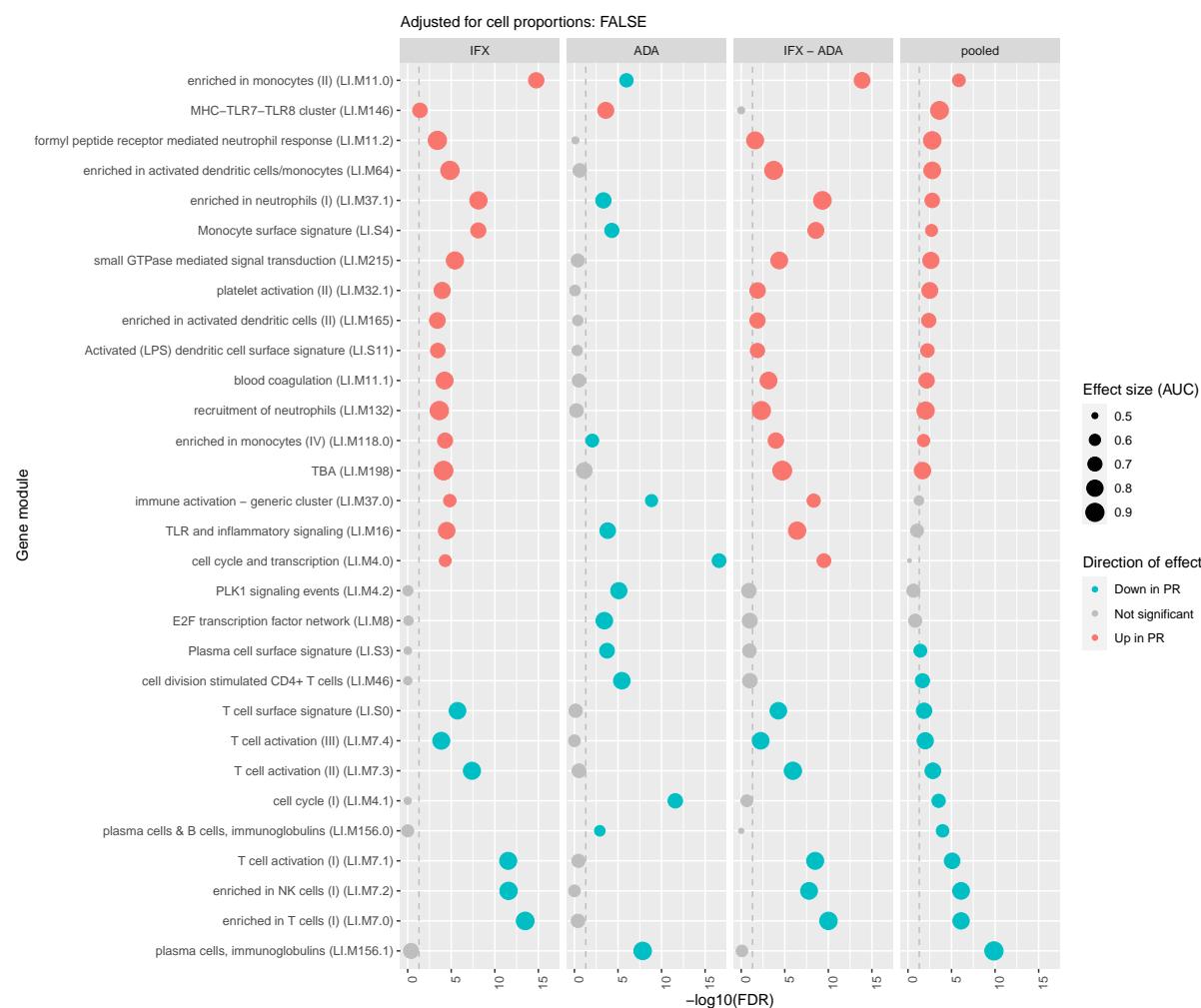
#### 4.3.3 Assessing previously reported baseline predictors of primary response

In addition to hits from this study, Figure 4.7 is annotated with genes whose expression in gut biopsies or blood has been previously evaluated for baseline prediction of primary response [333, 334, 338, 346]. Some genes expressed in gut mucosa (e.g. *IL13RA2*) were not appreciably expressed in this whole blood dataset, and most other genes that were expressed were not significantly differentially expressed. Only *TNFRSF1B* and *PTGS2* were associated with primary response, specifically in the infliximab-only comparison, unadjusted for cell composition.

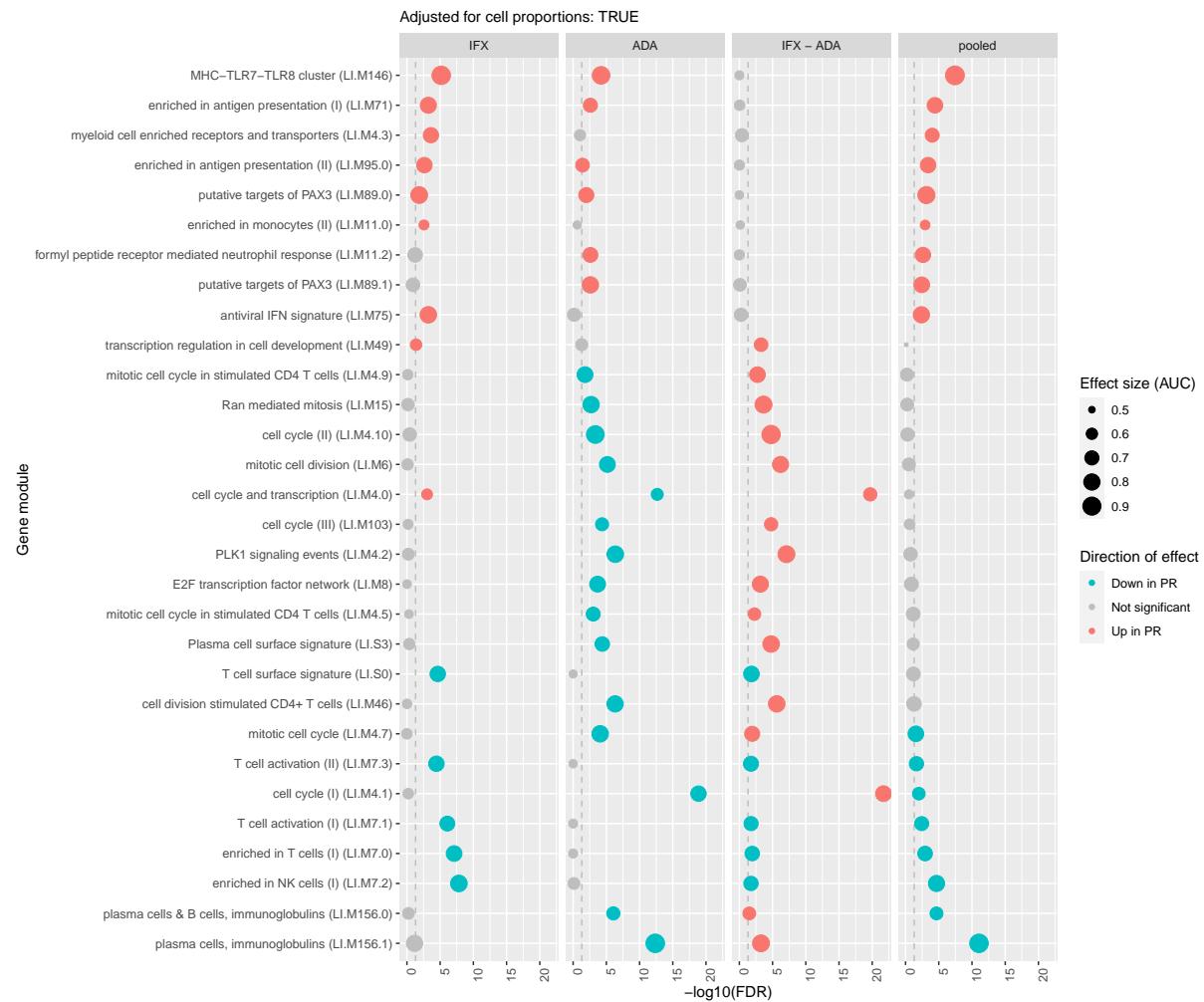
\*It is likely the study is not powered to detect gene-level three-way interaction effects between timepoint, drug and response. I am not aware of which subgroup analyses may have been prespecified during the study design and sample size calculations for the PANTS RNA-seq cohort.



**Figure 4.7:** Volcano plots of DGE between primary responders and non-responders at week 0; unadjusted (top row) and adjusted (bottom row) for cell composition; for infliximab (IFX), adalimumab (ADA), or with both drugs pooled. Annotated genes include significant associations from this study and previously reported associations from subsection 4.1.4. Dashed line shows significance threshold at  $FDR = 0.05$ .



**Figure 4.8:** Top modules differentially expressed between primary responders and non-responders at week 0, unadjusted for cell composition. Columns correspond to results from infliximab (IFX), adalimumab (ADA), infliximab-adalimumab difference and pooled analyses. The top 30 modules ranked by minimum FDR in any column are shown. Vertical dashed line shows significance threshold at FDR = 0.05.



**Figure 4.9:** Top modules differentially expressed between primary responders and non-responders at week 0, adjusted for cell composition.

A previously identified marker in blood, *TREM1*, found to have opposing in two studies [337, 338] was not significantly associated with response in this study, neither before ( $\log FC=0.29$ ,  $FDR=0.06$ ) nor after adjusting for cell composition ( $\log FC=0.05$ ,  $FDR=0.99$ ).

#### 4.3.4 Post-induction gene expression associated with primary response

The same methodology applied at week 0 was applied at week 14 to identify differences in post-induction expression associated with primary response. A larger proportion of the transcriptome is differentially expressed at week 14: 1364 for the infliximab-only comparison, 1544 for the adalimumab-only comparison, and 4841 pooling both drugs (Figure 4.10). No significant interactions between drug and response were detected at the gene-wise level. Given that sample sizes at week 0 and week 14 are comparable (Figure 4.5), the overall signal-to-noise ratio is much stronger than at baseline.

Adjusting for cell composition, 1320/1367, 1515/1544 and 4653/4841 genes have damped effects; and the numbers of significant genes drop to 379, 177, and 1302 for infliximab, adalimumab, and pooled analyses respectively. This again suggests many effects are mediated by differences in immune cell composition between responders and non-responders.

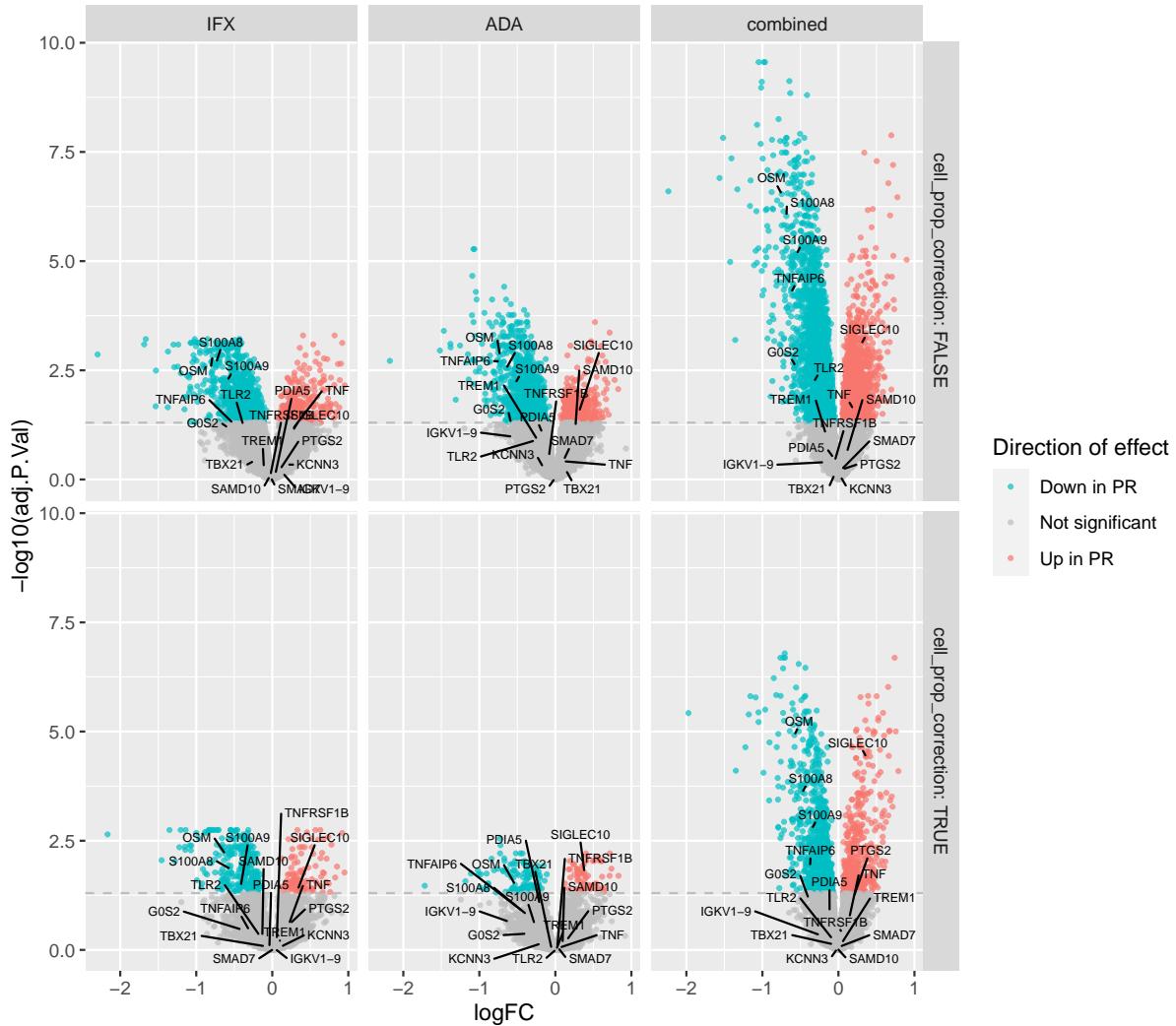
Modules including generic immune activation, monocytes, TLR and inflammatory signalling, and neutrophils were downregulated in responders; whereas B cell and plasma cell modules were upregulated (Figure 4.11). These modules remained differentially expressed with the same direction of effect after adjusting for cell composition (Figure 4.12), suggesting there is per-cell up or downregulation on top of abundance changes of the cell types expressing these modules. Modules related to antigen presentation (LI.M71, LI.M97.0, LI.M5.0), interferon (LI.M75, LI.M127, LI.M111.1), and dendritic cells (LI.M64, LI.M165) also appear among significantly downregulated modules after cell composition adjustment. Directions of effect for the most significant modules were largely consistent between drugs. The significance of drug by response interaction effects compared to main effects is less prominent than in the baseline analysis, where many of the strongest effects were driven by one drug.

*SIGLEC10* from the baseline analysis retains its significant association with primary response post-induction, with the same direction of effect (adjusted  $\log FC=0.37$ ). Some genes previously proposed as baseline markers of response in gut mucosa: *GOS2*, *TNFAIP6*, *S100A8* and *S100A9* by [334]; and *OSM* by [335], were differentially expressed in post-induction blood in this study. The direction of effect in both cases, downregulation of markers in primary responders, also matches this study.

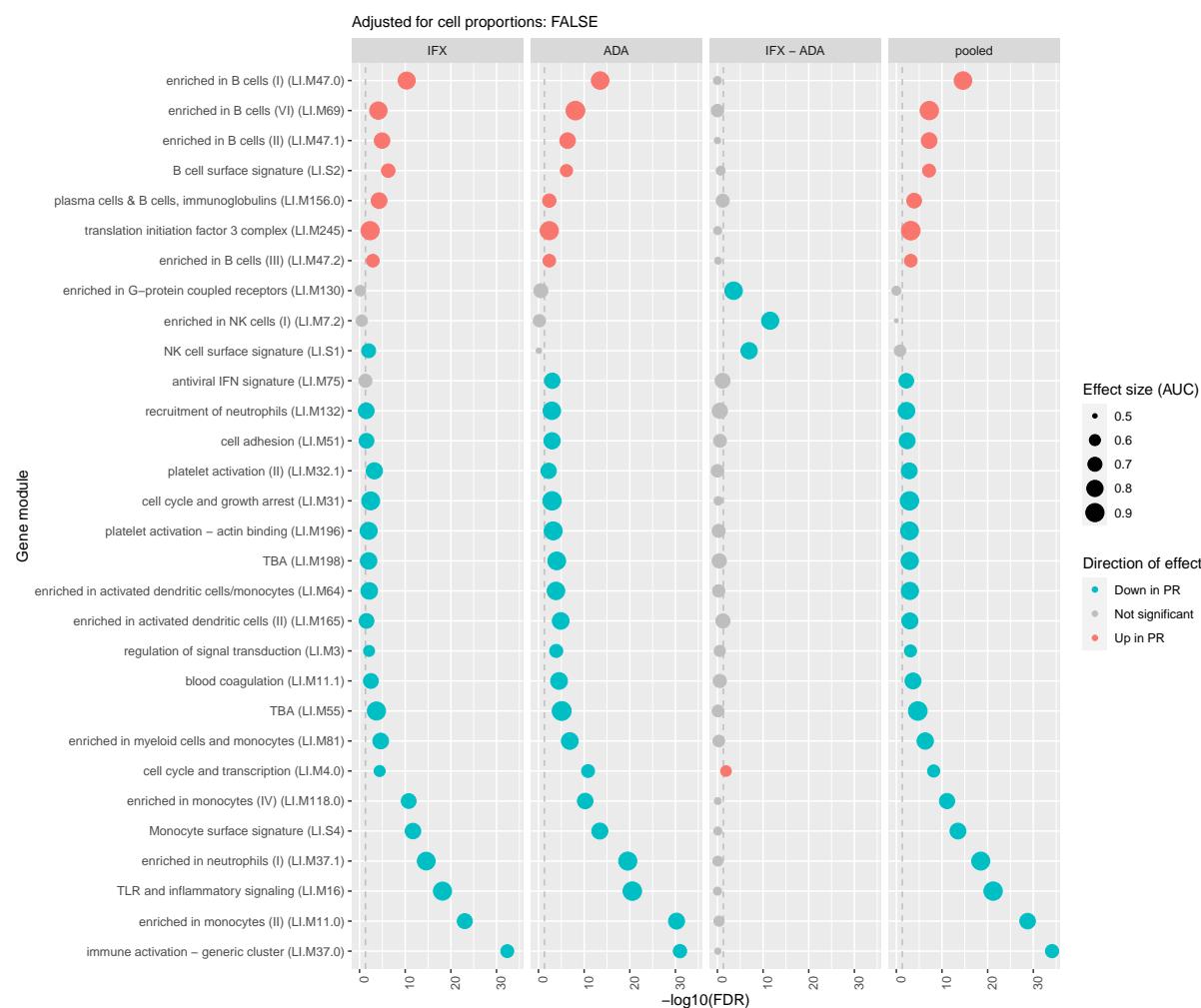
#### 4.3.5 Magnification of expression change from baseline to post-induction in responders

Given the stronger differences in expression between primary responders and non-responders at week 14 versus week 0, I estimated the change in expression from week 0 to week 14 within the two groups, and also estimated the timepoint by response interaction. I perform only the pooled comparison here both to simplify the analysis, and because similarly to the within week 14 comparison, change from week 0 to week 14 was relatively consistent between drugs, with exceptions noted.

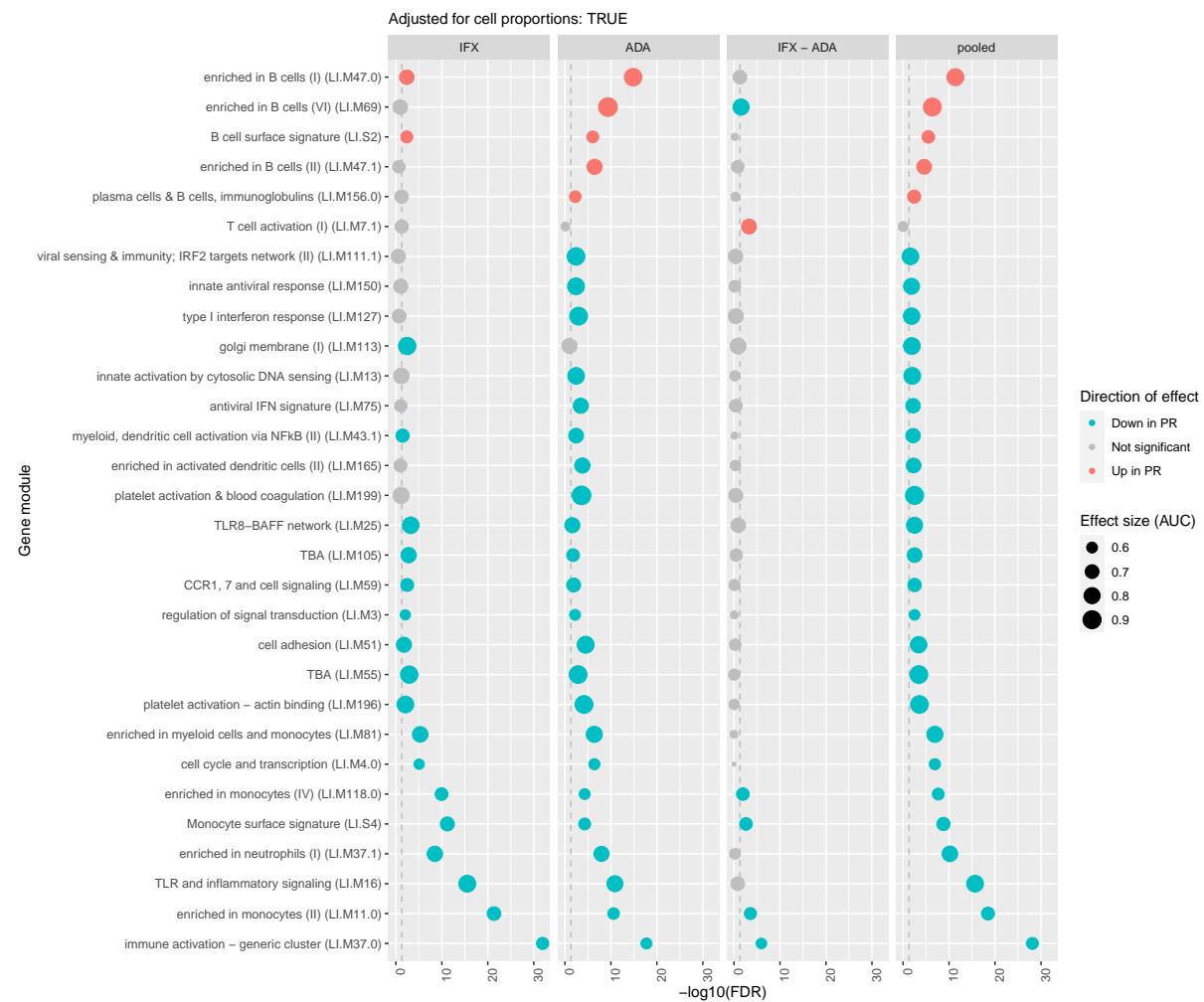
highlight a few more individual genes specific to this analysis too? not sure how to pick them at the moment.



**Figure 4.10:** Volcano plots of DGE between primary responders and non-responders at week 14; unadjusted (top row) and adjusted (bottom row) for cell composition; for infliximab (IFX), adalimumab (ADA), or with both drugs pooled. Annotated genes include significant associations from this study and previously reported associations from subsection 4.1.4. Dashed line shows significance threshold at  $\text{FDR} = 0.05$ .



**Figure 4.11:** Top modules differentially expressed between primary responders and non-responders at week 14, unadjusted for cell composition.



**Figure 4.12:** Top modules differentially expressed between primary responders and non-responders at week 14, adjusted for cell composition.

Without adjusting for cell composition, 12862 genes were differentially expressed in primary responders at week 14 vs week 0 in the pooled analysis, 8310 genes in primary non-responders, and 6320 genes had a significant interaction. After adjusting for cell composition, 5572 genes were differentially expressed in primary responders, 626 genes in primary non-responders, and 179 genes had a significant interaction. Of the genes differentially expressed between week 14 and week 0 in both primary responders and non-responders, and with a significant interaction between timepoint and response, nearly all (4885/4891 unadjusted for cell composition, 31/32 adjusted) were magnified by primary response, such that the same genes have larger fold-changes in the same direction for primary responders ([Figure 4.13](#)).

The most significant modules that change from week 0 to week 14 in responders included upregulation of B cell (LI.M47.0), plasma cell (LI.M156.0), and T cell activation (LI.M7.1); and downregulation of immune activation (LI.M37.0), monocyte (LI.M11.0), neutrophil (LI.M37.1) and TLR and inflammatory signalling (LI.M16) modules ([Figure 4.14](#)). Many of these are the same modules associated with response within the week 0 and week 14 timepoints.

Adjusting for cell composition decreases the significance of a majority of modules ([Figure 4.15](#)), with T cell modules in the adalimumab-only analysis especially decreased. Magnification is also observed at the module level, with nearly all module effects aligned in the same direction in responders and non-responders, with significant interactions also in the same direction.

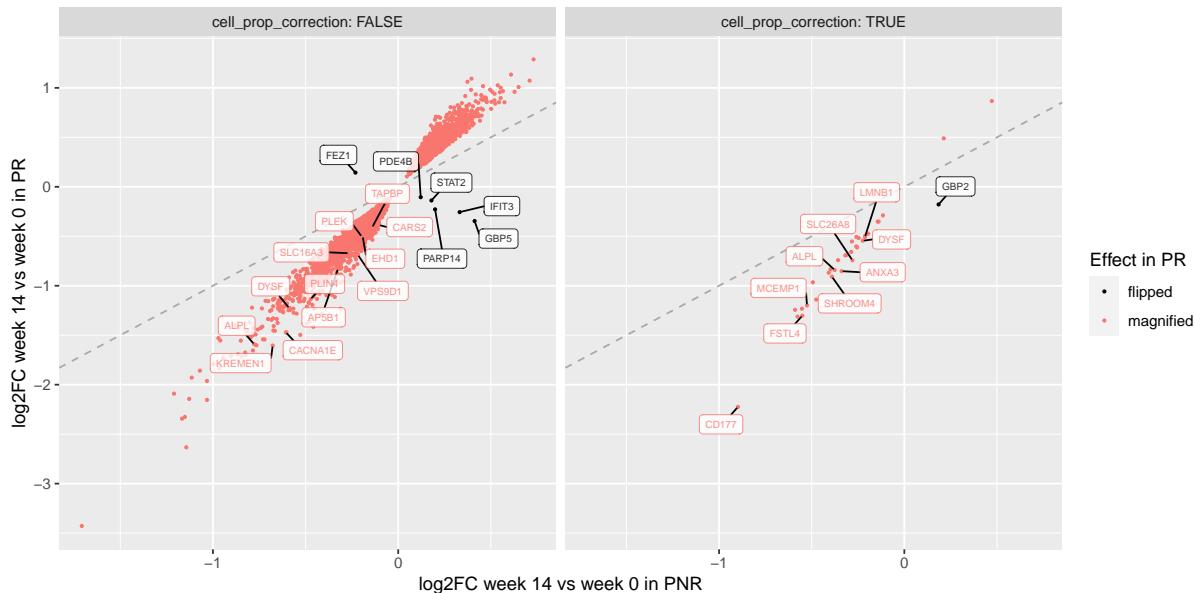
#### 4.3.6 Interferon modules with opposing differential expression in responders and non-responders

[Figure 4.13](#) also contains genes that were downregulated from week 0 to week 14 in responders, but upregulated in non-responders (“flipped”). At the module level these opposing effects were most apparent after cell composition adjustment for antiviral interferon signature (LI.M175), type I interferon response (LI.M127), and antigen presentation (LI.M95.0) ([Figure 4.15](#)). I extended my module analysis to include modules from [233] (prefixed “DC”). Although these modules are on the whole poorly annotated compared to modules from [234], interferon modules are annotated. *STAT2*, *GBP5*, and *PARP14* from [Figure 4.13](#) are annotated into an interferon module (DC.M3.4). *IFIT3* and *GBP2* are also annotated into separate interferon modules (DC.M1.2, DC.M5.12). Adjusted for cell composition, these modules are all significantly upregulated at week 14 in non-responders only: DC.M3.4 FDR=3.45 × 10<sup>-21</sup>, DC.M1.2 FDR=9.49 × 10<sup>-16</sup>, and DC.M5.12 FDR=1.36 × 10<sup>-13</sup> ([Figure 4.16](#)).

#### 4.3.7 Sustained expression differences between primary responders and non-responders during maintenance

As **PANTS** is an observational study, it was able to include some patients who continued with anti-**TNF** therapy even after meeting the definition of primary non-response at week 14. For both responders and non-responders, expression data could also be available from blood samples around week 30 and week 54, and at additional visits scheduled in the event of secondary LOR.

I fit a natural cubic spline to the expression of each gene as a function of study day, and tested for general differences in expression over time between responders and non-responders. This



**Figure 4.13:** Expression logFC from week 0 to week 14 in primary responders versus non-responders, shown for all genes differentially expressed from week 0 to week 14 in both responders and non-responders, with a significantly different effect size in responders and non-responders. Identity line shown by dashed line.

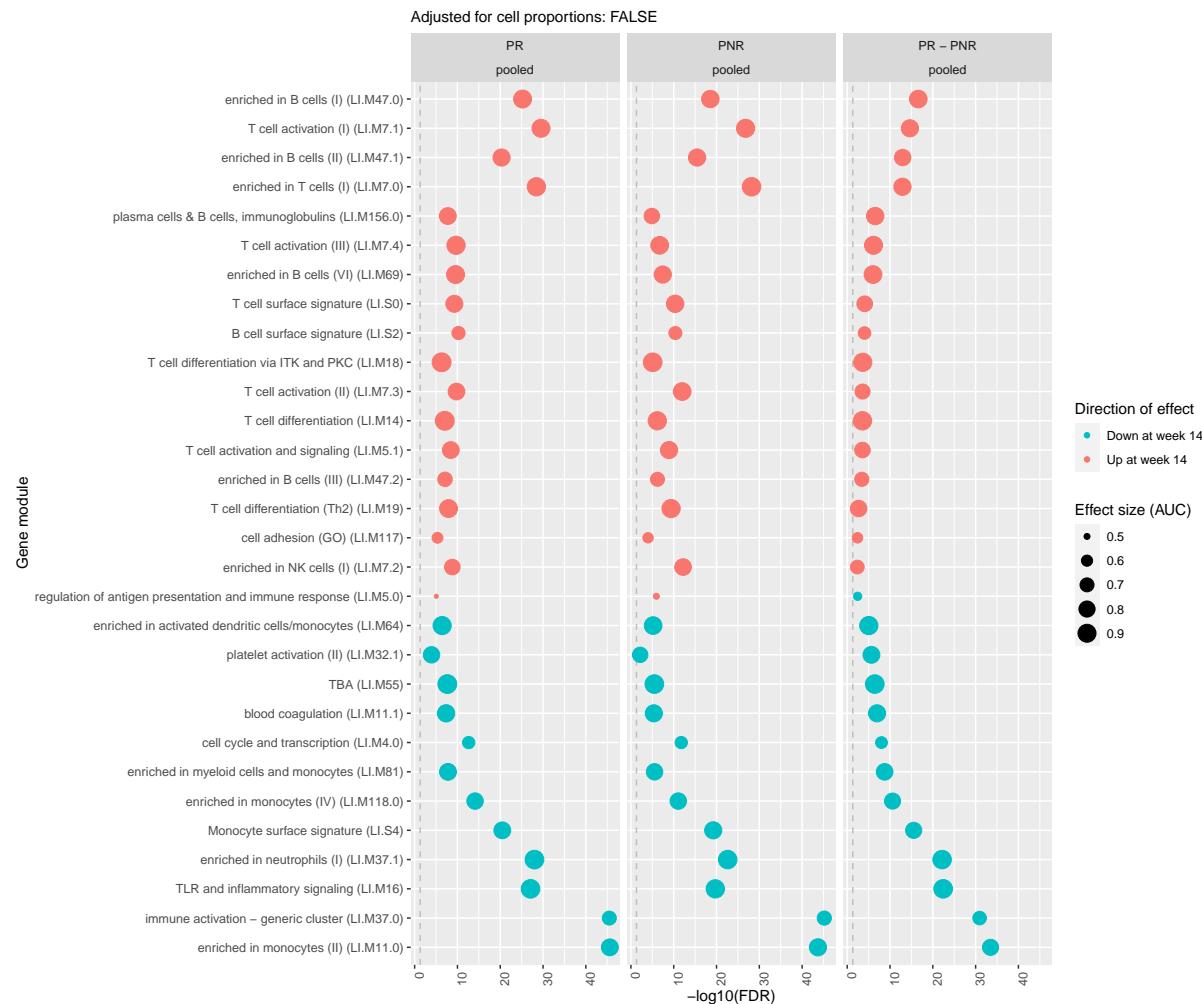
analysis was done only with drugs pooled due to lower sample sizes for later timepoints. Without adjusting for cell composition, 4426 genes were differentially expressed between responders and non-responders; 210 genes were differentially expressed after adjustment. To identify distinct trajectories of expression over time, I hierarchically clustered those 210 genes by their mean expression in responders and non-responders at each timepoint, and determined the optimal number of clusters by the gap statistic method (Figure 4.17). Six distinct clusters were proposed (Figure 4.18).

Many of these genes had previously been identified as having significant differences in expression between responders and non-responders either within week 14, or for change in expression from week 0 to week 14. Cluster 1 contained mainly previously identified genes (Figure 4.19), and was enriched for modules including myeloid cells and monocytes (LI.M81, hypergeometric test,  $FDR=2.11 \times 10^{-6}$ ), platelet activation (LI.M196,  $FDR=1.35 \times 10^{-5}$ ), immune activation (LI.M37.0,  $FDR=1.44 \times 10^{-4}$ ), and TLR and inflammatory signalling (LI.M16,  $FDR=2.36 \times 10^{-3}$ ). The spline analysis highlighted that expression differences at week 14 are maintained at week 30 and week 54.

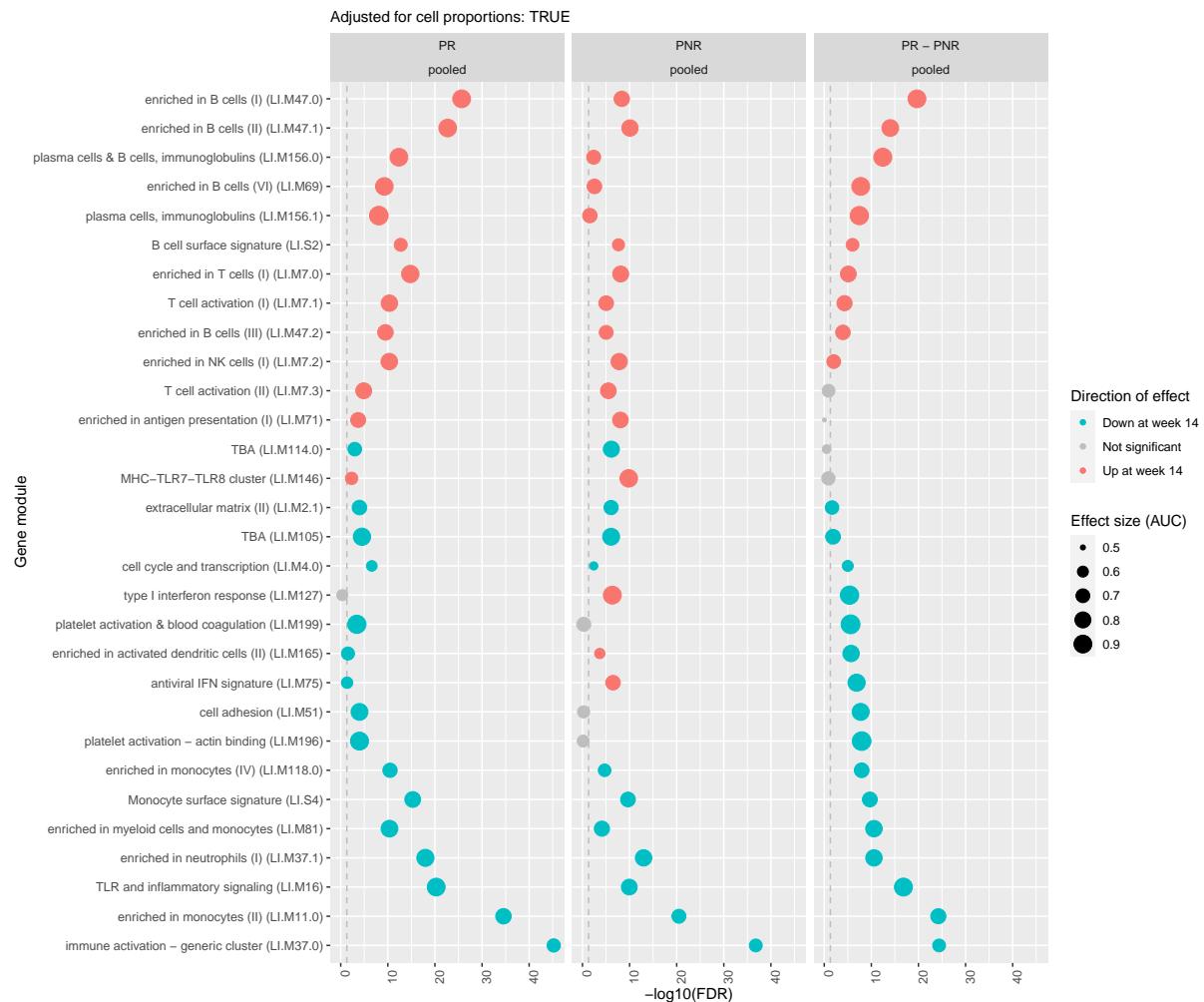
The highest proportion of genes uniquely identified as significant by the spline analysis were in cluster 2 (26/31) and cluster (15/20). Cluster 2 was enriched in [234] B cell modules (LI.M47.0,  $FDR=1.53 \times 10^{-6}$ ; LI.M47.1,  $FDR=4.53 \times 10^{-5}$ ) previously identified as having a greater increase from week 0 to week 14 in primary responders versus primary non-responders (Figure 4.15), matching the observed cluster trajectory. Cluster 4 was not enriched in any modules from Li *et al.* [234], but is enriched for a B cell module (DC.M4.10,  $FDR=0.00$ ) from Chaussabel *et al.* [233]. Although no genes were significantly associated with response at week 0 (Figure 4.7), the genes in cluster 4 are coordinately downregulated as a set in primary responders (CERNO test,  $p=6.18 \times 10^{-25}$ ).

Cluster 3 is also of interest, enriched for type I interferon response (LI.M127,  $FDR=0.01$ ) and

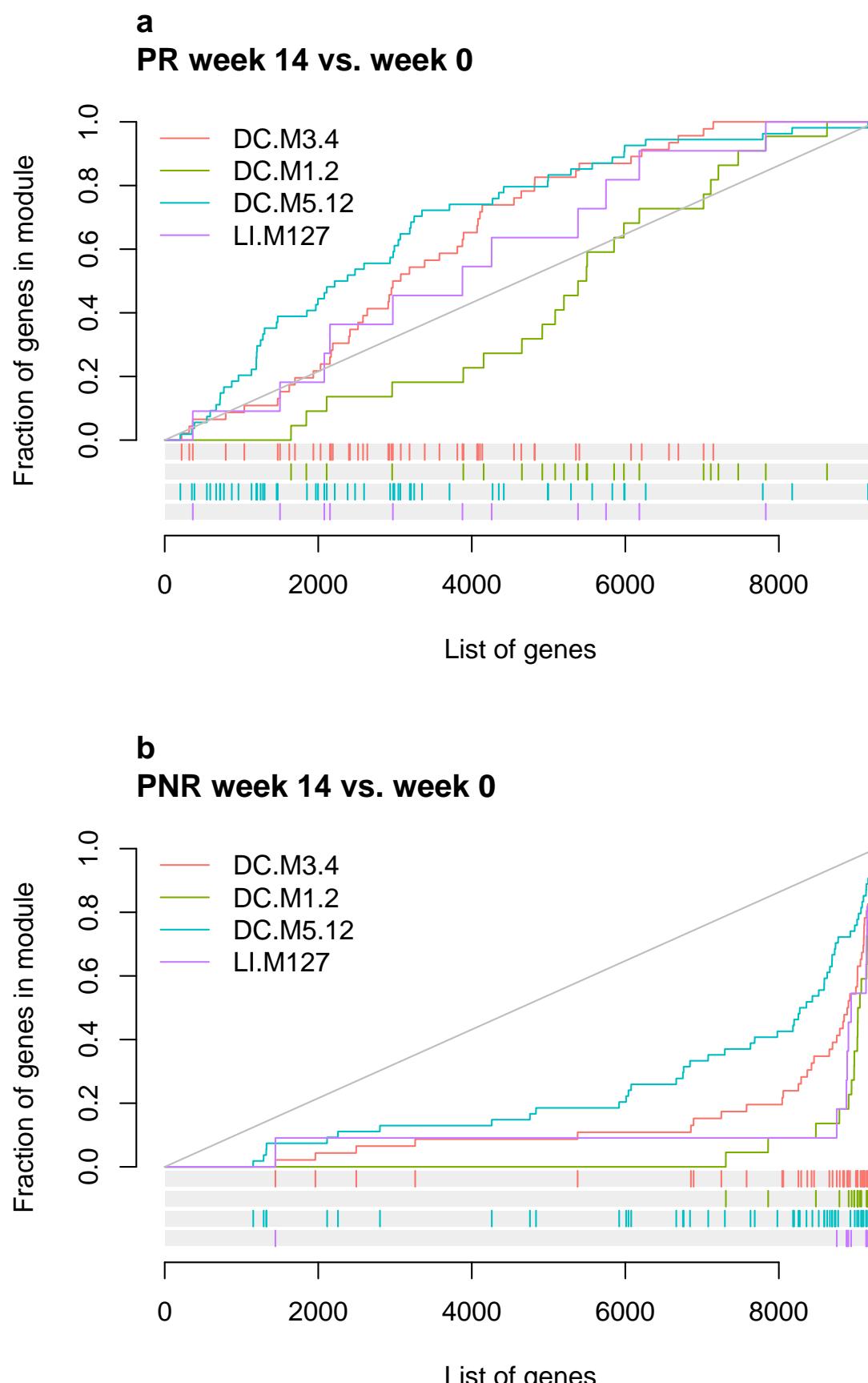
TODO I forgot to include the non-ranked hypergeometric test and gprofiler tests in the gene set enrichment section in the methods.



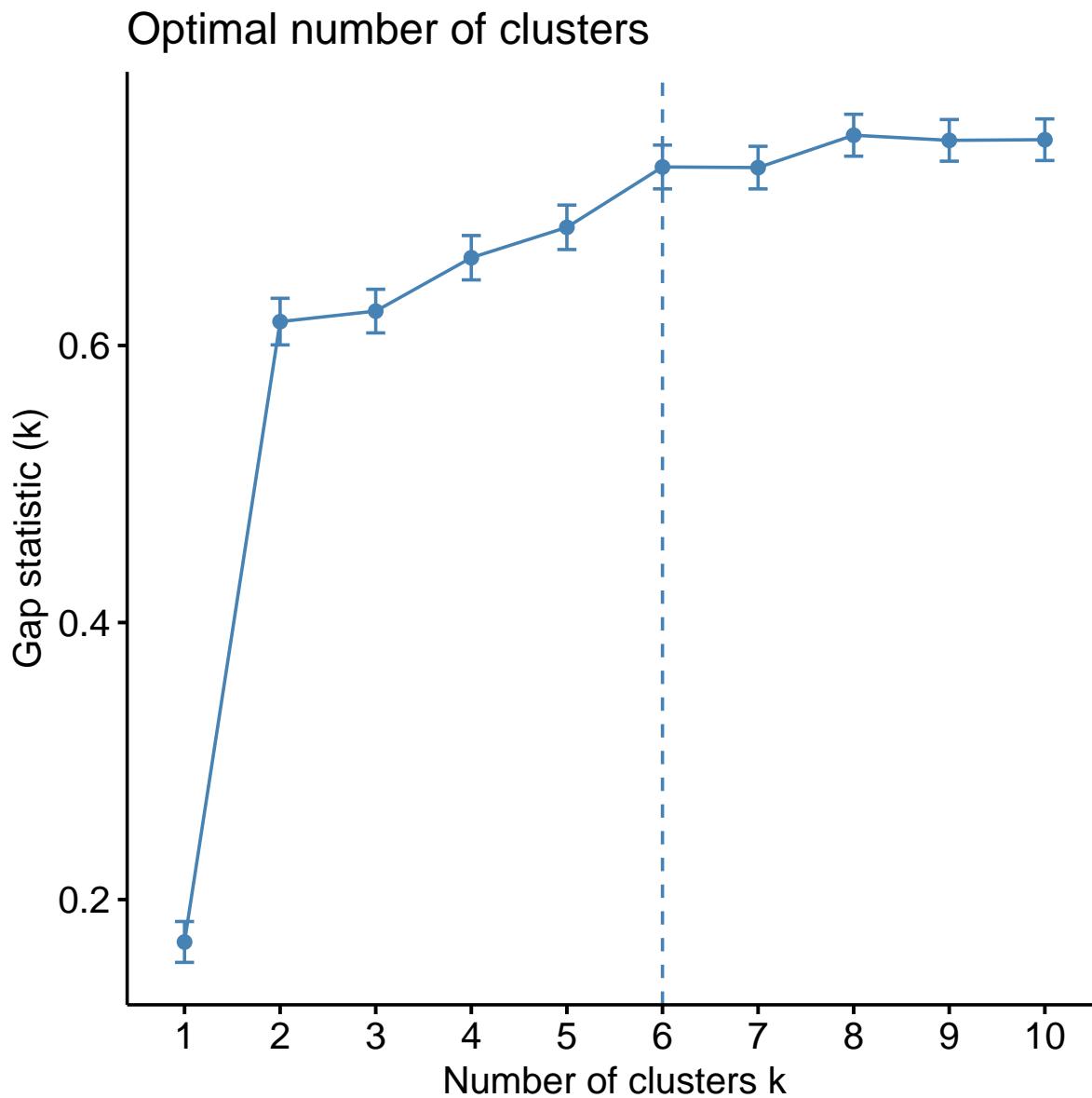
**Figure 4.14:** Top modules differentially expressed between week 14 and week 0, unadjusted for cell composition. Columns show effects in primary responders (PR), non-responders (PNR), and the primary responder minus non-responder difference. The top 30 modules ranked by minimum FDR in any column are shown. Vertical dashed line shows significance threshold at FDR = 0.05.



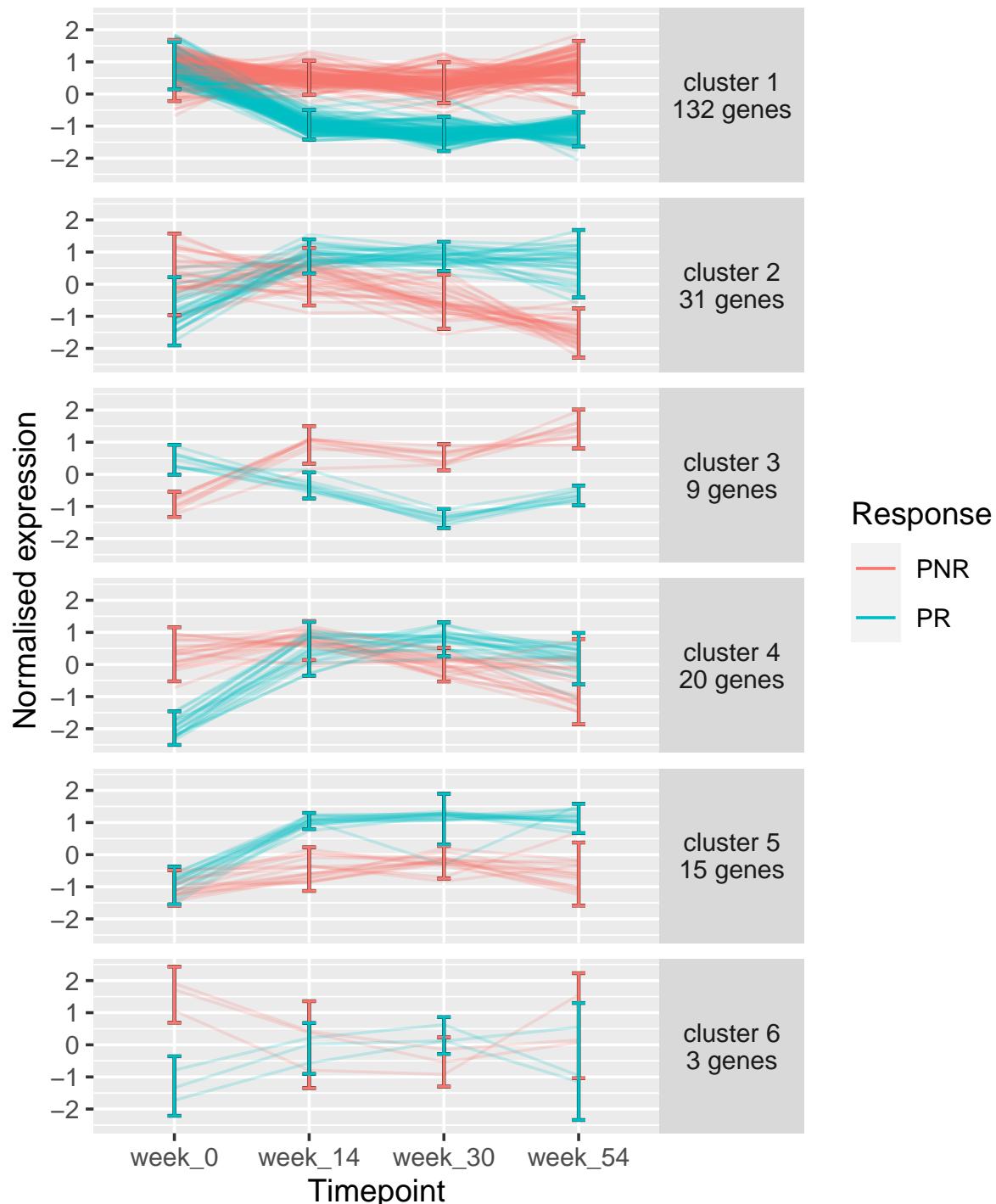
**Figure 4.15:** Top modules differentially expressed between week 14 and week 0, adjusted for cell composition. Columns show effects in primary responders (PR), non-responders (PNR), and the primary responder minus non-responder difference. The top 30 modules ranked by minimum FDR in any column are shown. Vertical dashed line shows significance threshold at FDR = 0.05.



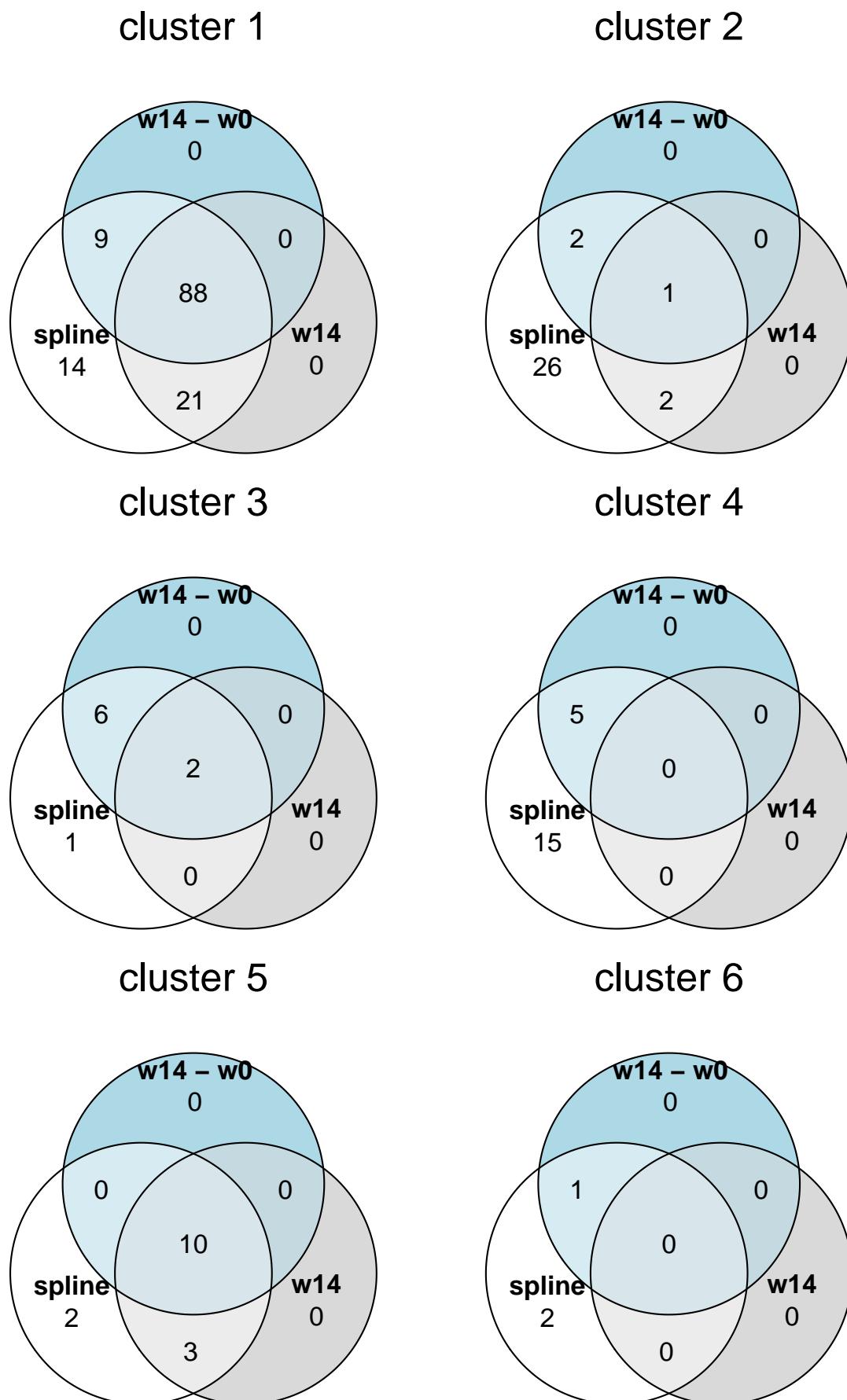
**Figure 4.16:** tmod evidence plots showing interferon-related modules specifically upregulated from week 0 to week 14 in primary non-responders. Genes were ranked in ascending order by week 14 versus week 0 DGE z-statistic. The ranks of genes in interferon-related modules are indicated by colored rug plots. Colored curves show the cumulative fraction of genes in each module. For non-responders, these modules are enriched for large ranks (large, positive z-statistics). The area under the colored curves are the effect sizes (area under the curves (AUCs)). The null of randomly-distributed ranks is the grey diagonal line.



**Figure 4.17:** Gap statistic versus cluster number  $k$ . Error bars derived from 500 bootstraps. The optimal number of clusters is defined as the smallest  $k$  after which the gap statistic does not significantly increase at  $k+1$ .



**Figure 4.18:** Normalised expression over the timepoints for genes in the six identified clusters. Error bars are the expression mean and standard deviation for the genes at each timepoint in primary responders and non-responders.



**Figure 4.19:** Venn diagrams showing which genes in each spline cluster were also significant in the week 14 responder versus non-responder contrast, or the interaction between week 0 to week 14 change and response status.

interferon (DC.M3.4, FDR=0.00) modules, as well as genes that contain putative transcription factor binding motifs for interferon regulatory factors *IRF7* (g:Profiler term ID TF:M00453\_1, adj. p value=0.01) and *IRF8* (TF:M11684\_1, adj. p value=0.01; TF:M11685\_1, adj. p=0.01). The cluster trajectory shows direction of expression change is opposing in responders and non-responders from week 0 to week 14, followed by sustained differences at week 30 and week 54. The trajectory and interferon-related gene set enrichments are consistent with those identified in subsection 4.3.6. Of the 9 genes in this cluster, 8 genes (*STAT1*, *BATF2*, *GBP1*, *GBP5*, *IRF1*, *TAP1*, *APOL1*, *APOL2*) have significant interaction between week 0 to week 14 expression change and response status, whether or not correcting for cell composition. However, only *GBP5* was differentially expressed from week 0 to week 14 in both responders and non-responders, and only when unadjusted for cell composition (Figure 4.13). This indicates that such small and opposite effects in responders and non-responders are best detected at a single-gene level in the interaction analysis that tests the difference, and in the spline analysis, with the support of additional data from week 30 and week 54.

#### 4.3.8 Limited evidence for change in genetic architecture of gene expression over time

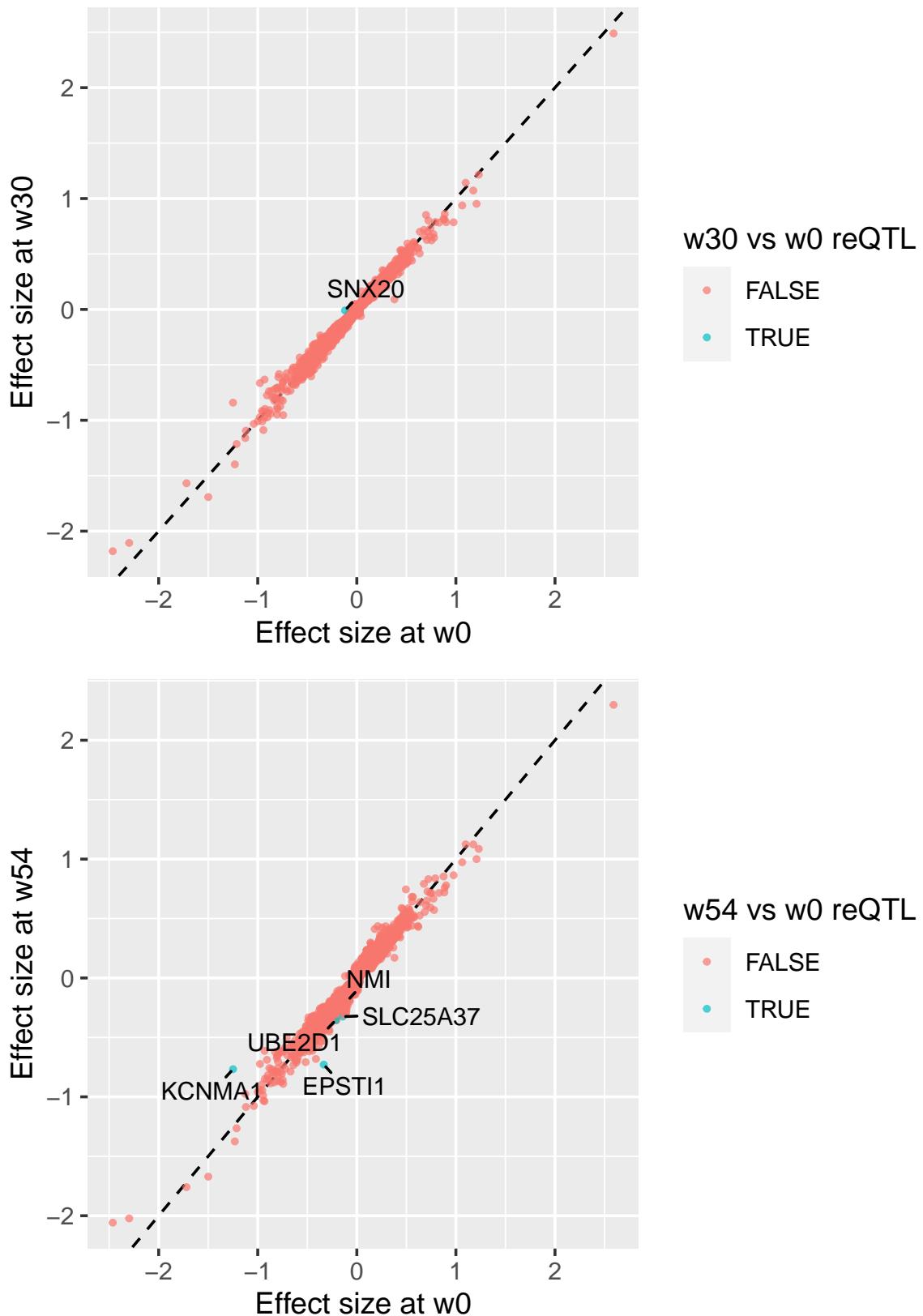
Given the substantial changes in expression from baseline to post-induction after starting the drug, and the differing trajectories observed in responders and non-responders, I performed eQTL mapping to identify common genetic variants associated with expression that may contribute to these differences. Variants cis (within 1 Mb of the TSS) to 15040 genes were tested for association. Mapping was done within each timepoint (weeks 0, 14, 30, and 54), followed by joint analysis of per-timepoint eQTL summary statistics and control for multiple testing using `mashr`.

The majority 11156/15040 (74.2 %) of genes were eGenes (a gene with at least one significant cis-eQTL) in at least 1 timepoint ( $\text{lfsr} < 0.05$ ). The variant with the lowest lfsr in any timepoint for each gene was chosen as the lead variant (eSNP) for that gene. Most eSNPs were significant in multiple timepoints: 999 significant in 1 timepoint, 381 significant in 2 timepoints, 526 significant in 3 timepoints, 9250 significant in all 4 timepoints. I compared eSNP effect sizes between week 0 and each of weeks 14, 30 and 54, to identify reQTLs with significant difference in effect versus baseline, as they may also explain changes in expression from baseline. Most eSNPs were shared across timepoints; only six eSNPs-eGene pairs were significant at BH FDR < 0.05: with 1/6 for week 30 versus week 0 and 5/6 for week 54 versus week 0 (Figure 4.20). Of the six eGenes, *NMI* and *EPSTI1* both had their respective eSNPs having magnified effects on expression at week 54 compared to week 0, and both are annotated to contain putative binding motifs for *IRF8* and *IRF2* (g:Profiler term IDs TF:M11685\_1 and TF:M11665\_1). However, direct interpretation of these reQTLs is complicated by confounding by cell composition in bulk expression data (discussed in subsection 3.2.11).

right word???

## 4.4 Discussion

In PANTS, a cohort of CD patients receiving infliximab or adalimumab anti-TNF therapy for the first time, there were substantial differences in whole blood gene expression between



**Figure 4.20:** Week 30 and week 54 eQTL effect sizes vs baseline. Significant reQTLs at FDR 0.05 are labelled.

So many modules associations here, maybe try to Google some of them...

primary responders and non-responders. At baseline, the greatest differences in expression were observed between future responders and non-responders to infliximab, with increased expression of monocyte, neutrophil and dendritic cell gene modules in responders, and decreased expression of T cell and NK cell modules. These effects appear to be infliximab-specific, and are attenuated after adjusting for the proportions of six major immune cell types, suggesting expression differences may be driven by mediation via the proportions of these cell types.

In contrast, future responders to adalimumab had lower baseline expression of plasma cell and cell division modules. The module-level results line up with the three gene-wise hits for the adalimumab-only analysis: *IGKV1-9* encodes the immunoglobulin light chain variable region that forms part of antibodies produced by plasma cells, *KCNN3* is annotated to plasma cell surface signature module (LI.S3 [234]), and the expression of both *KCNN3* and *PDIA5* are correlated with blood plasmablast frequencies [160]. It was reported by Gaujoux *et al.* [337] that baseline plasma cell abundances are lower for infliximab responders, hypothesising that plasma cell survival is supported by increased TNF levels in non-responders. Plasma cells also formed a part of a correlated module of cell populations identified by [336], where lower module expression was associated with better response to anti-TNF in a cohort with patients taking both infliximab and adalimumab. However, both these studies were done in gut biopsy samples, and there was no mention of strong between-drug heterogeneity.

The adalimumab-specific associations I found were more significant after cell proportion adjustment, which may indicate per-cell downregulation rather than cell abundance being associated with response. However, cell composition differences mediated by rarer cell types that have abundances poorly captured by the six major types used in the model will be poorly adjusted for. For example, plasma cell proportions are only weakly correlated with other immune cell types in the healthy immune system [347], although the relationship may differ for CD patients. It has also been shown that differentially expressed genes in blood with correction for only common cell types will identify associations that are proxies for rare cell types <https://www.biorxiv.org/content/10.1101/2020.05.28.120600v1>. If this is the case, the role of the cell composition estimates for adalimumab-specific effects may be more akin to precision variables, which would be consistent with increased significance after adjusting.

The differences between drugs are puzzling, especially the greater effect of cell composition adjustment for infliximab. Baseline patient differences between drugs may offer a partial explanation. There may be characteristics not listed in Table 4.1 that differ between patients on different drugs [326]. In the full PANTS cohort, lower albumin, higher CRP, and higher faecal calprotectin in infliximab patients suggest that they may have had greater disease severity. Differences may be driven by patient or physician preference, for example, patients with more severe disease are often given infliximab rather than adalimumab\*. I have not yet been able to access clinical variables such as CRP and faecal calprotectin levels to consider as variables to adjust for in my modelling. A richer phenotype dataset containing some of these variables has been requested from collaborators.

The strongest single-gene association in the pooled analysis was *SIGLEC10*, which had reduced significance post-adjustment with a comparable effect size, where baseline expression

\*Kennedy, N. A., personal communication, 4 June (2020).

was approximately 25% higher in responders. Direction of effect was consistent between drugs, but most significant in infliximab without cell composition adjustment. In IBD, small molecules called **damage-associated molecular patterns (DAMPs)** are released due to tissue damage and cell death, and further promote inflammation through pathogen sensing **pattern recognition receptor (PRR)** pathways that include **Toll-like receptor (TLR)** family receptors [310, 348]. For instance, faecal calprotectin, a marker for IBD activity, is a complex of two **DAMPs**, S100A8 and S100A9 [310]. SIGLEC10 has been shown to repress **DAMP**-mediated inflammation through binding CD24 [348]. *SIGLEC10* is expressed on B cells, monocytes and eosinophils <https://www.nature.com/articles/nri2056>, and of these cell types, module level results posit monocytes as the most likely candidate cell type to have increased module expression in responders. In monocytes, *SIGLEC10* expression is more specific to the CD16+ monocytes [349], and in particular the CD14+CD16++ non-classical monocytes rather than the classical CD14++CD16- or intermediate CD14++CD16+ subsets [350]. In PANTS, it was suggested by Kennedy *et al.* [326] that higher inflammatory load as indicated by low baseline albumin levels may result in low week 14 drug levels due to faster drug clearance, and low drug levels at week 14 were in turn associated with non-response. A hypothetical model might be high baseline *SIGLEC10* expression reflecting higher proportions of CD16+ monocytes (or lower proportions of CD16- monocytes), decreased **DAMP**-mediated inflammation, and increased chance of primary response, possibly by affecting drug clearance rate. This is an extremely tentative model: both the cell proportion estimates and module definitions used thus far only represent monocytes as a whole, lacking the resolution to properly explore shifts in the three monocyte subsets. It may be possible to use expression of monocyte subset marker genes such as those identified by Villani *et al.* [350] to improve the resolution of the cell proportion estimates.

Despite the strong heterogeneity in effects between drugs, one consistent effect that emerged after adjusting for cell composition was baseline upregulation of MHC-TLR7-TLR8, antigen presentation, and interferon modules in responders. As mentioned above, **TLR** receptors are involved in pathogen sensing, and TLR7 and TLR8 are endosomal proteins primarily expressed in monocytes, macrophages and **dendritic cells (DCs)**, part of an antigen presentation pathway that senses bacterial DNA and activates downstream innate immune pathways including type I interferon response <https://www.nature.com/articles/cmi201238>. Type I interferons have pathogenic or protective roles in many **IMIDs** <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4084561/>. It has been suggested that type I interferon responses induced via TLR7 and TLR8 can suppress colitis in mouse models, and play a role in maintaining gut homeostasis <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5797585/> <https://www.frontiersin.org/articles/10.3389/fmed.2018.00032/full>, so upregulation here may again represent a less severe baseline disease in future responders.

How does the MHC come in here?

Most previously reported baseline markers in blood and gut biopsies were non-significant in this study. For gut markers, this may not be unexpected. Although a subset of gut infiltrating immune cells and their precursors may also be circulating, genes specific to epithelium and immune cell types that differentiate after they migrate into tissues (e.g. monocyte-derived macrophages), will be difficult to observe in blood. For blood markers, I sought to clarify the conflicting results in the literature about the association of *TREM1* expression in blood with

anti-TNF response [337, 338]. I did not find *TREM1* to be significantly differentially expressed in PANTS, although the direction of effect is increased expression in responders, matching the Gaujoux *et al.* [337] direction of effect in blood. *TREM1* is expressed on myeloid lineage cells such as monocytes and macrophages; Villani *et al.* [350] reported that *TREM1* expression is most specific to classical monocytes and a newly identified subtype within the intermediate monocytes ("Mono3"). The *TREM1* effect is one of the infliximab-specific differentially expressed genes that is much stronger without cell proportion adjustment, so it may reflect association of baseline monocyte cell proportions with response.

There are many factors could explain failures to replicate reported markers, or identification of different markers from study to study. Many existing studies pool cohorts with different anti-TNF biologics due to the scarcity of large datasets, yet even within this study, there is heterogeneity between drugs. There are between-study differences in the definition of primary response, such as endoscopic healing [337] versus scoring on clinical parameters [338]. Any two studies are unlikely to have adjusted for the same combinations of covariates in modelling, and some covariates like cell composition are very influential for bulk expression data. Finally, small sample sizes have considerable sampling error. Set-based association tests that draw on changes in multiple genes, such as the expression module associations for blood in this study, may be more reproducible compared to single-gene markers.

Although this study is purely descriptive, a future aim will be to see if the identified baseline module associations also imply that response status can be predicted from baseline expression. Because modules associated with response appear to be mediated by cell proportions, much of the predictive ability may also lie in differences in cell proportions between responders and non-responders. Indeed, Gaujoux *et al.* [337] noted that adjusting expression for cell composition resulted in gut gene signatures that were worse at discriminating responders from non-responders. Testing specific subpopulations such as CD16+ monocyte or plasma cell abundance for association with response can also be viewed as a type of set-based test that represents a set of cell-type specific genes, and thus may also be more reproducible than single-gene markers.

Much larger proportions of the transcriptome are associated with response after the induction period at week 14. Module associations showed downregulation of immune activation, TLR, inflammatory, monocyte and neutrophil modules in responders; and upregulation of B and T cell modules. Similar module associations were also found when considering modules differentially expressed from week 0 to week 14. The differences between responders and non-responders at week 14 were qualitatively similar to the differences pre and post anti-TNF induction, suggesting there may be relatively little change in the transcriptome of non-responders after induction. Associations were generally consistent between drugs for both the within week 14 and change from week 0 to week 14 analyses, perhaps because the effect of baseline differences between patients taking different drugs on the transcriptome is diluted by the large transcriptomic perturbation caused by taking an anti-TNF drug. Many of the same modules were also significant regardless of cell proportion correction.

There appears to be a general reduction in immune activation in responders at week 14, presumably due to successful inhibition of TNF, which is consistent with reduced neutrophil activation and reduced monocyte recruitment <https://www.ncbi.nlm.nih.gov/pmc/article>

s/PMC5820413/. Apoptosis of monocytes induced by anti-TNF in CD patients has also been previously observed [https://www.gastrojournal.org/article/S0016-5085\(01\)32104-2/fulltext](https://www.gastrojournal.org/article/S0016-5085(01)32104-2/fulltext). Certain B cell subsets are reduced in the blood IBD patients compared to controls <https://www.frontiersin.org/articles/10.3389/fimmu.2019.00361/>, so upregulation of B cell modules after treatment may represent a shift towards health. Another potential explanation would be increased immunogenicity due to higher drug levels in responders [326]. Although lack of between-drug heterogeneity does not support the greater immunogenicity of infliximab versus adalimumab. Overall, it is difficult to determine exact mechanisms in this observational study design, with bulk expression data, using such broad module definitions.

Some previously identified baseline gut markers of response that were not differentially expressed in blood at week 0, were differentially expressed at week 14. *S100A8* and *S100A9*, identified as markers by Arijs *et al.* [334], which encode components of the inflammatory marker CRP, were downregulated in week 14 responders. The cytokine *OSM*, which promotes inflammation in gut stromal cells [335], was similarly downregulated. Although it is pointless to use a week 14 marker to predict a response that is defined at week 14, this does demonstrate that gut markers can coincide with blood markers if expressed in immune cells present in both tissues.

When considering the interaction between change from week 0 to week 14 and response, the general pattern is magnification in responders, where the same expression changes occurring in both responders and non-responders tend to have greater magnitude in responders. A potential hypothesis is a continuum of response from non-response to response. Gaujoux *et al.* [337] found changes in cell proportions in response to anti-TNF treatment were magnified in responders, also supporting response as continuous phenotype. This study confirms a similar trend at the transcriptional level.

There were some rare exceptions to magnification for genes and modules in the type I interferon pathway. These showed upregulation in non-responders from week 0 to week 14, yet were either downregulated or not significantly different for responders. Single-gene examples include the interferon-induced guanylate-binding proteins *GBP2* and *GBP5* <https://rupress.org/jem/article/216/3/482/120360/Interferon-induced-guanylate-binding-proteins>, and *STAT2*, a key transcription factor for interferon-stimulated genes [238]. Genes such as *IFIT3* and *STAT2* are more strongly induced by type I interferons compared to type II <https://www.pnas.org/content/109/11/4239>. A study of RA, an IMID also treated with anti-TNF drugs, also found increases in type I interferon-regulated gene expression in blood after infliximab treatment associated with poor clinical response <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2875639/>.

A spline model of expression over all four timepoints confirmed the above observations made in week 0 and week 14 samples. Two main clusters of genes (clusters 1 and 5) contained mostly genes significantly associated with response in the two pairwise comparisons: within week 14, and change from week 0 to week 14. An example is the most significant single-gene association from the cluster 1 in spline model, *KREMEN1*, which was also among most significant associations in the pairwise comparisons. *KREMEN1* is part of an inflammatory apoptotic pathway in gut epithelium [https://academic.oup.com/ibdjournal/article/14/suppl\\_1/S4/4653822](https://academic.oup.com/ibdjournal/article/14/suppl_1/S4/4653822), and is downregulated in responders post-induction. The trajectories of expression for genes in

move some of this to results section

these cluster 1 and 5 confirmed changes in expression post-induction were generally greater for responders. and in addition demonstrates that post-induction expression differences between responders and non-responders are sustained in samples taken around week 30 and week 54 during the anti-TNF maintenance period. In PANTS, “continuing standard dosing regimens after primary non-response was rarely helpful” for inducing remission by week 54 [326]. This phenomenon may have a transcriptomic basis.

Making use of data from later timepoints allowed more subtle effects to be detected in the spline analysis. Clusters 2 and 4 are enriched for B cell genes that were not significantly different at the single-gene level in the within week 0 comparison, although some downregulation of B cell and plasma cell modules were detected. Cluster 3 reproduced the observation that interferon-induced genes have opposing trajectories of expression in responders and non-responders. Expression of these genes was higher in responders at week 0 and lower at all post-treatment timepoints. Here, the cluster contains genes such as *STAT1*, *IRF1* and *TAP1* that are induced by both type I and type II interferons <https://www.pnas.org/content/109/11/4239>. I propose that blood expression of interferon-related genes is an attractive target for future studies of the biological basis of anti-TNF response, or prediction of primary response status. If one assumes the model where response and non-response lie along a phenotypic continuum, it is less likely that the opposing directions of regulation can be explained by unmodelled variables such as serum drug level being higher in responders. Since the difference is maintained until week 54, by which time patients would have received many doses of drug, it is also more likely that response is due to some biological property of an individual patient. Studies of anti-TNF response in RA patients have also found high baseline interferon activity in blood to be associated with good clinical response <https://academic.oup.com/rheumatology/article/54/1/188/1840617> <https://onlinelibrary.wiley.com/doi/full/10.1002/art.27226>.

not entirely sure this this  
is statistically rigorous  
due to third var effects?

It should be noted that the number of clusters is only the optimal number determined in this dataset, and does not imply that genes in different clusters represent biologically distinct pathways. Clusters 2 and 4 have similar trajectories and enrichments for B cell genes, and interferon pathway genes appear in both clusters 1 and 3.

Finally, I also attempted to determine if there were changes in genetic architecture of expression over time, which could indicate that expression response to anti-TNF has a genetic component. Out of all significant lead eQTLs for 11156 genes, only six reQTLs were detected with significantly different effect sizes at baseline versus one of the three post-treatment timepoints. Although no enrichment analyses are reported due to the small number of associations, *NMI* and *EPSTI1* are both interferon-induced genes with significant reQTLs that have their strongest effect size on expression at week 54. Given the issues with doing this reQTL analysis in bulk expression data are similar to those encountered in chapter 3, I did not place emphasis on interpreting these small numbers of associations. Before proceeding, I would also like to verify that these significant reQTLs are not artifacts from shrinkage of effect sizes in the joint eQTL model, as their posterior effect sizes from `mashr` were very different from the inputs from the timepoint-stratified models. If these hits are indeed reproducible by complementary methods such as allele-specific expression (ASE) [351], it may then be worth introducing genotype-response interaction terms in the eQTL models to prioritise eQTLs with differing effects in responders and non-responders. Given there

is prior interest in the interferon pathway from **DGE** analyses, a more statistically powerful approach may be to generate a continuous interferon pathway score for each sample, which would then act as the interacting variable, similar to the approach of Davenport *et al.* [94].

Several threats to the validity of the study remain to be discussed. The most pressing may be the meaning of time in the study. For pairwise **DGE** comparisons, expression trajectory clustering, and **reQTL** mapping, samples were divided into four timepoints that corresponded to the major visits in **PANTS**. The **DGE** spline model was fit to study day directly. Study day has substantial variation around the target for later timepoints. The particular targets (weeks 14, 30, 54) for post-baseline samples were chosen so that patients on infliximab (8 weeks between doses) and adalimumab (2 weeks between doses) could both be sampled with the same visit structure. Drug levels peak sharply after each dose and decline exponentially over time. Visits were scheduled to be as close as possible (within a week) to the next scheduled drug dose to capture trough drug levels. Neither approach is perfect, as matching patients by timepoint and study day are only attempts to gather samples matched by trough drug level.

A further complication is the inclusion of **LOR** samples in analyses. One treatment option after **LOR** is dose escalation, which may raise trough drug levels for all subsequent visits for those patients. However, since the **PANTS** protocol allows for **LOR** visits that coincide with major visits to be labelled as a major visit, there is no guarantee that simply excluding samples labelled as **LOR** would resolve this.

The best solution may to explicitly model measured serum drug levels as a covariate, where like cell proportions, it would likely act as a mediator of some associations with response. I did not do this as data missingness would reduce the sample size by about 40% in this study. Finding a suitable normalisation of drug level for use in pooled drug analyses is also challenging. Infliximab and adalimumab have differing pharmacokinetics: infliximab has higher peak concentrations, higher peak-trough ratios, and shorter half-life. The same serum concentrations of infliximab and adalimumab also have different biological effects due to differing therapeutic windows [321, 352] <https://onlinelibrary.wiley.com/doi/full/10.1111/apt.15643>.

Finally, the effects of differential drop out in responders and non-responders has not been explored. The three main mechanisms of missing data are: **missing completely at random (MCAR)**, probability of data being missing is independent of both observed and missing data; **missing at random (MAR)**, probability of data being missing conditional on observed data is independent of missing data; and **missing not at random (MNAR)**, probability of data being missing depends on missing data <https://doi.org/10.1016/B978-0-12-801342-7.00014-9>. Even conditional on response status, it is more likely that expression data from more extreme non-responders is missing for later timepoints, so the likely mechanism here is **MNAR**, and the linear mixed models used in this study may be biased. If it is indeed the most extreme non-responders dropping out, the estimation of responder versus non-responder effects may be conservative. Note there is no sidestepping a **MNAR** mechanism by analysing only the complete cases, since they will differ systematically from the sample as a whole <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3016756/>.

In conclusion, it remains unclear whether there are any robust single-gene markers for anti-**TNF** response in baseline whole blood of **CD** patients. Baseline module associations were observed,

but there was unexpected heterogeneity between infliximab and adalimumab patients, so it remains to be seen if such associations will be replicated in separate cohorts. Large upcoming datasets with drug response phenotypes such as the 1000IBD project [353] will be invaluable for attempted replication of the associations found in PANTS. Expression differences between responders and non-responders were more distinct at timepoints after the induction period. I found type I interferon genes went against the general trend of greater transcriptomic change from baseline in responders, being more upregulated post-treatment in non-responders. Given the type I interferon expression in blood has also been associated with anti-TNF response in RA patients, there may be an opportunity to consider the shared biology of anti-TNF response in IBD and RA. Much work has been done generating and validating signatures for anti-TNF response in RA <https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0033199>; but not much work on validating RA signatures in IBD cohorts and vice versa.

This chapter has been purely descriptive. I have deliberately avoided the term “signature” in my own results, as I have not yet had a chance to assess their predictive capability. I also did not find strong evidence for strong reQTL effects over time in whole blood, so was unable to form hypotheses on the genetic mechanisms influencing anti-TNF response. However, the presence of eQTLs for most genes and the presence of strong differences in expression post-induction may allow testing for causal mechanisms where genotype affects drug response via expression. Strategies for moving onto both prediction and causal inference will be discussed in chapter 5.

**Table 4.1:** Table caption.

	ADA	IFX	pooled	p-value
<b>Sex</b>				0.317
(Col %)				Fisher exact
FEMALE	78 (48.4%)	89 (54.6%)	167 (51.5%)	
MALE	83 (51.6%)	74 (45.4%)	157 (48.5%)	
<b>Age of onset (years)</b>				0.774
Mean (SD)	33.3 (15.4)	32.8 (15.3)	33.1 (15.3)	Wilcoxon rank-sum
Missing	0	0	0	
<b>Disease duration (years)</b>				0.546
Mean (SD)	6.1 (8.1)	5.9 (7.7)	6.0 (7.9)	Wilcoxon rank-sum
Missing	0	0	0	
<b>Smoking status</b>				0.263
(Col %)				Fisher exact
Current	28 (17.4%)	36 (22.1%)	64 (19.8%)	
Ex	55 (34.2%)	43 (26.4%)	98 (30.2%)	
Never	78 (48.4%)	84 (51.5%)	162 (50.0%)	
<b>Crohn's-related surgery</b>				0.549
(Col %)				Fisher exact
FALSE	114 (70.8%)	110 (67.5%)	224 (69.1%)	
TRUE	47 (29.2%)	53 (32.5%)	100 (30.9%)	
<b>On immunomodulator ever</b>				0.543
(Col %)				Fisher exact
FALSE	23 (14.3%)	28 (17.2%)	51 (15.7%)	
TRUE	138 (85.7%)	135 (82.8%)	273 (84.3%)	
<b>On immunomodulator at baseline</b>				0.912
(Col %)				Fisher exact
FALSE	79 (49.1%)	81 (49.7%)	160 (49.4%)	
TRUE	82 (50.9%)	82 (50.3%)	164 (50.6%)	
<b>On corticosteroids at baseline</b>				0.011
(Col %)				Fisher exact
FALSE	113 (70.2%)	92 (56.4%)	205 (63.3%)	
TRUE	48 (29.8%)	71 (43.6%)	119 (36.7%)	
<b>Baseline BMI</b>				0.237
Mean (SD)	25.2 (6.2)	24.3 (5.5)	24.8 (5.9)	Wilcoxon rank-sum
Missing	0	0	0	
<b>Primary response status</b>				0.263
(Col %)				Fisher exact
Primary non-response	76 (47.2%)	66 (40.5%)	142 (43.8%)	
Primary response	85 (52.8%)	97 (59.5%)	182 (56.2%)	
<b>CD8+ T cell (%)</b>				0.380
Mean (SD)	2.8 (4.2)	2.8 (5.2)	2.8 (4.7)	Wilcoxon rank-sum
Missing	38	18	56	
<b>CD4+ T cell (%s)</b>				0.752
Mean (SD)	9.2 (6.3)	9.2 (6.8)	9.2 (6.5)	Wilcoxon rank-sum
Missing	38	18	56	
<b>B cell (%s)</b>				0.094
Mean (SD)	1.9 (2.0)	1.5 (1.9)	1.7 (1.9)	Wilcoxon rank-sum
Missing	38	18	56	
<b>Monocyte (%s)</b>				0.497
Mean (SD)	8.9 (3.5)	9.2 (3.7)	9.0 (3.6)	Wilcoxon rank-sum
Missing	38	18	56	
<b>NK cell (%s)</b>				0.683
Mean (SD)	1.9 (3.2)	1.9 (3.8)	1.9 (3.5)	Wilcoxon rank-sum
Missing	38	18	56	
<b>Granulocyte (%s)</b>				0.911
Mean (SD)	74.3 ( 9.7)	74.3 (10.8)	74.3 (10.3)	Wilcoxon rank-sum
Missing	38	18	56	



## Chapter 5

# Discussion

- In this thesis, ... <a summary of the thesis projects>
  - Chapters 2 and 4 focus on describing the transcriptomic response of circulating immune cells to perturbation with uncontrolled longitudinal designs
    - \* looking at how expression changes over time, and differences in transcriptomic response associated with phenotypic definitions of response
    - \* associations are identified at a gene and gene set level
  - Chapter 3 (and the last part of chapter 4) focus on finding common genetic variants associated with transcriptomic response to perturbation
    - \* reQTLs are identified at lead eQTL variants for each gene
    - \* this is a first foray into defining causal molecular mechanisms that explain individual variation in response to these perturbations
  - Each chapter discusses the results and limitations of each study, but being very similar studies in design and analysis, they also suffer from a core set of limitations.
  - This chapter discusses these, and considerations for design and analysis of similar longitudinal studies in the future to better understand the biology of immune response to drugs and vaccines.

### 5.1 Increasing the power to detect associations

- It has been challenging to find robust single gene-level associations between expression and response, especially at baseline.
  - The biological signal may be small compared to other sources of variation: measurement platform (ch2); drug, response definition (ch4)
  - The obvious thing to do is increase sample size.
    - \* Under a fixed resource constraints, longitudinal studies tradeoff more samples over time for fewer individuals
    - \* Multiomic designs further tradeoff against richness/number of layers sampled

- there are distinct advantages to these designs
  - \* e.g. repeated measures allows modelling of within patient covariance between timepoints with mixed model DGE (ch2 and ch4)
  - \* e.g. spline analysis and clustering in ch4 using multiple timepoints to separate responders and nonresponders
  - \* e.g. ability to test for association between layers (eQTLs), to explore molecular mechanisms
- but especially if the intent is to consider the small effect of genetic variants, a lesson learnt in the field of complex diseases from years of underpowered candidate gene studies, is that even a single complex phenotype requires large samples
- with rich datasets, be careful about subgroup analyses, subgrouping quickly attenuates your effective sample size
  - e.g. looking for timepoint, responder, cell type interactions
  - be wary of rules of thumb for sample size,
    - \* e.g. in ch3, the intention was to map eQTLs at each timepoint, look for timepoint x G interaction, but it became apparent that cell proportion interactions were necessary for interpretation
  - prespecify interactions of interest at the power analysis stage in design of new experiments
  - for existing datasets, a workaround like the two stage strategy in ch3, assuming that interactions are only interesting at significant main effects
- Rather than increasing the sample size, can change the unit of analysis from single gene to multiple genes
  - use information from coordinated changes in multiple genes to detect subtle effects
  - use prior biological knowledge to define set of genes
  - this is the basis for gene set analyses used throughout this thesis
  - tradeoff between better interpretability but worse resolution
- <reproducibility of gene set vs single gene associations>
  - reports about any single gene associations e.g. SIGLEC10 in ch4 of this thesis, should be treated with caution pending replication
  - while the rank of a single gene may vary from sample to sample due to sampling noise, a summary measure computed from multiple genes should be more robust
  - it is hoped that the replicability of gene sets will be greater

## 5.2 Responder analysis

- <how well these models correspond to reality>
  - What does it mean to be a responder?
  - this has been discussed on this in the field of personalised medicine in the context of RCTs, but similar issues pertain to response in observational studies. [354]
  - Is being a responder is a stable personal characteristic of an individual over time, or would the same individual vary in response status over time?
  - Observing between individual variation in response for a single measure is not sufficient to imply response is personal.
  - e.g. a hypothetical agent with a 60% response rate in a group of individuals: “60% of the time, it works every time”
  - what does this mean? working 60% of the time on 100% of individuals, 100% of the time on 60% of individuals, or anything in between would be compatible
  - cannot distinguish with a single measure, yet the assumption is often made at the study design stage that it is the 2nd option
  - 1st option means no associations to detect
- Need to establish how consistent response is over time
  - to determine within-individual variation, needs replication at the level of the individual, i.e. need to perturb and measure the same person more than once [355]
    - \* in ch4, repeated anti-TNF dosing showed expression differences between responders and NR, at least, were stable over time
    - \* although probably partially due to selection of non-remission by w54
  - note for the specific case of genetic factors, the field of complex trait genetics has long had a solution for this: twin studies are analogous to measuring the same individual twice
    - \* For phenotypes like vaccine response in ch2 that can be, twin studies have already demonstrated heritability of certain response phenos like influenza vaccine Ab titres [249]
    - \* In pharmacogenetics, twin studies are less common <https://www.sciencedirect.com/science/article/abs/pii/S0928098719300326> and have not been done for response to anti-TNFs (the ch4 setting)
    - \* repeated crossover trials can be a feasible alternative to twin studies [https://www.researchgate.net/profile/Laszlo\\_Endrenyi/publication/13553486\\_Hypothesis\\_Comparisons\\_of\\_inter\\_and\\_intra-individual\\_variations\\_can\\_substitute\\_for\\_twin\\_studies\\_in\\_drug\\_research/links/59e97c2e458515c36370e6a7/Hypothesis-Comparisons-of-inter-and-intra-individual-variations-can-substitute-for-twin-studies-in-drug-research.pdf](https://www.researchgate.net/profile/Laszlo_Endrenyi/publication/13553486_Hypothesis_Comparisons_of_inter_and_intra-individual_variations_can_substitute_for_twin_studies_in_drug_research/links/59e97c2e458515c36370e6a7/Hypothesis-Comparisons-of-inter-and-intra-individual-variations-can-substitute-for-twin-studies-in-drug-research.pdf) [355]

- <How a responder to a perturbation was modelled in this thesis>
  - As discussed in subsection 2.2.2 in ch2, a binary definition of response based on dichotomisation is inefficient and assumes a sharp change in biological relevance at the threshold
  - In ch2, used **titre response index (TRI)**, a continuous change score residualised on the baseline, which gets around the dichotomisation and dependence of change score on baseline
    - \* two-stage approach here, so df is wrong
  - In multiPANTS, subsection 4.2.3 in ch4 sets out the binary definition of response, which is complex and based on many inputs
    - \* having response dichotomies based on multiple inputs can lead to large discontinuities and non-monotonicity in response probabilities under small changes in input [171]
  - neither approach perfect, but the driving force was pragmatism
    - \* for DGE, the model traditionally requires the response variable to be gene expression, and a predictor variable to be response status
      - \* thus I needed an approach that generates a single predictor variable to represent response status
      - \* In ch2, needed to combine pre-post titre data from two assays
      - \* In ch4, the clinical algorithm already combines many measures into one.
    - having complicated response definitions can hinder replication by adding to interstudy variation e.g. the failure to replicate the TREM1 association in ch4
    - it may be better to directly with the constituent phenotypes: ch2 (log titre levels), ch4 (CRP level, HBI score), but then the fundamental modelling approach for both DGE/eQTL would need to change to not be restricted to a single response x variable
    - also applies to continuous measures of response, as what is being considered is that it only makes sense to talk about response if the response measure is tightly correlated within an individual over time

might be worth subbing predictor for independent and response with dependent in all chapters, but then that gets confused with statistical independence...

### 5.3 Challenges in the interpretation of bulk expression data

- bulk data is a mixture of cell types with different expression patterns
  - one of the largest sources of variation in bulk expression data is cell proportions
  - the more cell type-specific a gene's expression, the more it is affected by cell proportions [356]
    - \* perfectly cell type-specific genes are often called marker genes, and are used in deconvolution methods to estimate cell proportions from bulk data when they are not directly measured

- both variation from true variation in proportions, and sampling noise
- in this thesis, estimated by:
  - \* In HIRD ch 3, xcell deconvolution from expression data
  - \* In PANTS ch 4, deconvolution from methylation data
- these are fit as covariates in models
  - \* could act as precision variables (for sampling noise in non cell type-specific genes),
  - \* but also mediators for cell type-specific genes, where the interpretation of DGE effects changes (perturbation -> cell prop -> expression)
- but coarse grained (just the main cell types) adjustment is not always sufficient, you'll still find associations that are proxies for rare cell types [https://www.biorxiv.org/  
content/10.1101/2020.05.28.120600v1](https://www.biorxiv.org/content/10.1101/2020.05.28.120600v1)
  - \* Recommend the use of e.g. PEER, as in ch3/4 eQTL analysis, some of those factors are likely to be rarer cell types
- <eQTL analysis>
  - analogous to DGE where independent variable of interest is now genotype
  - as discussed in subsection 3.2.11, it is model misspecification to not have the genotype x cell proportion interaction if the effect of genotype changes depending on cell proportions
    - \* in fact, it is popular to use genotype x cell proportion (or a proxy of) interactions to call cell type-specific eQTLs e.g. [69, 72]
    - \* but you cannot distinguish between correlated cell types this way
- <in vivo reQTL analysis>
  - here the cell props are causally affected by the perturbation (active recruitment, differentiation, proliferation of immune cells)
  - consider the contrived case, where vaccine perturbation causes active increase of a rare cell type that is near absent at baseline, but is a greatly increased proportion of the bulk mixture after perturbation.
 

would an in vitro stimulation of a mixture of cells be immune to this? differentiation and proliferation could still occur
  - further assume this is true for all individuals (no variation in cell proportions).
  - an eQTL specific to this cell type will show up as a reQTL in the post-perturbation timepoint because expression of that cell type contributes more to the bulk mixture.
    - \* this will happen even if you adjust for proportion of the cell type, since there is no variation between individuals, it will only offset the regression line
    - \* this does not require the gene to be upregulated on average, as the effect of interest is G -> delta E, not delta E.
  - if the aim of a reQTL study is to identify variants that causally affect transcriptomic response to perturbation, such that if we changed the genotype of an individual (observe the counterfactual), the transcriptomic response would be different.
 

assumes eQTL is finemapped

I cannot figure out what sort of conditioning would need to be done to block this sort of effect even if you had perfect cell proportion measurements

- does this achieve that aim? yes, as the change in expression after perturbation differs when you change someone's genotype, as there is no difference between genotypes at baseline, but there is after perturbation.
- for genotype to explain more variance in bulk expression after perturbation, there are multiple compatible mechanisms
  - \* a cell type with a cell type-specific eQTL increases in proportion (recruitment)
  - \* a gene with an eQTL increases in expression (activation or recruitment depending on if you condition by cell proportions)
  - \* the effect of a cell type-specific eQTL increases within that cell type (activation)
- one could imagine crude ways to falsify each hypothetical model e.g. interaction/coloc with each cell type (ch3), but always at risk of missing a cell type
- the challenge is distinguishing these scenarios in bulk *in vivo* data to form mechanistic hypotheses for expression response
- future studies should consider alternatives to bulk before they can fully take advantage of benefits of *in vivo* design
  - rather than conditioning on cell proportion, effectively looking at the subset of data with same cell proportions, just control them
  - If you want a mechanistic interpretation, need to control
  - single-cell RNAseq has the advantage of getting expression and composition simultaneously, and can be comparable in cost to bulk on FACS sorted cells <https://arxiv.org/ftp/arxiv/papers/1909/1909.12550.pdf>
    - \* but lower coverage of the transcriptome due to drop out, and smaller sample sizes
  - do DGE/map eQTLs within each cell type
    - \* combines advantage of *in vivo* stimulation with the controlled cell composition of *in vitro* studies
  - can also be used to annotate bulk reQTLs such as those found in ch3 e.g. find the likely cell types for bulk reQTL effects by looking at eGene expression in single cell data [88]

## 5.4 From association to prediction

- I have now discussed both the independent and dependent variables used in descriptive models of expression vs response
  - so far, always put expression as dependent, and response status as independent, and estimated the effect size of response status on expression
  - did this even when response is measured after expression (baseline expression)
    - \* this is the assumption that response is a stable individual characteristic

- \* also assumes it is measured without error, otherwise would stray into the realm of error in variables models
- but might also want to consider if given expression, you could predict response (probability) as a dependent variable
- this is also directly relevant to clinical goal of predicting patient response from baseline expression
- a large  $p \gg n$  prediction problem
  - given the few gene-level associations with response is it futile to try?
  - Efron [357] provides an encouraging counterexample on  $n=102$  (52 prostate cancer, 50 controls),  $p=6033$  genes
    - \* random forest to predict cancer status from gene expression: 2% test set error
    - \* removed the 348 genes with positive importance scores, these are all the genes that were ever involved in a splitting rule
    - \* rerun on resulting  $102 \times 5685$  matrix, still a similar error rate
    - \* repeat that process, removing 364 genes. rerun on resulting  $102 \times 5321$  matrix, still a similar error rate
  - performance of such purely predictive models is dominated by combining many weak predictors
  - pure prediction is an easier problem than the traditional approach trying to attribute statistical significance to a few strong predictors
  - this may be why there is sometimes little overlap in the gene signatures from different studies on the same trait
- Need to consider what it takes for a gene expression prediction model to be clinically useful?
  - Useful to look at examples from cancer, one of the earliest fields where the approach generated interest
  - Despite the early gene expression signatures being reported in the early 2000s, only a handful in use [358] <https://clincancerres.aacrjournals.org/content/21/21/4743>
  - many hurdles: need to be accurate enough to base changes in therapy on, but incrementally more accurate than existing clinical markers, and cost effective. <https://doi.org/10.1093/annonc/mdw307>
  - measuring a whole transcriptome is likely not cost effective. what are potential methods that might be?
  - for predicting vaccine response from transcriptomic data, popular methods are:
    - \* DAMIP e.g. [243], which gives rulesets composed of small sets of genes
    - \* elastic net
    - \* sparse partial least squares e.g. [160]

- Note the sparsity assumption for these methods (most genes are not predictive) is in opposition to the idea of combining many weak predictors to maximise predictive power, but will be less costly to translate to clinical practice

## 5.5 From association to causality

- uncovering “mechanism”
  - Knowing the molecular mechanisms of response are crucial for conceiving of possible interventions.
    - \* e.g. ch4 baseline SIGLEC10 expression is associated with anti-TNF response, but would changing baseline SIGLEC10 affect response?
  - In observational data, a causally upstream anchor is required: genetic variation
  - the regression analyses in this thesis:
    - \* DGE describes expression response association with phenotypic response (such as Ab titre)
    - \* reQTLs describe genotype association with expression response
  - Need a model that encodes causal assumptions integrating multiple data layers: genotype -> gene expression -> phenotypic response
  - there are several families of complementary methods that integrate multiple data layers
- <Mendelian randomisation>
  - <explain the analogy to RCTs: segregation should be independent of env factors>
  - is a type of IV analysis that uses genetic instruments: can use eQTLs as instrumental variables (IV) to estimate causal effect between expression (exposure) and phenotype (outcome)
  - three assumptions that define a valid IV [359–361]
    - \* IV1 SNP is associated with expression i.e. an eQTL (no need to be fine mapped [97, 359])
    - \* IV2 SNP is not associated with confounders of the expression-phenotype association
    - \* IV3 SNP has no association with phenotype except through expression
  - combined, these assumptions mean that expression is a complete mediator of the causal effect of the SNP on phenotype (a vertical pleiotropy is assumed)
  - two-sample MR is where G -> E and E -> pheno are estimated in two non-overlapping samples [360, 361], and can come from large existing QTL datasets
    - \* a related family of methods, TWAS <https://www.nature.com/articles/ng.3506>, tests association of genetically predicted expression to phenotypes, have their methodological basis in two-sample MR <https://link.springer.com/article/10.1007/s40484-020-0207-4>

- assumption violations will lead to bias in estimating causal effect of E on pheno
    - IV1 is satisfied by definition of an eQTL
    - IV2 violations are not likely, as genetic variants are unlikely to be associated with environmental confounders
    - IV3 violation is most likely
  - <coloc>
    - IV3 violated by linkage: if the instrument eQTL is actually not causal, but simply correlated with another variant that causally affects phenotype
      - \* use colocalisation methods to test whether the same variants are associated with E and phenotype [360]
      - \* described in ch1, and used in ch3
  - <mediation analysis>
    - IV3 violated by horizontal pleiotropy: instrument eQTL causes expression and phenotype independently (e.g. by also being an eQTL for another gene whose expression causally affects pheno), such that expression and phenotype are not causally related
    - use mediation analysis e.g. (CIT[257], findr[362]) that model comparison to distinguish between models of horizontal from vertical pleiotropy
      - \* [257] used by Franco *et al.* [92] in a vaccine response reQTL setting, although they concluded they were underpowered
      - however, requires individual level data, and more susceptible to measurement error than MR [360]
  - IV3 violated by reverse causation: assumed expression  $\rightarrow$  response, but the causal direction might actually be the reverse: G  $\rightarrow$  phenotype  $\rightarrow$  expression
    - if suspected, recommendations to distinguish [359–361] <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5036871/>
      - \* perform MR in the reverse direction if there are instruments for the phenotype (bi-directional MR)
      - \* extensions that test the directionality based on variance explained (MR Steiger) <https://journals.plos.org/plosgenetics/article?id=10.1371/journal.pgen.1007081>
      - \* incorporate biological knowledge, e.g. if eQTL variant is in a TF motif for a gene, more likely G  $\rightarrow$  E than G  $\rightarrow$  pheno  $\rightarrow$  E
- citation needed,  
 try davey-smith2020MendelLawsMendelian

## 5.6 Triangulation

- Triangulation is the use of methods with different assumptions, biases, and limitations that address the same question [363]

- discussed above is one example of triangulation, using complementary methods MR, colocalisation, mediation analysis to tease apart causal mechanisms from  $G \rightarrow E \rightarrow \text{pheno}$ 
  - \* e.g. Taylor *et al.* [364]: an example combining MR, coloc (HEIDI), MR Steiger, CIT, to disentangle causal effect of SNPs on DNA Me and expression
  - \* [365] Predicted associations between proteins and phenotypes may indicate four explanations: causality, reverse causality, confounding by LD between the leading SNPs for proteins and phenotypes or horizontal pleiotropy (Supplementary Fig. 3). Given these alternative explanations, we conducted a set of sensitivity analyses to evaluate whether each MR association reflected a causal effect of protein on phenotype: tests of reverse causality using bidirectional MR22 and MR Steiger filtering;<sup>23,24</sup> heterogeneity analyses for proteins with multiple instruments<sup>25</sup>; and colocalization analyses<sup>26</sup> to investigate whether the genetic associations with both protein and phenotype shared the same causal variant (Fig. 1).
- another example, how  $G \rightarrow E$  effect changes in response to perturbation
  - \* combine reQTL mapping (between individuals), dynamic ASE (within heterozygous individuals), (and maybe variance QTLs)
  - \* dynamic ASE example for multiple T cell activation states <https://www.nature.com/articles/s41588-020-0579-4>
- another example, multiomics integration
  - different layers have non-redundant readouts
  - e.g. pQTLs
  - e.g. foreshadowing of eQTL by caQTLs
  - network approaches, MOFA
- many limitations discussed cannot be solved by increasing n
- triangulation will be key in moving from a descriptive to mechanistic understanding of immune response to perturbation

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# List of Abbreviations

**AC** allele count

**APC** antigen-presenting cell

**ASC** antibody-secreting cell

**ASE** allele-specific expression

**AUC** area under the curve

**BCR** B cell receptor

**BH** Benjamini-Hochberg

**BMI** body mass index

**BTM** blood transcription module

**CD** Crohn's disease

**CDR** complementarity-determining region

**CIT** causal inference test

**CPM** counts per million

**CRP** C-reactive protein

**CyTOF** cytometry by time-of-flight

**DAMP** damage-associated molecular pattern

**DC** dendritic cell

**df** degree of freedom

**DGE** differential gene expression

**ELISA** enzyme-linked immunosorbent assay

**ELISPOT** enzyme-linked immune absorbent spot

**eQTL** expression quantitative trait locus

**FACS** fluorescence-activated cell sorting

**FC** fold change

**FDR** false discovery rate

**FWER** family-wise error rate

**GWAS** genome-wide association study

**HA** haemagglutinin

**HAI** haemagglutination inhibition

**HBI** Harvey Bradshaw index

**HIRD** Human Immune Response Dynamics

**HLA** human leukocyte antigen

**HSC** hematopoietic stem cell

**HWE** Hardy-Weinberg equilibrium

**IBD** inflammatory bowel disease

**IIV** inactivated influenza vaccine

**IMID** immune-mediated inflammatory disease

**INT** inverse normal transformation

**LAIIV** live attenuated influenza vaccine

**LD** linkage disequilibrium

**lfsr** local false sign rate

**LMM** linear mixed model

**LOCO** leave-one-chromosome-out

**LOR** loss of response

**LRT** likelihood ratio test

**MAF** minor allele frequency

**MANOVA** multivariate analysis of variance

**MAR** missing at random

**MCAR** missing completely at random

**MHC** major histocompatibility complex

**ML** maximum likelihood

**MN** microneutralisation

**MNAR** missing not at random

**molQTL** molecular expression quantitative trait locus

**mRNA** messenger RNA

**MS** multiple sclerosis

**NA** neuraminidase

**ncRNA** non-coding RNA

**NK** natural killer

**OVB** omitted-variable bias

**PAMP** pathogen-associated molecular pattern

**PANTS** Personalised Anti-TNF Therapy in Crohn's Disease

**PBMC** peripheral blood mononuclear cell

**PC** principal component

**PCA** principal component analysis

**PNR** primary non-response

**PRR** pattern recognition receptor

**PVE** proportion of variance explained

**QTL** quantitative trait locus

**RA** rheumatoid arthritis

**RBC** red blood cell

**REML** restricted maximum likelihood

**reQTL** response expression quantitative trait locus

**RNA-seq** RNA-sequencing

**SLE** systemic lupus erythematosus

**SNP** single nucleotide polymorphism

**T1D** type 1 diabetes

**T2D** type 2 diabetes

**TF** transcription factor

**TIV** trivalent inactivated influenza vaccine

**TLR** Toll-like receptor

**TMM** trimmed mean of M-values

**TNF** tumour necrosis factor

**TPM** transcripts per million

**TRI** titre response index

**TSS** transcription start site

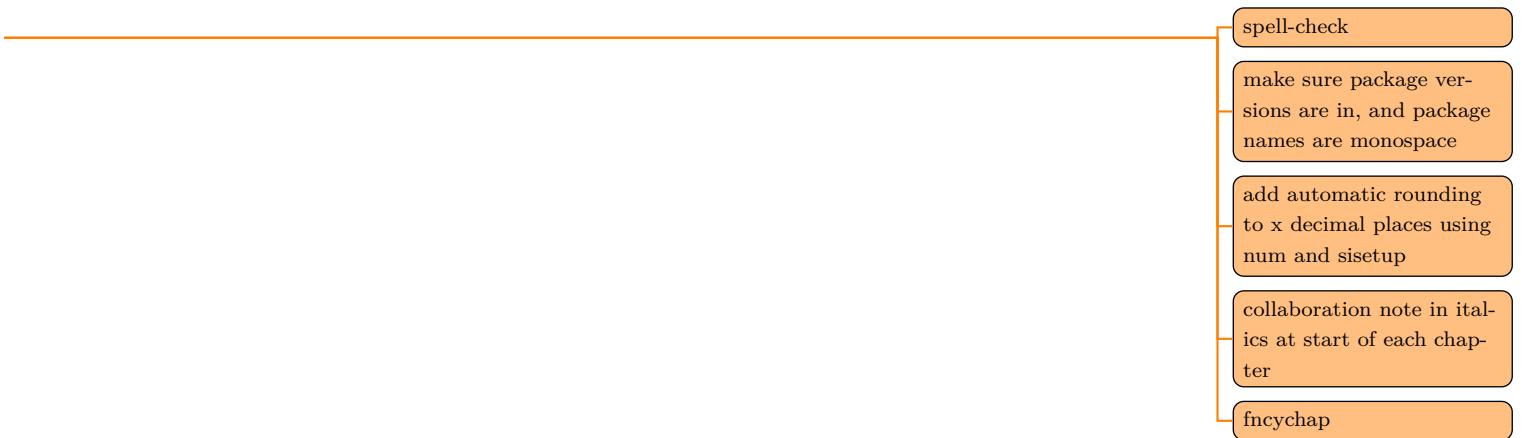
**UC** ulcerative colitis

**UTR** untranslated region

**WES** whole-exome sequencing

**WGS** whole-genome sequencing

**WHO** World Health Organization





# Todo list

make shorter to keep on one page . . . . .	iii
I agree the intro is built around genetics. I have tried to keep the genetics parts concise while elaborating on gene expression more in the later two sections. . . . .	1
Prioritisation of context is mentioned shortly. . . . .	9
maintain a pool naive lymphocytes, each having a receptor specific for a different possible antigen . . . . .	11
add TCR . . . . .	11
distinguish plasmablast/plasma cell and add long lived plasma cells . . . . .	11
add B cell activation mechanism by cd4, BCR . . . . .	11
I elaborate on this in the methods . . . . .	19
no longer spoils results . . . . .	19
yes, this paragraph is needed here to accompany the figure . . . . .	20
192 and 176 should be correct, 169 is the number after QC. . . . .	21
still some missing software versions and references . . . . .	21
no in both cases, I mean the genes are removed from the analysis, no use increasing the multiple testing burden . . . . .	29
will get to consistency of top hits in the next section when i discuss meta-analysis results . . . . .	41
no formal tests for heterogeneity of effect here, i don't think it's worth the effort unless reviewer 2 says so. . . . .	44
I think the best place for 'lessons learnt' is in the discussion chapter, since similar conclusions are relevant to pants . . . . .	50
if they don't have the signature until day 8,9,10 or ever, then it will probably add unexplained variation to TRI, more noise . . . . .	50
it doesn't compare, sobolev did not find any baseline associations . . . . .	50
no gwas studies that i can find . . . . .	54
hopefully sufficient background is covered in the intro for this to be understandable . . . . .	54
upend change score bit, here expression is a y variable. compare all the options as glms etc. . . . .	56
Can this really demonstrate genotype-dependent change in gene expression between time-points? i.e. need understand how the change score/ANCOVA approaches differ from repeated measures ANOVA differ from the interaction/stratified approach I take? . . . . .	56
why I didn't just do a mega-analysis in chapter 2 then, given I haven't any evidence if it's better or worse than Bayesian meta-analysis in that context. . . . .	56
add -7 note as with ch2 . . . . .	56
add some indication of how much inflation can be reduced by LMMs . . . . .	57

add chr1 loco kinship matrix as example, note the estimates for self-relatedness on the diagonals are not constrained to be 1 . . . . .	57
helps with coloc . . . . .	58
emph here that the sims match what my def of reqtl is for rest of chapter . . . . .	58
log scale: as interactions depend on the scale at which departure from additivity is detected	58
add sample sizes and model for expression sim . . . . .	58
determine appropriate citations from existing refs in intro . . . . .	60
?? . . . . .	60
add comment on existence of chosen cell types in samples, and clustering by visit . . . . .	60
does not bias least squares regression, but unstable (vary sample to sample) to changes in data due to sampling var, and more std error of estimates will be high (tending to inf if perfect multi) . . . . .	60
no need for both size and color, use one for contribution percent . . . . .	60
add info on the markers used for the chosen FACS counterparts . . . . .	60
get subset size . . . . .	64
change corr scatterplots to corr matrix . . . . .	64
remake this with only top k factors, and prune the possible covariates . . . . .	64
add approximate MAFs, then cite hierach paper . . . . .	64
add note on treating x chrom variants with caution . . . . .	64
lift proper vector notation from limix, then redo this with a timepoint subscript . . . . .	67
add formulation of the 0-mean random effect to show exactly how the kinship matrix is used [289] . . . . .	67
note stacking of kinship for day -7 repeated measures . . . . .	67
i leave the pcs in to guard against unusually differentiated between pop markers, where random effect alone may not be enough [274], <a href="https://www.nature.com/articles/srep06874">https://www.nature.com/articles/srep06874</a> . . . . .	67
recheck if did I do a SNPs only filter . . . . .	67
note this is critical, since we know a priori not independent due to eqtl sharing . . . . .	67
not sure whether this is conservative or anti-conservative . . . . .	68
mashr does not provide by default . . . . .	68
RNAseq does test about 7000 more genes though... . . . . .	70
be more specific: "moderator", 'modify'????? . . . . .	70
point is, doesn't make sense to assume the genotype effect is the same at all levels of cell type abundance . . . . .	70
can we interpret with peer in? add note of CLAIM here that although peer is correlated with xcell, interactions are only formed with xcell, so the interaction term can be interpreted per unit of genotype increase when xcell=0 . . . . .	70
this analysis is incomplete, and is one of the things I would suggest to round off this chapter	70
this analysis is incomplete, and is one of the things I would suggest to round off this chapter	80
FYI the IBD/T cell coloc fine maps to chr2:24935139 T C (rs713586) with PP=1 . . . . .	80
add obesity GWAS . . . . .	80
compare sharing with mashr and ongen2017EstimatingCausalTissues . . . . .	80

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I'm not exactly sure why at the moment. Enrichment analyses so far have not turned up much. Up regulation of cell cycle TFs is a possibility. . . . .	81
replace mcgovern2015GeneticsInflammatoryBowel with more recent . . . . .	83
add lfsr.dge . . . . .	83
need to consider: if this kind of thing is what bulk <i>in vivo</i> reQTL can find, they what is the additional value over FACS? . . . . .	83
dge is coupled to reqtl, if you do an enrichment of dge+reqtl overlap genes, likely their enrichment is driven by DGE signal . . . . .	83
harmonise terminology for 'opposite' . . . . .	84
check "rs2223286 is associated with profound directional effects in the expression of SELL dependent upon genotype, with the minor C allele associated with increased expression of SELL in B-cells and reduced expression of SELL in monocytes " . . . . .	84
note coloc doesn't distinguish pleiotropy from mediation? . . . . .	84
add 1 concluding line . . . . .	84
Overall I feel like the chapter is too descriptive, and falls short of making biological insights into Pandemrix response. Any additional analyses would hope to address that. . . . .	84
difficult to separate out CD from IBD in literature, section probably needs to decide to focus on CD only or IBD. . . . .	85
the subsection on anti-TNFs in the intro chapter may be merged here . . . . .	86
I assume dosing follows the induction and maintenance schedule from [320]. Can't find anything about it in the PANTS protocol, although Sim confirmed the 2w/8w frequencies.	86
add ref to Alex's ppt . . . . .	88
trying not to 'spoil' any results in the intro, I guess . . . . .	88
compute maximum deviation? . . . . .	89
Still discussing with Sim on the exact def of LOR and exit visits to decide whether this is sensible. . . . .	89
The observational study design does not allow straightforward estimation of causal effects, so this is only assumed . . . . .	93
Could cell proportions act as colliders? . . . . .	94
Alter and move this to ch2 . . . . .	94
trying to understand how exactly the B-spline basis for the natural spline works will take a few more youtube lectures... . . . . .	96
move this to ch2, then refer to it . . . . .	96
collab note: QC done by Alex . . . . .	96
I've collected the QC details here from Alex's thesis . . . . .	97
precision for integers . . . . .	97
much of this section is brief, since the same pipeline as ch3 . . . . .	97
as with most of this section, this is more explained in ch3 . . . . .	99
yes, there could be ties in lfsr . . . . .	100
what to put in results vs discussion. going with the pattern of providing enough info for the reader to interpret the data in the results, then doing a summary and my own interpretation in the discussion . . . . .	100

Some primary non-responders have loss of response samples. Not sure why. . . . .	100
add caption and label after finalising table data . . . . .	100
highlight a few more individual genes specific to this analysis too? not sure how to pick them at the moment. . . . .	106
TODO I forgot to include the non-ranked hypergeometric test and gprofiler tests in the gene set enrichment section in the methods. . . . .	111
right word??? . . . . .	118
So many modules associations here, maybe try to Google some of them... . . . . .	120
How does the MHC come in here? . . . . .	121
move some of this to results section . . . . .	123
not entirely sure this this is statistically rigourous due to third var effects? . . . . .	124
might be worth subbing predictor for independent and response with dependent in all chapters, but then that gets confused with statistical independence... . . . . .	132
would an in vitro stimulation of a mixture of cells be immune to this? differentiation and proliferation could still occur . . . . .	133
assumes eQTL is finemapped . . . . .	133
I cannot figure out what sort of conditioning would need to be done to block this sort of effect even if you had perfect cell proportion measurements . . . . .	134
citation needed, try daveysmith2020MendelLawsMendelian . . . . .	137
spell-check . . . . .	169
make sure package versions are in, and package names are monospace . . . . .	169
add automatic rounding to x decimal places using num and sisetup . . . . .	169
collaboration note in italics at start of each chapter . . . . .	169
fncychap . . . . .	169