An evolutionary epigenetics approach to schizophrenia

Niladri Banerjee

Thesis for the Degree of Philosophiae Doctor (PhD) University of Bergen, Norway 2018



UNIVERSITY OF BERGEN

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Scientific Environment

The present work has been conducted in the Department of Clinical Science, Faculty of Medicine & Dentistry, University of Bergen, Norway where I have been privileged to be part of the Dr Einar Martens group for Biological Psychiatry. As part of the group, I feel deeply thankful to have had the chance to expand my knowledge and understanding of the several aspects of schizophrenia through a multitude of methodologies including clinical, statistical and genetic approaches. Professor Stéphanie Le Hellard acted as my main supervisor with senior researcher Timothy Hughes, PhD at the Oslo University Hospital acting as the first co-supervisor and Tatiana Polushina, PhD at the Department of Clinical Science, University of Bergen as second co-supervisor.

The Martens group is part of the K.G Jebsen Centre for Psychosis, a joint endeavour between the University of Oslo and University of Bergen with the Centre of Excellence(CoE)- Norwegian Centre for Mental Disorders Research (NORMENT): a joint collaboration between University of Bergen, University of Oslo and Oslo University Hospital funded by the Research Council of Norway (RCN). This allowed me national and international level access to knowledge, expertise and networks all involved in dissecting the complex aetiology of mental disorders.

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Bergen, June 2018

Niladri Banerjee

कर्मण्येवाधकिारस्ते मा फलेषु कदाचन। मा कर्मफलहेतुर्भूर्मा ते सङ्गोऽस्त्वकर्मण॥ि २-४७

Karmanye vadhikaraste Ma Phaleshu Kadachana, Ma Karmaphalaheturbhurma Te Sangostvakarmani Bhagwad Gita, Chapter 2: Verse 47

Translated,

- You have the right only to perform the work, but never to its fruits.

Let neither the fruits of action be your motive, nor let your attachment be to

inaction.

Summary

Schizophrenia is a psychotic disorder with an estimated lifetime prevalence of ~1% worldwide. Despite reduced fecundity of patients, this rate is stable across population groups separated by geography and time. There is also evidence from the Mesopotamian culture ca 5000 years ago of symptoms that today would be classified as schizophrenia. To explain this stable occurrence of the disorder, the so-called *'Evolutionary hypothesis of schizophrenia'* has been gaining ground. The most well known of which was propositioned by T.J. Crow in 1998, though others including Huxley (1964) and Essen-Möller (1959) have also argued about selective advantages of the disorder. A key assertion made by Crow was the emergence of schizophrenia as a by-product of human evolution, as 'the price humans pay for language'.

In the past two decades, the emergence of genomic technologies and resources have made it possible to test the evolutionary aspect of Crow's hypothesis. There is a growing body of evidence from the field of genomics that suggests human evolution may have played a role in the susceptibility to schizophrenia.

Developments within the last five years have allowed researchers to trace the evolution of epigenomes giving an unprecedented window on gene-environment (GxE) interactions of the past several thousand to millions of years. In the present thesis, I undertake a body of work that investigates the evolutionary question of schizophrenia from this new field of evolutionary epigenetics. We first test whether human-specific methylated regions, determined in comparison to Neanderthals and Denisovans are enriched for schizophrenia markers. These methylated regions represent at least 750,000 years of evolution since the last common ancestor diverged from Neanderthals and Denisovans (**Paper I**). This was followed up by investigating primate-methylated regions that represent at least 13 MYA of epigenomic evolution (**Paper II**). Finally, we investigate whether human-specific methylated regions, as

defined in the first study are amenable to methylation variation in patients with schizophrenia (**Paper III**).

We find evidence that recent evolution denoted by human-specific methylated regions tracing ~750,000 years of methylation development are enriched for schizophrenia markers. Primate methylation markers are not enriched for schizophrenia variants with the exception of the extended Major-Histocompatibility Region (MHC) region. Finally, we find evidence of methylation disruption in brain samples of patients with schizophrenia in regions that underwent human-specific methylation evolution.

Our results provide support that recent evolution, denoted by methylation changes since the divergence of the common ancestor of humans, Neanderthals and Denisovans, harbour more schizophrenia associated markers than expected by chance, and thus, may have played a role in susceptibility to schizophrenia at a group-level.

Publication List

Paper I

Banerjee N, Polushina T, Bettella F, Giddaluru S, Steen VM, Andreassen OA, Le Hellard S. Recently evolved human specific methylated regions are enriched in schizophrenia signals, *BMC Evolutionary Biology*, 2018, 18:63, https://doi.org/10.1186/s12862-018-1177-2

Paper II

<u>Banerjee N</u>, Polushina T, Bettella F, Giddaluru S, Steen VM, Andreassen OA, Le Hellard S. Analysis of differentially methylated regions in primates and nonprimates provides support for the evolutionary hypothesis of schizophrenia, *Schizophrenia Research* (Submitted March 2018, Under review)

Paper III

Banerjee N, Polushina T, Stavrum AK, Steen VM, Le Hellard S. Functional analyses of evolutionary human-specific methylated regions in schizophrenia patients (Manuscript)

Abbreviations

Word	Full form
450k array	Illumina Infinium HumanMethylation450
	BeadChip array
А	Adenine
AA	Arachidonic Acid
ADHD	Attention Deficit Hyperactivity Disorder
BDNF	Brain Derived Neurotrophic Factor
BMI	Body Mass Index
bp	base pairs
BCE	Before Common Era
BPD	Bipolar Disorder
ca	circa
С	Cytosine
CE	Common Era
CERS3	Ceramide Synthase 3
CNV	Copy Number Variation
CpG	Cytosine-phosphate Guanine di-nucleotide
DBP	Diastolic blood pressure
DDX43	DEAD-Box Helicase 43
DHA	Docosahexaenoic acid
DPPA5	Developmental Pluripotency Associated 5
DISC1	Disrupted-in-schizophrenia 1
DMP	Differentially methylated position
DMR	Differentially methylated region
DNA	Deoxyribonucleic acid
DNMT1	DNA Methyltransferase 1
DSM	Diagnostic & and Statistical Manual of Mental Disorders
ecdf	Empirical cumulative distribution function
e.g.	exempli gratia (for example)
etc.	et cetera
EWAS	Epigenome-wide association study

FDR	False Discovery Rate
FOSB	Finkel-Biskis-Jinkins murine osteosarcoma viral oncogene homolog
	В
FGFR1	Fibroblast growth factor receptor 1
G	Guanine
GABA	Gamma-amino-butyric acid
GEO	Gene expression omnibus
GWAS	Genome-wide association study
GxE	Gene by environment interaction
HAR	Human accelerated region
H1	Histone H1
H2A	Histone H2A
H2B	Histone H2B
Н3	Histone H3
H4	Histone H4
hg18	Human genome build 18
hg19	Human genome build 19
HDL	High-density lipoprotein
ICD	International Statistical Classification
	of Diseases and Related Health Problems
i.e.	id est (that is)
INRICH	Interval enRICHment Analysis
IPA	Ingenuity pathway analyses
LD	Linkage disequilibrium
LDL	Low-density lipoprotein
LINC00606	Long Intergenic Non-Protein Coding RNA 606
LY6G5C	Lymphocyte antigen 6 family member G5C
MAF	Minor allele frequency
MAOA	Monoamine oxidase A
MARK3	Microtubule Affinity Regulating Kinase 3
MEK1	Mitogen-activated protein kinase kinase 1
МНС	Major histocompatibility complex

MYA	Million years ago
NIMH	National Institute of Mental Health
NSS	Neanderthal Selective Sweep
PRDM9	PR-domain containing protein 9
PUFA	Polyunsaturated Fatty Acid
QQ	Quantile-quantile
r ²	Squared correlation coefficient (linkage disequilibrium)
RA	Rheumatoid arthritis
RNA	Ribonucleic acid
REC8	REC8 meiotic recombination protein
RELN	Reelin
RDC	Research Diagnostic Criteria
RDoC	Research Domain Criteria
SBP	Systolic blood pressure
SCZ	Schizophrenia
SNP	Single nucleotide polymorphism
SOX10	Sex-determining Y-box 10
Т	Thymine
TC	Total cholesterol
TG	Triglycerides
UCSC	University of California, Santa Cruz
USA	United States of America
WHO	World Health Organization
YA	Years Ago
ZSCAN12P1	Zinc finger and SCAN domain containing 12 pseudogene 1

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1. Introduction

1.1 Schizophrenia

Schizophrenia is a debilitating mental disorder that causes considerable loss in quality of life to the patient affected [1–3] as well as significant costs to society [4–8]. The term 'schizophrenia' was first coined by Eugen Bleuler in 1908 to classify a constellation of symptoms observed in the disorder using the Greek roots *schizen* ('to split') and *phren* ('mind, spirit, soul') [9–11].

It can be diagnosed as per the Diagnostic and Statistical Manual for Mental Disorders 5 (DSM 5) by the presence of characteristic symptoms such as delusions, hallucinations or disorganised speech in addition to catatonia or avolition. Additionally, there is a marked decrease in social and occupational function such as work, self-care and interpersonal relations. For a diagnosis, symptoms must be present for six months, including at least one month of characteristic symptoms. It is also necessary that schizoaffective or bipolar disorder with psychoses is ruled out, and that the patient is not abusing any drugs. Furthermore, if autism is present, then it needs to be accompanied by hallucinations for at least one month [12].

1.1.1 Historical perspectives

The modern definition of schizophrenia owes a lot to the work of Eugen Bleuler and Emil Kraepelin from late 19th-early 20th century. However, they were neither the first to observe the disorder, nor the first to describe its symptoms. The disorder has accompanied mankind at least since humans started keeping written records [13,14].

Cuneiform tablets of Mesopotamia from the third millennium BCE [13,14] describe some of the earliest examples of symptoms that today would be classified as schizophrenia. The ancient Hindu texts of Vedas (ca 1400 BCE) provide descriptions of psychoses that is distinct from manic-depressive illness [14,15]. Other descriptions lie in the satires of Horace from the first century BCE and the writings of Roman physicians Caelius Aurelianus and Alexander of Tralles from the fifth and sixth century CE. The first century CE Hindu treatise on Ayurvedic medicine, '*Charaka Samhita*' also describes symptoms akin to schizophrenia [16]. Reviewing the literature from the Middle Ages in Europe led Nigel M. Bark to conclude the existence of schizophrenia for at least 2000 years [17–19].

1.1.2 From Dementia praecox to Schizophrenia

Industrialization in Europe in the 18th-19th centuries led to an increased medical observation of patients with mental illnesses [18]. Several physicians from across Europe, therefore, took a keen interest in the development, diagnoses and nomenclature of the disorder. In 1801, Phillipe Pinel from France laid the groundwork for what Emil Kraepelin later termed 'dementia praecox' and Eugen Bleuler, 'schizophrenia'. Pinel used the word '*démence*', meaning 'loss of mind' to describe the degradation of mental faculties of chronically ill, hospitalised mental patients. The word itself had been used in French literature since 1381 to describe the condition of mental deterioration [14]. In 1847, Millingen emphasised the post-pubertal onset of the disease [20]. To highlight this aspect of the disorder, Benedict Augustin Morel coined the French term '*démence précoce'* in 1852 that literally means 'loss of mind at a young age' that differentiated it from '*démence senilis*' or 'loss of mind due to old age'.

In 1893, Emil Kraepelin introduced the term 'dementia praecox' in the 4th edition of his book [21]. Amongst the major contributions of Kraepelin were his division of psychotic illnesses into two categories: dementia praecox and manic-depressive insanity [14]. He made the observation that age of onset, familial history and premorbid personalities could

distinguish between the two kinds of illnesses and emphasised the presence of hereditary factors in his patients with dementia praecox. Furthermore, he was the first to challenge the notion of schizophrenia as a European phenomenon caused by industrialisation. He observed the remarkable similarity of symptoms in cases as far away as Singapore and in populations of Chinese, Malay, Tamils and Japanese [22]. He stated the necessity of finding the real cause of a disorder that did not depend on race, climate or food [14,22].

The Swiss psychiatrist Eugen Bleuler, however, differed with Kraepelinian concepts of the disorder [14]. He asserted that not all patients displayed symptoms at a young age, nor were they all equally likely to be predisposed to deterioration of their mental faculties [11]. Furthermore, Bleuler was influenced by the works of Wundt, Freud and Jung in his approach to mental illnesses [11,23]. He, therefore, brought forward the psychological aspects of the disorder in his work with Carl Jung [24] and introduced the concept of 'schizophrenia' from '*schizen'* meaning 'to split' and *phren* meaning the 'mind' [11]. While expanding the scope of the disorder, Bleuler's work also helped characterise the disorder not as a single entity but rather as a heterogeneous mixture of several disorders-'a genus, not a species' [14,25].

Finally, Kurt Schneider [26], a German psychiatrist, paved the way for a systematic diagnostic system that was replicable between different psychiatrists (inter-rater reliability) [27] and whose principles were incorporated into current psychiatric diagnostic criteria [14].

1.1.3 The modern diagnostic system(s)

The modern understanding of the disorder as described in Diagnostic and Statistical Manual for Mental Disorders (DSM), the International Statistical Classification of Diseases and Related Health Problems (ICD), as well as the Research Diagnostic Criteria (RDC), incorporates several concepts not only from Kraepelin and Bleuler, but also from Schneider [14].

The RDC system was established in the 1970s [28–31] and had strict diagnostic criteria that excluded labelling patients as schizophrenics if they exhibited major affective disorder or other borderline disorders. Furthermore, the age of onset and duration of symptoms was also limited to forty years and six months respectively. These features helped improve the reliability of the psychiatric diagnostic systems in existence at the time [32,33]. This system was instrumental in the development and refinement of the diagnostic system from the American Psychiatric Association- the 'Diagnostic and Statistical Manual of Mental Disorders (DSM)'. Before the RDC, the DSM-II had vague descriptions of the symptoms and diagnostic criteria [32,33]. Subsequent development of DSM-III [34] incorporated several elements from RDC and eventually became the *defacto* standard for diagnoses of psychiatric illnesses [32].

The subsequent revision to DSM-IV [35] established one of the most widely used diagnostic criteria with high reliability and fair validity [36,37] that was also used in one of the largest genetic investigations of the disorder [38]. The system emphasises the positive (hallucinations, delusions) [39,40] and negative symptoms of the disorder (avolition, anhedonia, affective flattening, alogia) while age restrictions have been dropped [14]. In this diagnostic system, the symptoms must have persisted over the previous six months with at least one month of hallucinations and delusions [14,35]. The latest iteration is the DSM-V [12,41]. It retains much of the diagnostic criteria used to define schizophrenia in DSM-IV but removes the classic schizophrenia subtypes, defines in further detail the relationship of schizophrenia to catatonia, expands upon the differences between schizophrenia and schizoaffective disorder and eliminates the prioritisation of Schneiderian 'first-rank symptoms' [12].

Parallel to the definitions and diagnostic criteria of the American Psychiatric Association, the World Health Organization (WHO) developed its own set of diagnostic criteria- the International Statistical Classification of Diseases and Related Health Problems (ICD), currently in its tenth iteration, ICD-10 [42,43]. This is a system that was entrusted to the WHO, upon its creation in 1948 and has undergone several revisions [44]. The eleventh revision, ICD-11 is due for release in 2018 [44]. The ICD system is much broader in scope, includes criteria for the classification of other diseases and is widely used around the world for reporting mortality and morbidity statistics in contrast to the DSM that is limited only to mental disorders [44]. The system has good descriptive validity for schizophrenia [45] and has been more widely used in the clinical setting than DSM-IV that finds more use in research environments [46,47].

Research Domain Criteria (RDoC) is the third initiative for diagnosis of mental disorders like schizophrenia. It is published by the National Institute of Mental Health (NIMH), USA and has a significantly different approach compared to either DSM or ICD [48–50]. It is an initiative that seeks to incorporate new findings from the field of genetics and neuroscience into the classification of mental disorders. The initiative was launched due to a disconnect between clinically diagnosed schizophrenia cases and the pathophysiology being discovered by genetic and neuroscience approaches. The ultimate aim of the RDoC initiative is to significantly influence the diagnostic system of the future by integrating precise biological markers into the definition, classification and treatment of mental disorders [50].

In summary, considerable effort is being put into diagnostic methods for psychiatric illnesses including schizophrenia. Many of these diagnostic methods share similarities, yet each system has its unique strengths and perspectives. The inter-rater reliability of the diagnostic systems also varies considerably [51,52]. This is a measure of how consistently a person would get diagnosed with a particular illness by different psychiatrists. For example, Cheniaux et al. [52] found that schizophrenia is diagnosed twice as frequently using ICD-10 compared to DSM-IV. Furthermore, the inter-rater reliability from a theoretical maximum of 1 was only 0.59 and 0.56 for DSM-IV and ICD-10 respectively. Thus, the same person might get a different diagnosis when analysed by a different psychiatrist or diagnostic system. The DSM-V fares even worse than DSM-IV with an inter-rater reliability of only 0.46 for schizophrenia [51]. This

makes the genetic and epigenetic study of schizophrenia challenging- genetic and epigenetic studies focus on discrete, quantifiable and measurable units (genes and chemical changes to the genome), unlike the diagnostic system used to categorise the patients in the first place. The findings in this thesis must be understood with this caveat in mind.

1.2 Brief primer on genetic studies of schizophrenia

1.2.1 Genetic studies on schizophrenia

Initial efforts to understand the genetics of schizophrenia relied on twin [53–56], family [15,57–59] and adoption studies [60,61]. These studies revealed a heritability between 60-90% [56,62,63] indicating a strong genetic component to the aetiology of the disorder. However, twin studies revealed a concordance rate of 40-60% for monozygotic twins [56,64,65] suggesting genetic factors did not entirely drive the disorder.

Additionally, the advent of cytogenetic techniques, such as karyotyping enabled researchers to perform linkage analyses that investigates global chromosomal abnormalities amongst patients with schizophrenia. Chromosomal abnormalities have frequently been associated with the disorder [66] and include copy-number variations (CNVs) [66–69].

Prior to the sequencing of the whole human genome [70,71] research in the genetics of schizophrenia was often informed by the neurobiology of the disorder [72,73]. As such the research was hypothesis-driven with a focus on candidate genes [74] and regions involved in the regulation of pathways implicated in the aetiology of schizophrenia such as dopamine [75,76], serotonin [77,78], glutamate [79,80] and GABA [81].

Although potential candidate genes involved in the aetiology of the disorder have been identified [82], such as *DISC1* (Disrupted in schizophrenia 1) [83–85], most of the genes identified in these studies have not been robust to subsequent replication studies [82,86,87]. This lack of replication at a population level may suggest that the genes implicated affect only the particular families studied. However, as recently reported, the evidence against the use of candidate gene approaches for schizophrenia genetics is conclusive due to the chance nature of the association of the top candidate genes [88,89].

Partly due to lack of success in determining consistent genes in the aetiology of the disorder and partly due to improvements in technology [90,91], a new wave of studies analysing the entire genome, namely genome-wide association study (GWAS) was performed [38,92–95].

1.2.2 Genome-Wide Association Studies(GWAS) on schizophrenia

After the sequencing of the human genome [70,71,96] and mapping of variation in human genomes at a population level [97], efforts were made to identify genome-wide candidates in the aetiology of schizophrenia. These GWAS have identified more than hundred different genetic loci associated with the disorder, giving support to the notion of schizophrenia as a complex disorder [38,92–95].

The biggest difference between the GWAS approach and candidate-gene studies is that GWAS is hypothesis-free [98,99]. The methodology employed involves genotyping millions of single-nucleotide polymorphisms (SNPs) on genotyping microarrays. Frequency differences of specific SNPs between patients and controls help associate variants with the disease [100,101]. Thus, compared to candidate-gene approaches where hypothesis-driven loci are analysed, GWAS approaches allow one to interrogate the variation across the entire human genome including genic and non-coding regions. This helps derive new insights into the biology of the disorder [102].

Results of most GWAS do not point to direct, causal associations between SNPs and disease. Instead, the majority of associations are non-causal, due to the phenomenon of linkage-disequilibrium (LD) between SNPs [100]. LD is the phenomenon where groups of markers tend to be inherited together more often than expected by chance due to common population ancestries [100]. LD is usually quantified by r^2 that denotes the correlation between two markers [100]. Furthermore, most of the significant markers in GWAS results are found in non-coding regions of the genome [103–107].

The latest GWAS on schizophrenia revealed 108 loci associated with the disorder from which more than eighty were previously unreported [38]. These loci together contain 128 SNPs that cross the genome-wide significance level (p < 5x10e-8). The loci provide support for known neurotransmitters implicated in the disorder such as those involving the dopaminergic and glutamatergic systems. Furthermore, the loci are not randomly distributed but show enrichment in enhancers of brain tissues and immune systems. The authors note the convergence of pathways from those obtained with rare-variant analyses and genome-wide approaches. Additionally, as observed in other GWAS, only a limited number of protein-coding variants were found [38].

One way to gain insight into the role of non-coding regions in the aetiology of diseases is to utilise epigenetic approaches [103,108,109] that are discussed in the subsequent sections.

1.3 Epigenetics in schizophrenia

1.3.1 General Introduction to epigenetics

Much work is going on to understand the genome [70,71,96,110,111], transcriptome [112–114] and proteome [113,115–118]. However, another layer of cellular information, stored in the form of epigenome has begun to attract attention and focused research [109].

This field has grown in importance in the last decade, especially after the sequencing of the human genome [70,71,119] and development of new sequencing technologies [120–122]. Epigenetics is the study of heritable changes in gene regulation that occurs independently of the DNA sequence [123,124]. 'Heritable' in epigenetics implies stable transmission of chemical marks from one cell division to another. Epigenetic phenomena include molecular processes such as DNA methylation, histone modifications and chromatin re-organisation. These modifications are preserved when cells divide [125]. The study of these processes on a genome-wide scale is referred to as epigenomics.

The main effect of epigenomic modification is to affect the organisation of the chromatin, which in turn affects gene expression or repression [126]. Indeed, researchers have begun looking at gene expression from the perspective of higher order DNA organisation, i.e. the chromatin. The chromatin is a protein-DNA complex comprised of DNA wrapped around a group of packaging proteins called histones, forming bead-like structures called nucleosomes. These nucleosomes subsequently help condense the DNA sufficiently to fit within the dimensions of a nucleus.



Figure 1: Depiction of various epigenetic factors affecting chromatin organisation.

Shown here is an expanded view of condensed chromatin found in a chromosome. Nucleosomes comprise of histone proteins whose tails are susceptible to chemical modifications. Individual CpG dinucleotides on the DNA strand can undergo methylation that influences DNA conformation that subsequently can regulate gene expression (Adapted from Brown WM, 2015 [127]).

There are five different histone proteins named H1, H2A, H2B, H3 and H4. H2A-H2B form a dimer while H3 and H4 form a tetramer giving rise to an octamer around which 146bp of DNA are wrapped. This forms a single nucleosome. H1 acts as a linker histone which holds the spool of DNA in place and locks it together with the rest of the nucleosome. These histone proteins have an amino acid tail, and the N-terminal ends of these amino acid tails are subject to chemical modifications which are added via post-translational modifications [128]. These modifications act as unique signatures determining gene regulation [109] and understanding these chemical signatures is one of

the key research areas in epigenetics. Thus, it is possible to predict which genes are going to be activated or repressed based on the presence or absence of these chemical groups.

In addition, DNA methylation also provides another layer of control over chromosomal conformation [129]. DNA methylation was the first epigenetic modification to be characterised [130]. In this particular epigenetic modification, methyl groups are added to the 5'ends of cytosine residues in Cytosine-phosphate Guanine (CpG) dinucleotides to form 5-methylcytosine [130]. The methylated CpG binding proteins such as meCP1 and meCP2 subsequently bind to such methylated CpG dinucleotides [131]. These proteins have DNA binding domains and a transcription repression domain and can additionally recruit other factors that condense the chromatin resulting in the formation of heterochromatin that represses gene activity [132–134].

DNA methylation is a highly stable and heritable epigenetic mark [123,131,135]. Postimplantation, *de-novo* methyltransferases DNMT3a and DNMT3b add methyl marks to the embryo [136]. Subsequent maintenance of methylation is carried out by another group of methyltransferases called DNMT1 with specificity to *hemi*-methylated DNA strands, i.e. the daughter DNA strands which are produced after each round of DNA replication [131].

DNA methylation is implicated in a whole range of functions such as transcriptional silencing of genes [137], genome imprinting [138,139], regulation of tumour suppressor genes [140–142], X-chromosome inactivation [131,139], maintaining genomic integrity through silencing of transposons [143] and repetitive regions [131,144–146]. The promoter regions of many genes have CpG dinucleotides clustered into what is known as CpG islands [131]. Such CpG islands are usually protected from DNA methylation [131,144]. In healthy human cells, tumour suppressor genes are often *hypo*-methylated, and intergenic regions and repetitive elements are *hyper*-methylated [131,137]. In cancerous cells, the reverse is usually observed, i.e. genome-wide *hypo*-methylation and CpG island *hyper*-methylation [137–140]. This brings to attention the increasing

relevance of studying DNA methylation in the context of diseases [137,146]. Among the unique characteristics of DNA methylation is the variation that occurs in the regions methylated between tissues [147], individuals [148] and related species [149]. Such regions are usually abbreviated as DMRs for differentially methylated regions. These variations are thought to contribute to phenotypic variations between people and may therefore potentially provide a way to describe susceptibility to complex diseases. Additionally, these regions have been found in or proximal to regions of recent evolution, indicating their role in the evolution of modern-day humans [150].

1.3.2 DNA methylation and schizophrenia

Efforts to understand the epigenetic machinery and especially DNA methylation in schizophrenia has primarily followed two approaches: candidate genes and genome-wide methodologies. Amongst candidate genes, aberrant DNA methylation has been implicated at the reelin gene (*RELN*) [151–154], brain-derived neurotrophic factor (*BDNF*) [155], DNA Methyltransferase 1 (*DNMT1*) [156] and Sex-determining Y-box containing gene 10 (*SOX10*) [157].

Reelin is produced in GABA-ergic neurons and is important for correct neuronal positioning during brain development [158]. It has been found to be hyper-methylated in the brain [153] as well as blood samples [152] of patients with schizophrenia. Mouse models of hyper-methylation of this gene have found a downregulation in Reelin gene expression levels [159,160]. A hypothesis involving increased activation of *DNMT1* leading to higher DNA methyltransferase activity has been proposed to explain the aberrant methylation at *RELN* [154,158]. Indeed, it has been observed that *DNMT1* also has aberrant methylation in patients with schizophrenia. Specifically, DNA-methyltransferase 1 is found to be overexpressed in the cortex of patient samples [156]. This increased activation of DNMT1 mirrors the subsequent downregulation of reelin observed in GABA-ergic neurons in patients [161].

Downregulation of BDNF has also been observed in schizophrenia patients [155,162,163]. BDNF is important for nerve cell survival, neural differentiation and synaptic plasticity [164]. Significant hyper-methylation was found in peripheral blood cells from Japanese patients [155]. However, an earlier study found an opposite direction of effect with patients from Iran showing hypo-methylation compared to controls [165]. This discrepancy could be due to different methods employed or due to population differences.

Abnormal DNA methylation has also been observed for *SOX10* gene. It is an oligodendrocyte-specific transcription factor [166], and oligodendrocyte dysfunction has been observed in patients with schizophrenia [157]. Hyper-methylation of CpG island of *SOX10* is associated with concomitant downregulation of the gene [157].

However, these candidate gene studies investigating the role of methylation in the disorder are not without their drawbacks. For example, different methods have been used to measure the methylation in candidate gene studies. This, however, may reflect the lack of a standardised technology in the then-nascent field, instead of poor study design. Furthermore, most of the candidate gene methylation studies were conducted on an insufficient number of sample sizes. Early studies on the *RELN* gene were conducted with only 5 [153] to 10 samples per group [151]. Furthermore, different studies analysed different regions of the brain making it challenging to make broad generalisations of methylation patterns in patient samples.

Improvements in technology and cost helped initiate epigenome-wide analyses (EWAS) of methylation patterns in patients with schizophrenia. Unlike the variant association findings in candidate-gene studies of schizophrenia which could not be replicated in genome-wide studies, a majority of findings from methylation studies using candidate-genes have been replicated in EWAS [166]. In addition, genome-wide scans of methylation have revealed novel pathways and genes involved in the aetiology of schizophrenia [166].

As an example, the first EWAS for patients with schizophrenia by Mill and colleagues, [167] confirmed the role of GABAergic pathways in the aetiology of schizophrenia. Additionally, they found variation in regions associated with glutamatergic pathways as well as antipsychotic mediated effects on DNA methylation levels in the promoter region of Mitogen-activated protein kinase kinase 1 (*MEK1*) gene. Compared to candidate gene studies investigating the role of methylation, the sample size was considerably higher (n = 105, 35 cases with schizophrenia, 35 cases with bipolar disorder and 35 controls). However, the technology used at the time was not standardised and has now been superseded by microarrays from Illumina.

Another paper by Xiao and colleagues [168] undertook a comprehensive look at the methylome and transcriptome of 2 brain regions: frontal cortex and anterior cingulate in patients with schizophrenia and those with bipolar disorders. They found significant differences in the methylation levels of these two regions between controls and patients with schizophrenia/bipolar disorder. Most interesting perhaps was their observation that the differentially methylated regions (DMRs) could accurately distinguish between cases and controls whereas differentially expressed genes could not.

Similarly, Wockner and colleagues [169] performed EWAS in the post-mortem brains from 24 schizophrenia samples and 24 healthy controls. Using Illumina 450k array, they found significant methylation differences in more than 4000 probes across nearly 3000 genes. It is known that antipsychotics can affect DNA methylation [170–172]. In this study all but two of the patients were consuming antipsychotics, so the effect of medication on the DNA methylation levels cannot be ruled out.

Subsequently, another group also published EWAS for patients with schizophrenia from two different brain sample datasets [173]. Combined analyses by Wockner and colleagues [174] across the three different datasets [169,173] revealed differentially methylated regions (DMRs) in *CERS3, DPPA5, PRDM9, DDX43, REC8, LY6G5C* that

were consistently differentially methylated in patients with schizophrenia across the three different brain datasets.

A recent review by Teroganova and colleagues [175] summarised the available evidence for DNA methylation alterations in schizophrenia from both candidate-gene and epigenome-wide approaches. They report that good agreement exists between candidate genes analysed for aberrant methylation and results from EWAS.

However, a significant challenge in the field is the tissue heterogeneity of brain. Epigenetic marks such as DNA methylation are cell and tissue-specific [135]. However, in the studies described previously, the methylation signal is obtained from various regions of the brain that makes a direct comparison between studies challenging. Another challenge when performing methylation studies to study schizophrenia is the lack of information on antipsychotic medications. This is because they are known to influence DNA methylation [176]. Additionally, it is useful to know the demographic background of the patient samples since this can influence DNA methylation as well [177].

To account for some of these limitations, two analyses were recently published with a large sample size that also included information on the cellular composition and patient demographics - one using post-mortem brain tissue [178] and the other using whole blood [179]. Jaffe and colleagues [178] analysed post-mortem prefrontal cortex brains from 191 patient samples and 240 controls and found small but significant hypomethylation across more than 2000 probes in patients with schizophrenia. Furthermore, these probes were found to be enriched amongst a set of probes differentially methylated in fetal life [178] supporting a neurodevelopmental model of schizophrenia that suggests aetiological origins before birth [173].

Hannon and colleagues [179] conducted the largest (n = 1714) EWAS of methylation differences in patients with schizophrenia performed to date using whole blood samples. The study focused on finding differentially methylated positions (DMPs) between

patients with schizophrenia and controls across three different cohorts – a 'discovery cohort' with n=675 (patients = 353, controls = 322); a 'replication cohort' with n = 847 (patients = 414, controls = 433) and 97 monozygotic twin pairs discordant for schizophrenia. In the discovery cohort, they identified over 1000 probes that were differentially methylated at a *p*-value < 10e-5 that were robust to methylomic variation from covariates such as cell composition, age, sex and smoking. Results from the replication and twin cohort showed high consistency in number and direction of methylation of top DMPs. A meta-analysis of the three datasets revealed a total of 343 DMPs at an experiment wide-threshold of *p*-value < 10e-7 [179].

To identify differentially methylated regions (DMRs), they used two different methods that resulted in 12 to 76 DMRs. Some of these DMRs occurred in known regions of association such as the major histocompatibility locus (MHC) on chromosome 6 [179]. Furthermore, they observed that several of these DMRs had a combined *p*-value that was more significant than the individual probes contained within the DMRs highlighting, the importance of finding extended regions that are differentially methylated in patients with schizophrenia [179].

The current consensus in the field is that patients with schizophrenia show global hypomethylation with local hyper-methylation of specific genes and that administration of antipsychotics partially reverses the global hypo-methylation [166]. In our studies, we focused on DNA methylation because it is the most widely studied of all epigenetic changes [175]. Furthermore, as DNA methylation patterns can be inherited [123,132,180], this is the epigenetic modification that has been most thoroughly investigated from an evolutionary standpoint [149,150,181–184].

1.3.3 Gene x Environment (GxE) interactions

Central to the premise of investigating the effect of methylation variation on the susceptibility to schizophrenia is the concept of gene by environment interactions (GxE).

Complex phenotypes, such as schizophrenia, can be influenced by both genetic and environmental factors. GxE analyses aim at understanding how the interaction between variation at the genotypic level and exposure to environmental risk can influence a phenotype. Different genotypes can cause different phenotypes even in the exposure to the same environmental stressors [185]. One of the first reports to look at such GxE interactions found evidence of the role of genotype in altering the phenotype in the presence of the same external stimuli of childhood violence. The study found that a polymorphism in the promoter region of the monoamine oxidase A enzyme gene (MAOA) modulates the susceptibility of developing aggressive tendencies in adulthood: those producing more MAOA were less susceptible to the detrimental effects of maltreatment [186]. However, investigating the role of GxE in a complex neuropsychological disorder like schizophrenia has been difficult because of the polygenic nature of the disorder. Existing literature points to the influence of environmental factors such as childhood trauma, cannabis consumption, migration and urban living environment as environmental risk factors for schizophrenia [187]. How exactly these environmental risks are influencing the development of the disorder remains unknown. Some studies have shown that environmental factors influence gene expression through epigenomic modifications. For instance, it is well known that physical exercise changes metabolism via epigenetic modifications [188,189]. However, the influence of environmental risk factors on the risk for schizophrenia through epigenetic mechanisms warrants future research.

1.4 Evolutionary Hypothesis of Schizophrenia

One of the most intriguing aspects of the disorder has been the remarkable persistence throughout recorded human history [13]. The incidence is roughly 1% [190,191] and is stable across populations separated by geography and time [192,193]. There are written records from the Mesopotamian culture ca 5000 years ago (YA) [13] that in today's time would be classified as schizophrenia symptoms.
Thus, the disorder has been maintained in the human population despite reductions in fecundity of patients with schizophrenia [194,195]. The analyses of Swedish birth registry data with more than 2 million individuals born between 1950 to 1970 revealed that male schizophrenia patients had on average a nearly 80% reduction in the number of children [194] compared to the general population while female schizophrenia patients had half as many as the general population [194]. To explain the persistence of a disorder with such a substantial effect on fitness, the evolutionary hypothesis of schizophrenia was put forward. While some have argued for the existence of selective advantages of the disorder [190,196], the version that is most well known today is attributed to Timothy J. Crow [192,193,197,198].

T.J. Crow argued the disorder to be a by-product of human evolution through language [192,193]. To explain this, he proposed that lateralisation is fundamentally involved in the pathophysiology of schizophrenia [192,193]. Lateralization and cerebral asymmetry of the brain is the concept wherein specific cognitive tasks tend to be more dominant in one hemisphere over the other. These cognitive tasks, for example, include language [199]. According to Crow and the so-called *bi-hemispheric theory* [193,200–203], the asymmetry of brain development permitted the separation of hemispheric function that enabled the evolution of language [192]. While lateralisation is observed in many species [204], it is the assertion of lateralisation of language that forms a key component of his evolutionary hypothesis.

He makes the observation that patients with schizophrenia often have abnormal brain structure especially reduced lateralisation [192,193]. He asserts that it is this abnormal lateralisation that subsequently affects both language development and language perception in patients with the disorder such that they suffer from a dissociation between thought and speech that ultimately leads to the auditory hallucinations [192,193,205]. Thus, the involvement of language is seen by him as a key feature of schizophrenia, indeed identifying it as a disorder of language [192]. Crow, therefore, lays down the

fundamentals of the evolutionary hypothesis by arguing schizophrenia to be the 'price humans pay for language' [198].

1.5 Why analyse through the prism of evolutionary epigenetics

It is a challenge to design experiments that can test T.J. Crow's assertion of the emergence of language during human evolution as a risk factor for schizophrenia. The technologies and resources available allow the possibility to investigate regions of the genome that have evolved [206–208] and test for enrichment of schizophrenia markers in regions specific to human evolution [209–211]. This does not directly test the language component of Crow's hypothesis.

Genomic methods allow determination of genetic level changes on evolutionary timelines, but an important mediator of genetic changes is the environment which is impossible to investigate using genomic approaches alone [212,213]. In present-day species, the environmental effects on the genome are often investigated via *epi*-genomic approaches [214,215]. This is because the environment interacts with the genome through chemical modifications of the genome that affect gene regulation and gene expression [214,215]. Such environmental effects often leave long-lasting changes [216] that in certain species have been observed to persist for as many as 14 generations [217]. It is, therefore, now possible to trace the development and maintenance of epigenomic (and potentially environmental changes) for multiple generations in present-day species [216,217].

However, if one were to be interested in tracing the development of epigenome across historical time (and as a proxy the influence of environmental factors), it becomes imperative to use evolutionary epigenetic approaches that allow comparison of epigenomes from different time points [149,150,181]. Recently, efforts have been made to trace the evolution of epigenomes from primates to humans [149], humans with other extinct hominids [150], and even between ancient and modern humans [182] using

mainly methylation data [149,150,182]. So, while the first anatomically modern humans emerged at least 300,000 years ago [218,219] and can be inferred to be human, it is known that modern human capabilities such as abstract thinking and organised societies did not develop until at least 70,000 years ago [220–227]. If we assume that the genome of the 300,000-year-old human fossil is similar to a modern-day human genome, then it is possible that GxE interactions mediated through epigenetic changes [215] could be one of the driving factors responsible for the emergence of intellectual abilities, language and possibly psychosis.



(Timeline estimates obtained from Smithsonian, Hasegawa et al 1985, Srinivasan et al 2017)

Figure 2: Depiction of a phylogenetic tree with estimated times of divergence

A phylogenetic tree providing a general view of evolution since the emergence of invertebrates. Except for the ancestors of the Homo lineage, all other species have survived to the present age. The tree of ancestors of Homo lineage is expanded in the next figure.



(Timeline estimates obtained from Smithsonian, Rogers et al 2017)

Figure 3: Depiction of the expanded phylogenetic tree of the ancestors of Homo species. All ancestral species of Homo sapiens are extinct except for chimpanzees that survive to the present age. Chimpanzees, as such, are our closest living relatives.

In this thesis, to test the evolutionary hypothesis of schizophrenia, we primarily use two different kinds of evolutionary methylation data and determine if they are enriched for schizophrenia markers. These methylation data contain regions of the human genome whose methylation levels have changed over evolutionary time frames. By checking for the enrichment of these methylated regions for schizophrenia markers, we can then determine if such regions where methylation levels have changed over evolutionary time in humans are localised in regions implicated in the aetiology of schizophrenia. We broadly categorise the two different methylation datasets as primate and non-primate differentially methylated regions (DMRs).

The non-primate DMRs were obtained from the dataset of Gokhman et al., 2014 [150]. These are a group of methylated regions whose levels have changed over evolutionary time between modern humans, Neanderthals and Denisovans. These regions depict changes in the methylation pattern since the divergence from the last common ancestor between the three hominids, ~750,000 YA [150].

The primate DMRs are another set of DMRs obtained from Hernando-Herraez et al. [149]. These trace the evolution of methylation through primate history from orangutans, through gorillas, chimpanzees and finally humans. Since the orangutans diverged from the human lineage ca 13 MYA and chimpanzees ca 6 MYA, these regions allow observation of methylation developments that took place in the lineage between 6 to 13 MYA. While these datasets would not allow one to test whether language and schizophrenia are linked with evolution as per T.J. Crow, they would, however, allow one to investigate whether epigenomic evolution has taken place in genomic regions implicated in the aetiology of schizophrenia.

Thus, using evolutionary epigenomic approaches allows one to not only investigate how methylomes evolved as species diverged from one another but also opens a window of research to investigate potential environmental changes that would accompany such epigenetic changes [182]. The latter aspect can be especially crucial in determining when humans developed superior intellectual capacities such as language and, according to T.J. Crow, the vulnerability to psychosis that came along with it [198].

2. Study Aims

The overarching goal of our analyses was to uncover evolutionary epigenetic loci that are enriched for association with schizophrenia.

GWAS studies have already implicated several genomic loci associated with schizophrenia while the various DMRs point to regions of the genome important from an evolutionary perspective. Methylation can influence the underlying genome sequence and conversely, the genome sequence may influence methylation. Therefore, we used both GWAS and DMR data, to test whether regions of the genome where methylation changes occurred over evolutionary time (DMRs) localise with markers associated with schizophrenia.

In order of progression, we sought to address this in the following way:

1. Determine whether evolutionary human-specific DMRs are enriched for human traits and phenotypes including schizophrenia. (Paper I)

2. Determine whether primate DMRs show enrichment of association with schizophrenia markers. (Paper II)

3. Determine whether evolutionary DMRs as defined in **Paper I** and containing significantly associated schizophrenia markers, shows a different methylation pattern in patients with schizophrenia, compared to healthy controls. (**Paper III**)

3. Method Summaries

A consolidated summary of all the methods and datasets are given below in two broad categories (data acquisition and data analyses). The individual **Papers I-III** provide the details.

3.1 Data Acquisition

All three papers extensively used publicly available datasets that are described below.

3.1.1 Differentially Methylated Region (DMR) data

Coordinates of differentially methylated regions (DMRs) were obtained from two primary sources. For analyses presented in Paper I, the data was obtained from Supplementary Table S2 of Gokhman et al., 2014 [150]. This file contained DMRs inferred by comparing genome sequence of fossilised Neanderthal and Denisovan limb samples with methylation data from osteoblasts of modern humans. From the genomes of the Neanderthal and Denisovan samples, Gokhman and colleagues inferred methylation by utilising the natural degradation of methylated cytosine (C) to thymine (T). Unmethylated cytosines degrade to uracils, which were removed in the sequencing reads of Neanderthals and Denisovans [150]. Using the published high coverage genomes of Neanderthal [228] and Denisovan [229], the pre versus post-mortem Cs and Ts were determined to create a C T ratio [150]. This was used to infer methylation in Neanderthals and Denisovans. The methylation information, in the form of $C \square T$ ratio, was then compared with each of the three species and classified according to the hominid in which the methylation change occurred, i.e. human-specific, Neanderthal-specific and Denisovan-specific DMRs. These DMRs do not represent tissue-specific methylation but species-specific methylation [150]. DMRs that could not be classified reliably (unclassified DMRs) [150] were not used.

The second source of DMRs was from Hernando-Herraez et al. [230] that was used in **Paper II.** The DMRs were determined by comparing the methylation profile from peripheral blood samples of orangutans, chimpanzees and gorillas with humans. This dataset contained hypo-methylated and hyper-methylated DMRs for each of the species. A pairwise comparison was performed to determine the DMRs, i.e. for a group of methylated regions in species A, regions that had lower (hypo-methylated) or higher methylation levels (hyper-methylated) in other species were found. If a particular region in species-A was consistently hypo-methylated while it was hyper-methylated in other species, that region was termed as 'species-A hypo-methylated region'. Similarly, hypermethylated regions for species-A was determined. Since our interest is in human evolution, we analysed human hypo and hyper-methylated DMRs for the enrichment of schizophrenia and other traits (Paper II). In comparison to DMRs from Paper I that comprised of a comparison between modern humans and extinct hominids, the DMRs in this paper are all from extant species. These DMRs can be inferred to represent methylation changes since the point of divergence of the common ancestors of primates from humans. Thus, they represent an evolutionary course of history spanning at least 13 MYA from orangutans [231,232] to 6 MYA when the common ancestors of chimpanzees and humans diverged from one another [231,232]. For distinguishing these DMRs from those used in **Paper I**, we refer to them as primate DMRs.

3.1.2 Human Accelerated Region (HAR) data

These are a group of regions in the human genome that are selectively accelerated. They were first described by Pollard et al. [206] by comparing human genomes with chimpanzee genomes to determine regions that remained conserved in chimpanzees but evolved rapidly in humans. Subsequent research by other groups has significantly expanded this list [208].

Genomic coordinates were obtained from publicly available data (docpollard.com/2x) for three classes of human accelerated region: HARs, in which regions conserved in

mammals are accelerated in humans; PARs, in which regions conserved in mammals are accelerated in primates; and pHARs, in which regions conserved in primates (but not other mammals) are accelerated in humans.

3.1.3 Neanderthal Selective Sweep (NSS) data

Just like HARs describe the selective evolution of human genome in comparison with primates and other mammals, the Neanderthal selective sweep (NSS) describes the particular selection of specific nucleotides in the human genome over the Neanderthal genome. It thus offers evolutionary insight at a genomic level on regions of the human genome that likely diverged since splitting up from the last common ancestor of humans and Neanderthals [233,234].

NSS data was obtained from Srinivasan et al. [209] as a list of markers with corresponding NSS values. Markers with negative values, indicating positive selection in humans, were selected and used for analysis.

3.1.4 GWAS data

In our analyses, we made extensive use of publicly available results from genome-wide association studies (GWAS). These studies analyse at a population level the frequency differences between groups of markers (single-nucleotide polymorphisms, SNPs) for specific phenotypes using a case-control study design. The final results from such studies usually provide information on SNPs with an association value in the form of the *p*-value. Summary statistics from thirteen different phenotypes were obtained from their respective published GWAS studies : schizophrenia (SCZ) [38], bipolar disorder (BPD) [235], attention deficit hyperactivity disorder (ADHD) [236], rheumatoid arthritis (RA) [237], blood lipid markers (high density lipoprotein (HDL), low density lipoprotein (LDL), triglycerides (TG), total cholesterol (TC)) [238], blood pressure (systolic blood

pressure (SBP), diastolic blood pressure (DBP)) [239], body mass index (BMI) [240], height [241] and intelligence [242].

3.1.5 Methylation datasets

Publicly available methylation datasets from GEO for brain at accession numbers GSE61107 [169], GSE6143 [173], GSE61380 [173], GSE74193 [178] and for blood at GSE80417 [179] were used. The analysis of methylation datasets requires a formatted text file, commonly called 'Sample Sheet' that details the information about the samples such as age, gender, specific well in the probe used for analysis etc. This was created with in-house scripts.

3.2 Data Analyses

3.2.1 SNP assignment to DMRs

SNPs were assigned to DMRs with LDsnpR [243] using positional binning and LD (linkage disequilibrium)-based binning in R [244]. We used both methods because DMR-localized SNPs that were not genotyped in a specific GWAS would be missed if we used positional binning alone [243].

3.2.2 Conditional Quantile-Quantile (QQ) plots

QQ plots are a useful tool to visualise the spread of data and any deviations from expected null distributions. They are frequently utilised in GWAS to depict enrichment of true signals. When the observed distribution matches the expected distribution, a line of equality is obtained that depicts the null hypothesis. If the observed and expected distributions differ, there will be a deviation from this null line. Due to the extremely low

p-values in GWAS, it is common to depict *p*-values by converting them to negative \log_{10} values so that with smaller *p*-values, higher negative logarithmic values are obtained. We plotted the negative \log_{10} of observed *p*-values against the expected negative \log_{10} of a normal distribution. Leftwards deflections from the null line represent enrichment because this suggests a higher than expected chance of the observed data possessing true signals [245]. Conditional Q-Q plots are similar to quantile-quantile (QQ) plots but depict distributions of data 'conditioned' on particular criteria such as genomic annotation. Thus, a specific stratum of data, e.g. *p*-values from a specific category of SNPs is compared against the whole dataset. In our case, we were interested to investigate the strata of data containing schizophrenia markers classified as being present within and in linkage disequilibrium (LD) with the DMR regions, compared to all the schizophrenia markers from the full GWAS. Enrichment occurred if the data distribution in the SNPs 'conditioned' on DMRs showed greater leftward deflection than what is observed for all GWAS markers.

3.2.3 INRICH

INterval EnRICHment Analysis (INRICH) is a robust bioinformatics pipeline to determine enrichment of genomic intervals implicated by LD with predefined or custom gene sets [246]. It takes into account several potential biases that can otherwise lead to false positives. It is well suited for testing GWAS-implicated SNPs for association with gene sets as it controls for variable gene size, SNP density, LD within and between genes, and overlapping genes with similar annotations. We followed the procedure described previously [211], with the extended MHC region (chr6:25-35Mb) masked and SNPs with minor allele frequency (MAF) <0.05 excluded in the schizophrenia GWAS.

3.2.4 Pathway analysis

Pathway analysis was performed using Ingenuity Pathway Analysis (IPA) from QIAGEN (www.qiagen.com/ingenuity, last accessed 26th August 2016). The reference set was Ingenuity Knowledge Base (Genes). Both direct and indirect relationships were analysed. All data sources were included with the confidence parameter set to experimentally observed and highly predicted pathways for humans. Under the category of 'Tissues & Cell Lines', we performed the analysis once with all organ systems and once with only the nervous system. 5338 enriched DMR SNPs were mapped to 349 unique RefSeq genes and 446 RefSeq genes in LD using the method of Schork et al. [245]. Genes in LD blocks containing enriched NSS markers were determined similarly. 4276 enriched NSS markers mapped to 648 overlapping RefSeq genes and 1363 RefSeq genes in LD. IPA was performed on these gene-lists.

3.2.5 Selection of DMRs for patient analyses

In **Paper III**, we use a total of 9 DMRs from more than 800 analysed in **Paper I** to test if they show disrupted methylation in patient samples. These 9 DMRs were selected for containing SNPs associated with schizophrenia based on a study-wide significance threshold using the method of Moskvina et al. [247]. The study-wide threshold with Bonferroni correction was determined to be 2.4x10e-5 at α = 0.05. SNPs were found at or above this threshold spread across 9 DMRs: *DMR10*, *DMR127*, *DMR203*, *DMR204*, *DMR236*, *DMR237*, *DMR291*, *DMR526* and *DMR527*.

3.2.6 Methylation analyses

The techniques for analysing methylation data from Illumina BeadChip platforms such as the 450k array [248,249] and the latest EPIC array [250] is an evolving field with several methods proposed for optimal pre-processing and normalisation of data [251–253].

In **Paper III**, altogether five different publicly available methylation datasets for schizophrenia patients were analysed. Four of these datasets were obtained from the prefrontal cortex of deceased schizophrenia patients while the fifth dataset was from peripheral blood samples.

Raw IDAT files were available for the brain methylation dataset from Wockner et al. [169]. The preprocessing step was similar to the one reported by them [169]. Samples with missing age information were removed along with probes that failed at a detection p-value< 0.05 in 50% of the samples. The original analyses [169] also removed the probes on the sex chromosomes but, this was not done for the analyses in **Paper III** as none of the evolutionary DMRs selected were present on them. Additionally, due to the extremely sparse probe coverage in the DMRs, we performed the analysis without removing probes with SNPs. Subsequent normalisation was done using functional normalisation [251].

For the datasets from Pidsley et al. [173], only the normalised beta matrices were available. These were used directly in downstream analysis. However, two of the DMRs lacked probes: *DMR526* and *DMR527*. These DMRs have only one probe each in the 450k array. It is possible that Pidsley et al. [173] removed them during the pre-processing step for their analyses.

The dataset from Jaffe et al. [178] initially comprised of more than 650 samples including prenatal samples. Since our interest in **Paper III** was to determine methylation variation in patients schizophrenia compared to a control population of similar age distribution, all pre-natal samples were excluded. The final analysis was performed on 191 schizophrenia samples and 231 control samples.

For the analysis from blood samples using the discovery cohort from Hannon et al. [179] with 675 samples, the normalised beta matrix was directly used.

To determine the statistical significance of differentially methylated positions (DMPs), linear regression modelling with the *limma* [254] package in R [244] along with empirical Bayes [255] in the *minfi* package [256] was implemented on the M values of individual probes. M values were obtained from the beta values as follows:

$$M \ value = \log 2(\frac{Beta}{1 - Beta})$$

3.2.7 Statistical significance of DMRs

After determining the statistical significance of the individual probes, it was essential to find a way to determine if the evolutionarily enriched DMRs show statistically significant methylation variation in patient samples compared to controls. Traditional methods of determining large regions of genomes with methylation variation rely on software such as *bumphunter* [257].

However, in our case, since the DMRs were already predefined, we utilised the *comb-p* algorithm [179,258] that can determine the statistical significance of custom regions. The algorithm is especially useful for array data due to the irregularly spaced nature of the probes. It calculates the correlation between probes and combines adjacent *p*-values using the Stouffer-Liptak-Kechris corrections [258]. Briefly, this correction weighs down a given *p*-value based on the correlation with nearby probes. We used the default parameters in the *region_p* programme [258] in this algorithm, to determine the statistical significance of methylation variation within the evolutionary DMRs. This programme also performs a Sidak one-step correction for multiple testing. We use the results from the Sidak correction to ascertain whether a given DMR shows statistically significant methylation difference in patient samples.

3.2.8 Visualisation of DMRs

To visualise the methylation variation in the evolutionary DMRs showing statistically significant difference between patients and controls, we utilize the *Gviz* [259] package in R. Amongst the many useful features of the package is the ability to visualise custom data tracks with trendlines and annotation from most data tracks in the UCSC table browser [260]. Annotation information on the probes in the 450k array was obtained from Zhou et al. [253]. CpG Island information was downloaded from the AnnotationHub package [261]. SNP data and RefSeq data in hg19 was downloaded from UCSC Table Browser [260].

3.2.9 Annotation of evolutionarily enriched DMRs with Roadmap Epigenomics Data

The evolutionary DMRs selected for containing schizophrenia-associated SNPs above the study-wide threshold were also annotated using the data available from the Roadmap Epigenomics consortia [262]. Prefrontal cortex data was available from sample E073 that was obtained from healthy controls aged 75 and 81 years old. The 18-state chromatin data was loaded in R and intersected with the coordinates of the 9 DMRs with the GenomicRanges package [263]. Information about the 18-states was downloaded from the Roadmap Epigenomics data portal.

4. Paper Summaries

4.1 Paper I

In this paper, we show that regions whose methylation levels changed specifically in the human branch compared to Neanderthals or Denisovans are enriched for markers of schizophrenia.

We come to this conclusion by analysing various phenotypes and testing for enrichment both visually and statistically.

For visual confirmation of enrichment, we implement the method from Schork et al. [245] that was also used successfully to depict enrichment in the Neanderthal selective sweep by Srinivasan et al. [209].

We did not find any evidence for enrichment of Neanderthal and Denisovan specific methylated regions for schizophrenia markers. However, the method may be suboptimal as the GWAS markers are based on the structure of human genome that may not be identical to Neanderthals and Denisovans.

Our paper lends evidence to the evolutionary hypothesis of schizophrenia and suggests recent human evolution at play.

4.2 Paper II

In this paper, we wanted to analyse if primate DMRs that denote methylation changes from ca 13 MYA could be enriched for schizophrenia markers. We undertook this study because we were interested in checking how far back the evolutionary lineage do methylation changes potentially remain enriched for schizophrenia (SCZ) markers. This could give clues to whether schizophrenia markers predated the Homo lineage.

We separately undertook analyses in hypo- and hyper-methylated human regions, i.e. regions in the human genome that were either a) hypo-methylated in humans and hypermethylated in primates or b) hyper-methylated in humans and hypo-methylated in primates.

We found evidence of enrichment for hypo-methylated human DMRs driven by the extended MHC region and a considerable reduction in enrichment when the MHC region was masked. This suggests that the risk loci for SCZ in the extended MHC region are of an ancient origin and that they tend to have lost methylation over evolutionary time. When we remove the extended MHC region from the analyses, we lose the hypomethylated DMRs and the markers contained therein.

In contrast, regions, which became hyper-methylated in humans compared to primates showed no evidence for enrichment in MHC region. The enrichment effect of hypomethylated DMRs was confirmed with INRICH for LD-implicated SCZ intervals below the genome-wide threshold.

Furthermore, there was a negligible overlap of the primate DMRs with other evolutionary annotations including the human-specific DMRs from **Paper I**, HARs and NSS. This may suggest that different regions of the human genome underwent evolution and that these changes occurred at different evolutionary time points.

4.3 Paper III

In this study, we investigated whether the evolutionary DMRs (from **Paper I**) that contain significantly associated schizophrenia markers above a study-wide threshold, also show variable methylation in patients with schizophrenia. We undertook the analyses using publicly available methylation datasets in brain and blood samples.

We find statistically significant evidence of variable methylation in evolutionary DMRs in patient samples from the brain. The findings, however, could not be replicated in blood samples. This may be because schizophrenia is considered a brain disorder rather than a blood disorder.

The DMRs showing variable methylation in patient samples occur in genes previously implicated in schizophrenia such as *ZSCAN12P1*, *LINC00606*, and *FGFR1*. These genes may be relevant from an evolutionary standpoint since they contain methylation regions important in human evolution. Finally, we find a major limitation of the Illumina 450k BeadChip platform that has inadequate coverage of several of the evolutionary DMRs.

5. Discussion & Conclusion

5.1 Methodological Considerations

5.1.1 Mapping of DMRs and SNPs with LDsnpR

A fundamental aspect of the present thesis has been the annotation of the evolutionary DMRs from Gokhman et al. [150] with SNPs from schizophrenia GWAS [38]. As presented in **Paper I**, this annotation was performed using the software LDsnpR [243] that was previously developed in the group [243]. Unlike other mapping tools such as Galaxy [264] and Genomic Ranges [263] that can provide information on overlaps, LDsnpR provides LD-based information as well [243]. This is useful because the individual nucleotides in the human genome are not independent of each other. There are places in the genome where groups of nucleotides tend to be inherited together and have low recombination. This biological phenomenon is exploited in designing GWAS chips where only a subset of all nucleotides is incorporated. This allows the chips to probe the entire genome by 'tagging' regions with a few select SNPs.

However, this advantage comes at the cost of resolution, i.e. any SNP associated with a trait actually specifies a particular region, but seldom the causative variant for the trait under investigation. Furthermore, since GWAS chips are designed using LD, utilising only overlapping SNPs to annotate the DMRs could potentially lead to an underestimation of DMRs containing schizophrenia-associated SNPs.





Using 'Positional binning', only SNPs overlapping a DMR are tagged. In this case, only 1 SNP is tagged to the DMR. This strategy would work if all SNPs were typed in a genotyping chip. However, due to the nature of LD in the human genome, there may be more SNPs within the DMR that are not directly genotyped in the GWAS chip. This is depicted in the case of 'LD-based binning' where an additional SNP that is in LD with SNP2 is tagged to the DMR as SNP2'. Thus using 'LD-based binning', one can 'capture' more SNPs tagging to a particular DMR than using only 'Positional-binning' alone.

Therefore, LDsnpR is an indispensable tool to circumvent the shortcoming of using only positional binning. The software was used for annotating all the GWAS SNPs to the DMRs through both LD-based and positional binning. A potential shortcoming of using LD-based information is that human populations have different LD-structures. However, this shortcoming was overcome using specific population background from the 1000 Genomes project [110] for the European population. This was done keeping in view that the markers used in our study are obtained from the schizophrenia GWAS in which 49

out of 52 cohorts were of European origin [38]. Similarly, the majority of samples from other GWAS were of European ancestry.

5.1.2 Enrichment analyses with conditional Quantile-Quantile (QQ) plots

The method of performing enrichment analysis with conditional quantile-quantile (QQ) plots is relatively new [245]. The regular QQ plots used in GWAS typically show the distribution of the observed *p*-values of SNPs from the expected distribution under the null hypothesis. Schork and colleagues [245] were the first to extend this method to depict distributions of SNPs selected (conditioned) on specific criteria and compare it to the overall distribution of SNPs. They found that trait association signals could be significantly enhanced with a concomitant improvement in false discovery rate (FDR) when SNPs were selected based on specific genomic annotations such as 5'UTRs, 3'UTRs, Exons, Introns etc. [245]. We, therefore, used the same method and applied it to SNPs selected for annotating to DMRs.

Traditionally, the deviations of test-statistics at the tail-end of QQ plots were assumed to occur due to population stratification or cryptic relatedness of cases [265]. However, as reported by another paper by Schork and colleagues [266], it is the polygenic architecture of complex traits that is displayed by the extreme deviations, and such deviations are not due to spurious association.

Schork and colleagues [245] also provide a way to quantify the enrichment observed using a two-sample *Kolmogorov-Smirnov* test that analyses the empirical cumulative distribution frequencies (*ecdf*) of specific strata of SNPs with that of intergenic SNPs. They also provide the so-called enrichment score given by normalised mean (z-score²-1) where z-score denotes the effect size of the SNP under consideration: the number of standard deviations away from the mean of a normal (0,1) distribution.

However, we could not quantify the enrichment observed in DMRs with these methods. We hypothesize this could be partly due to an inadequate number of SNPs tagging DMRs compared to the overall number of SNPs in the GWAS. The two-sample *Kolmogorov-Smirnov* test is dependent on sample sizes. In our case, we had a disproportionately smaller number of SNPs tagged to DMRs (~27,000) compared to the overall number of SNPs in the GWAS (~9.4 million full schizophrenia GWAS). Furthermore, Schork and colleagues [245], implement the test by comparing the specific category of SNPs against intergenic SNPs. In our opinion, intergenic SNPs would not be an appropriate background since many DMRs are themselves at intergenic regions, while others are in the gene bodies or promoters. This made the use of any other category of SNPs such as those tagging 5'UTR, exons, introns or 3'UTRs extremely challenging.

Similarly, the enrichment score of the mean (z-score²-1) was implemented by normalising the various SNP categories against the category of SNPs possessing the highest z-scores. In the study by Schork et al. [245], this was the 5'UTR region, and therefore the z-scores of all other SNP categories (exons, introns etc.) were normalised against it. The method, therefore, could not be implemented for our dataset as our genomic category of DMR could not be normalised against any specific background set of known genomic annotation of exon, intron etc. There are several DMRs that are present in gene bodies and promoters, and since we wanted to test for enrichment of the entire DMRs, we could not directly implement the enrichment score as described by Schork and colleagues.

It is due to these limitations that we chose to implement the INRICH pipeline [246] to quantify the enrichment observed in conditional QQ-plots [267].

5.1.3 Enrichment analyses with INRICH

The INterval enRICHment analysis tool [246] implements permutation and bootstrapping procedures, to test LD-implicated genome intervals for the enrichment of specific genesets. It is extremely valuable for testing regions implicated by GWAS studies as it corrects for several confounding factors such as variable gene size, overlapping genes, overlapping intervals, SNP density, LD within and between genes. The default

parameters involve performing 10,000 rounds of permutation to generate empirical significance values for each gene-set. This is followed by 5000 rounds of bootstrapping to correct for testing several different gene-sets [246]. Xu and colleagues [211] used this method to demonstrate enrichment of genes flanking HARs for schizophrenia. We implemented a similar procedure as them to demonstrate enrichment of genes flanking DMRs for schizophrenia and also independently verified enrichment of genes tagged by NSS for schizophrenia [267].

However, we failed to replicate the original findings of Xu and colleagues [267]. This might have been due to a different gene annotation or version. Additionally, they used specific background gene-sets in their INRICH analysis that we did not implement. During the INRICH analysis, it is possible to compare the enrichment of test gene-sets against a background gene-set. As Xu and colleagues test for enrichment the primate HARs, i.e. regions conserved in non-human primates but evolved in humans, they make the argument of using a background set of primate orthologous gene-set instead of all human genes.

However, Xu and colleagues fail to mention if any enrichment was observed when using all human genes as background. This is important because the schizophrenia regions tested by them are generated on a genome-wide GWAS. If only primate orthologs are used as background, then it becomes crucial also to limit the schizophrenia-associated LD intervals to the orthologous regions. It is unclear whether this correction was performed. Hence, in our study, we utilized all human genes as background because a) the LD-implicated intervals are derived from a genome-wide schizophrenia GWAS, b) NSS was generated on genome-wide scale, and c) we tested a set of genes flanking DMRs, NSS and HARs that together covered ~50% of known human genes. It is for these reasons we chose to argue against using specific background gene-sets in our INRICH analyses.

An important caveat of the INRICH analyses is that the final *p*-values generated after permutation and bootstrapping procedures are dependent on the number of gene-sets

being tested. Testing only the DMR gene set will give a different *p*-value compared to testing a combined gene set flanking DMRs, NSS and all the different HARs. Furthermore, due to a random seed generator in the computational pipeline of INRICH, repeating the analysis will never give the same *p*-values as before, although the trend and direction remain same. It is, however, possible to obtain the same *p*-values if the same random seed generator is used in the new analyses.

Lastly, as INRICH tests for gene sets, it is not directly comparable to polygenic enrichment methods such as conditional QQ plots that test enrichment at a SNP level. It is therefore important to consider how the gene sets are constructed. We used the identical procedure as described by Xu and colleagues of a 100kb flanking window for HARs [211]. However, this may or may not be an ideal window to tag genes for DMRs simply because we do not yet know the full functionality of the DMRs. An ideal gene set for DMRs would be genes that have been experimentally verified to be affected by the variable methylation brought about when the ancestors of modern humans diverged from those of Neanderthals and Denisovans ~750,000 years ago [268]. This would require future work.

5.1.4 Evolutionary DMR analyses in patient samples

From the results of **Paper I** that described the enrichment of human-specific DMRs for schizophrenia associated markers, the next task was to determine which of the DMRs should be analysed for functional analysis in patient samples. Since we wanted to focus on the DMRs that contained significantly associated schizophrenia markers, it was important to determine an appropriate threshold for the significance cutoff of the SNPs. Traditionally, for GWAS data containing millions of SNPs, the significance threshold is assigned using the Bonferroni correction for multiple testing [100]. This is an arbitrary figure based on the assumption of a million independent SNPs [269] on the GWAS chip that gives a genome-wide significance threshold of 5x10e-8 at $\alpha = 0.05$.

However, unlike in a GWAS, the genome-wide threshold could not be used to determine DMRs containing significantly associated SNPs. In our case, we had ~27,000 SNPs tagging DMRs in LD. These SNPs are thus not independent of one another. It was, therefore, necessary to determine the appropriate number of independent SNPs to correct for in multiple testing.

The method of Moskvina [247] was implemented in R [244]. The effective number of SNPs is estimated based on pairwise correlation, which accounts for underlying LD and provides more realistic estimates of independent SNPs. This was estimated to be ~2048 SNPs that was used to determine the study-wide significance threshold at α = 0.05 as follows:

 $Studywide threshold = \frac{0.05}{actual number of independent tests (2048)}$

This gave a value of 2.4x10e-5. Subsequently, 9 DMRs were found to possess SNPs that crossed this threshold.

Thus, in the analysis presented in **Paper III**, we assume that it is the DMRs possessing significantly associated schizophrenia SNPs that are relevant for an investigation. It is possible to speculate that there may be other evolutionary DMRs from Gokhman et al. [150] that do show methylation variation in patients with schizophrenia, despite not possessing significant schizophrenia-associated SNPs. This should be investigated in future studies, ideally with an upgraded Illumina methylation array that has improved coverage for these DMRs. This aspect of coverage of the evolutionary DMRs is discussed in the following section.

5.1.5 Methylation analyses in brain and blood samples

The datasets utilised for carrying out the methylation analyses were performed in Illumina's HumanMethylation450 BeadChips also known as the 450k array [248,249]. Briefly, this is a microarray-based technology that measures methylation variation in the samples with the help of probes. In the 450k array, there is a little more than 450,000 probes (hence the name) spread across the genome. These probes are used for measuring methylation variation at a specific CpG site in the genome and together cover 99% of all RefSeq genes, more than 19,000 unique CpG islands as well as 3000 probes at non-CpG sites [248].

When using this platform, each plate can analyse 96 samples at a time. These samples are distributed across eight slides, where each slide can handle 12 samples. The 12 samples are arranged in a grid of 2x6 cells, i.e. two columns and six rows. Each cell in this grid contains probes with two different types of chemistries: Infinium Type I probe and Infinium Type II probe.

Type I probe was initially designed for the predecessor of the 450k array namely the Infinium 27k array [270]. This probe design utilizes two bead-bound probes per CpG location - one probe measures the methylated signal, the other measures the unmethylated signal. After bisulphite conversion of sample DNA that converts unmethylated cytosines to uracil, for an unmethylated CpG, the probe for detecting unmethylated position hybridises to the DNA, followed by a successful single base pair extension of a fluorescent labelled nucleotide. The bead-bound probe for detecting methylation fails at the single base extension step and therefore does not emit a colour signal.

For the methylated CpG, the other bead-bound probe for detecting methylated position hybridises, followed by a successful allele-specific single base extension. The methylation level at each CpG locus is then determined as the ratio of the signal from the

methylated probe to the total signal intensity (β). This value has a range from 0 for a completely unmethylated locus to 1 for a completely methylated locus.



Figure 5: Depiction of the Type I probe design in the 450k array on methylated locus (Locus 1). Bisulphite treatment preserves the methylated cytosine base. The probe for detecting methylation (green), hybridises and successfully performs a single base amplification while the same results in failure for the probe detecting unmethylated loci (red) (Adapted from Illumina 450k array technical note at https:// www.illumina.com/documents/products/ technotes/ technote_ hm450_ data_ analysis_ optimization.pdf)



Figure 6: Depiction of the Type I probe design in the 450k array on an unmethylated locus (Locus 2).

Bisulphite treatment converts a non-methylated cytosine to thymine. The probe (red) for detecting an unmethylated locus successfully hybridises and performs single base extension while the same results in failure for the methylation detecting probe (green) (Adapted from Illumina 450k array technical note at https://

www.illumina.com/documents/products/technotes/technote_hm450_data_analysis_
optimization.pdf)



Figure 7: Depiction of the Type II probe design in the 450k array.

Locus 1 is a methylated CpG while Locus 2 is an unmethylated CpG. Bisulphite treatment converts all unmethylated cytosines to thymines (locus 2). A fluorescent-labelled nucleotide gets hybridised indicating presence or absence of methylation at a specific locus (Adapted from Illumina 450k array technical note at https://

www.illumina.com/documents/products/technotes/technote_hm450_data_analysis_ optimization.pdf)

About 70% of the probes in the 450k array are of Type 2 design [248]. This probe design utilises only one probe per CpG locus. This enables more probes to be assimilated in the array design, thereby expanding the coverage of CpG sites across the genome. In the Infinium Type II probe, after the probe hybridises to the bisulphite treated DNA, single base extension with a differentially labelled fluorescent nucleotide indicates the

methylation status. If the CpG site initially was methylated, then the 3' end of the probe incorporates a complementary nucleotide of G that has a green fluorescent label while a red fluorescent labelled A is incorporated if the original CpG site was unmethylated.

Probes in the 450k array are 50bp in length

(https://www.illumina.com/documents/products/technotes/technote_hm450_data_analysi s_optimization.pdf). For the evolutionarily enriched DMRs, as depicted in the table below, the coverage is weak except for *DMR204* where more than half of the DMR can be analysed with the probes. The results in **Paper III**, therefore, need to be viewed with this caveat in mind.

DMR	Chr	Start	End	Length	No. of probes	Percentage	Probes
name					overlapping	covered of	needed for
						DMR	100%
							coverage
DMR10	1	2378997	2379771	774	1	6.4%	15
DMR127	3	10805466	10809820	4354	11	12.6%	871
DMR203	6	28058845	28060341	1496	6	20.0%	30
DMR204	6	28833654	28834570	916	10	54.6%	18
DMR236	7	1952455	1953065	610	4	32.8%	12
DMR237	7	2048069	2049043	974	3	15.4%	19
DMR291	8	38287269	38289920	2651	1	1.8%	53
DMR526	14	103745950	103746209	259	1	19.3%	51
DMR527	14	104006646	104008448	1802	1	2.7%	16

Table 1: Depiction of probe coverage of the 450k array in DMRs selected for patient analyses.The table summarises information on the 9 DMRs analysed in Paper III with genomiccoordinates provided in hg19 and probe coverage in these DMRs from the 450k array.

Assuming that 100% probe coverage in these DMRs is needed for a more accurate understanding of methylation variation in patients with schizophrenia, the 450k platform is under-equipped to paint a full picture. Since CpG sites are correlated to at least 50bp, one may not need as many probes as depicted in the table above. However, for a more accurate representation of the methylation variation in these evolutionary DMRs, the probe coverage needs to increase substantially.

The poor probe coverage is especially relevant when considering the statistical tests in the comb-p algorithm [258]. As described previously under the Methods section, this algorithm is highly suitable for analysing methylation arrays where the probes, and thus their respective *p*-values, are unevenly spread across the genome. *Comb-p* determines the correlation between adjacent probes and helps combine adjacent p-values to determine true significance of probes or regions. In **Paper III**, the region p programme of comb-p was used for determining the statistical significance of the methylation variation in the evolutionarily enriched DMRs. This programme initially computes the auto-correlation of probes up to the maximum length of the regions to be tested. It then performs the Stouffer-Liptak-Kechris correction where the *p*-value of each probe within a particular DMR is adjusted according to adjacent *p*-values as weighted according to the autocorrelation. When neighbouring *p*-values are low, a given *p*-value gets pulled lower. Finally, a Sidak one-step correction for multiple testing is performed. For a given DMR, the number of tests to correct for is determined by the total length of bases covered by probes divided by the size of the region. Since this correction takes into account the number of bases covered by the probes in the DMRs, it may vary if a) probe coverage in the region is inconsistent, and, b) probes are dropped during pre-processing steps.

An additional confounder in the analyses presented in **Paper III** relates to the variable cell composition of all the brain datasets analysed [174]. Although all the studies utilised brain samples from the prefrontal cortex, there is considerable variation in the ratio of neuronal to non-neuronal cells between the different datasets. In fact, when comparing the prefrontal cortex dataset from Wockner and colleagues [169] to the two datasets from

Pidsley et al. [173], the Pidsley datasets contained twice the proportion of neuronal cells in the schizophrenia samples as the dataset from Wockner et al. [174]. This may partly explain the opposite direction of effect in methylation observed in schizophrenia patients for *DMR127*. Furthermore, the data from Jaffe et al. [178] estimates cell composition using three additional cell populations apart from the neuronal and non-neuronal cell types.

Finally, an interesting point to consider is the fact that the methylation in brain samples are all post-mortem while the methylation in blood samples is antemortem. We, therefore, do not know for sure, if the methylation difference observed in the brain samples from schizophrenia patients has more to do with the fact that the subjects had passed away or the fact that brain and blood do not share the same methylation profile in these evolutionarily enriched DMRs. One way to unravel this conundrum could be to test post-mortem blood samples with post-mortem brain samples. Additionally, it has been previously reported that the vast majority of probes do not show similar methylation profiles between brain and blood [271]. Thus, using blood to infer methylation variation in these evolutionary DMRs for patients with schizophrenia may not be optimal.

Furthermore, antipsychotics are known to influence DNA methylation levels and as such their effect cannot be ruled out [176,272,273]. As reported previously by Mill and colleagues [167], DNA methylation of a CpG island located upstream of *MEK1* is correlated with lifetime antipsychotic usage in the brain. Similarly, *FOSB* is activated by administration of antipsychotic medications and was found to be hypo-methylated in female patients with major psychoses [167].

However, as reported previously [274], DNA methylation differences can be observed in antipsychotic-free patients using peripheral leukocyte samples. But the study may have potential limitations such as the relatively young age of patients (mean age: 31.9 ± 9.7 years) that suggests they were unlikely to be stable long-term patients with schizophrenia. Furthermore, the results may also be confounded due to the fact there are several

different cell types in leukocytes with their own specific DNA methylation signatures [275].

It has been suggested that certain antipsychotics like clozapine are superior to haloperidol due to the ability of clozapine to induce hypo-methylation in GABA and glutamatergic promoters [273]. A recent study [276] used peripheral blood samples and 450k array to look into the effects of clozapine on treatment-resistant patients with schizophrenia. They found significant methylation differences at more than 29,000 positions after one year of clozapine treatment. However, the study did not take into account the peripheral blood cell composition.

5.1.6 Limitations of the study

The epigenetic change of DNA methylation of CpG dinucleotides has been of prime focus in **Papers I-III**. This is, however, not the only epigenetic modification in the human genome. There are reports of variation in DNA methylation termed 5hydroxymethylation that we did not consider for investigation. Furthermore, research has revealed that 5-hydroxymethylation is a more common methylation modification in the brain [277,278] than in other organs. This makes the investigation of this epigenetic mark very relevant for brain disorders such as schizophrenia. We were however limited by the fact that the evolutionary epigenetic changes were investigated only in CpG (5methylcytosine) methylation and not 5-hydroxymethylation. We, therefore, limited ourselves to investigating only 5-methylcytosine and not 5-hydroxymethylation.

Additionally, we did not investigate histone marks for similar reasons. To the best of our knowledge, they have not been investigated from an evolutionary point of view. RNA is also a vital component of epigenetic machinery [123,279], not considered in the present study. Although some forms of RNA molecules have been shown to be responsible for intergenerational inheritance [280], they have yet to be investigated from an evolutionary

standpoint. So far, it is only CpG methylation in the form of 5-methylcytosine that has been investigated from an evolutionary perspective [181–183].

In the context of psychiatric disorders, bipolar disorder is known to share genetic similarity with schizophrenia [281]. We failed to find evidence of enrichment of evolutionary human-specific DMRs for bipolar disorder associated SNPs. This could partly be due to the fact that bipolar disorder GWAS was underpowered [235] because of a moderate sample size (n = 7,481 cases and 9,250 controls). There is a new bipolar disorder study currently available as a pre-print on bioRxiv that we did not use [282]. Furthermore, as a limitation for the polygenic enrichment method employed, a future GWAS study on schizophrenia with more power could shift the *p*-value distribution entirely. This could cause more SNPs to cross the significance threshold and as such more evolutionary DMRs may be relevant for an investigation.

5.2 Biological significance of our results

5.2.1 Discussion of results in Papers I-III



Figure 8: Depiction of all evolutionary datasets tested in literature for the enrichment of schizophrenia markers

The diagramme depicts various evolutionary annotations, superimposed on a phylogenetic tree, which have been tested in literature for the enrichment of schizophrenia markers. Red denotes lack of enrichment while green depicts positive enrichment for markers associated with schizophrenia. (Timeline estimates from the Smithsonian (http://humanorigins.si.edu/), Hasegawa et al 1985 [283], Srinivasan et al 2017 [210], Rogers et al 2017 [268])

Taken altogether, our results hint at epigenomic evolution through methylation, having taken place in genomic regions implicated in the aetiology of schizophrenia (**Paper I**).

These regions harbour markers that are involved in the regulation of various neurodevelopmental pathways. The fact that methylation changes also took place in the very same regions suggest a complex gene by environment interaction in the evolution of humans, especially pathways that led to the development of our brain. It is known that various factors from the environment can make long-lasting changes in the DNA methylation patterns that can be subsequently inherited at a population level [284–286]. Thus, the true significance of our findings from an evolutionary standpoint suggests, the interaction of the epigenetic machinery through DNA methylation with environmental factors over the past 300,000 years when the first anatomically modern humans appeared on Earth [218,219]. These gene by environment interactions may in part have been responsible for changes in neuro-developmental pathways, some of which also affected neuro-developmental pathways implicated in the aetiology of schizophrenia.

We also show that DNA methylation variation that occurred in *Homo sapiens* since the divergence of the common ancestor from the great apes are not enriched for markers of schizophrenia, with the exception of the extended MHC region (**Paper II**). This suggests that the evolutionary events of the past 300,000 years but not ca 6-7 MYA, may have influenced the DNA methylation of genomic regions associated in the aetiology of schizophrenia at a genome-wide level. In Paper II, we call the DMRs observed in humans by comparison with chimpanzees, gorillas and orangutans as primate DMRs. The observation of enrichment of primate DMRs for schizophrenia risk markers only in the extended MHC region might suggest that the immune system markers associated in schizophrenia have been undergoing evolution from a very long time. Indeed it has been shown that the MHC region bears signatures of both recent and ancient natural selection [287].

The exact biological consequences of this enrichment of primate DMRs in the extended MHC region are however not easy to infer. This is because the extended MHC region is the most gene-dense region of the human genome containing over 250 genes at an average gene density of one gene every 16 kb along with extended linkage-
disequilibrium [287]. Thus it is challenging to infer which genes might have had their regulation affected by variation in DNA methylation. When we remove the extended MHC region from the analysis, any evidence of enrichment of primate DMRs disappears suggesting a highly localised evolution of the immune system markers in schizophrenia since the divergence from great apes.

Finally, in **Paper III**, we investigate whether the DMRs from Paper I that contain schizophrenia markers above a study-wide threshold show disrupted methylation in patients with schizophrenia. We observe that some of these DMRs do show variation in patients samples. The variation is observed however only in brain tissue and not blood samples. This is the first attempt at investigating if regions whose methylation has evolved in *Homo sapiens* shows disrupted patterns of methylation in patients with schizophrenia. The results suggest *LINC00606*, *ZSCAN12P1* and *FGFR1* to be relevant from an evolutionary perspective and also important in the aetiology of schizophrenia as they contain SNPs associated with schizophrenia at or above the study-wide threshold of $p = 2.4 \times 10e-5$. Additionally, we find statistically significant variation in a DMR that does not overlap any particular gene. Data from the Roadmap Epigenomics Project [262] in the prefrontal cortex tissue suggests it to be present in a region demarcated as a 'bivalent enhancer'. Using Hi-C data in the hippocampus [288], we may speculate that this particular DMR could be important in the regulation of *MARK3*, a gene that has been implicated in disorders of astrocytes.



Figure 9: The potential regulatory role of DMR526 on MARK3

The depiction of a Hi-C contact matrix with the approximate position of DMR 526 at chr14: 103,745,950-103,746,209. Figure derived from Hi-C results on Hippocampus published by Schmitt et al., 2016 [288] and visualised in 3D Genome Browser at http://promoter.bx.psu.edu/hi-c/view.php

5.2.2 An epigenetic perspective of the results in the broader context of recent human evolution

It is important to place the results of the present body of work in the broader understanding of human evolution. A variety of factors could have driven the human-specific methylation changes. One could speculate about the potential environmental agents that might have influenced the methylation patterns over the past 300,000 years in *Homo sapiens*.

Climate fluctuations have often occurred over the past 800,000 years [289]. The period of rapid expansion of the human intellectual capacity and colonisation of the world cooccurs with the last ice-age in which average temperatures in the South Pole reduced as much by 10 °C along with a concomitant reduction in global CO₂ levels [290]. These climatic changes could potentially have affected the food sources available to our ancestors. Food and dietary patterns are well known to affect DNA methylation patterns [291–293].



Figure 10: Depiction of the global climatic shifts over the past 800,000 years.

The figure depicts variations in temperature and carbon dioxide (CO_2) levels as observed at the South Pole. The emergence of modern Homo sapiens ca 70,000-40,000 YA occurs during the last ice age, while the oldest fossil of an anatomically modern H. sapiens is dated to ca 300,000 YA. (Source: National Research Council, 2010a, Lüthi, D et al., 2008 [290], Jouzel J et al. 2007 [289], Reproduced with permission from National Academies Press).

Long-chain polyunsaturated fatty acids (PUFA) are important components of brain phospholipids [294]. These include arachidonic acid (AA) from meat and docosahexaenoic acid (DHA) from fish. Abnormal brain phospholipid metabolism has been observed in patients with schizophrenia [294]. It has been suggested that the diet of our ancestors, especially of those living along the sea-coast and inland lakes, was rich in consumption of fish [295]. A diet rich in fish would provide DHA to babies via their mother's milk [295,296]. Long-term availability of PUFA from such food sources may have influenced the development of the brain [294] through epigenetic mechanisms [297]. This may represent yet another environmental means of altering DNA methylation in our ancestors. It remains unknown, however, the extent to which the consumption of fish and meat can influence methylation in the human-specific DMRs analysed in the present body of work.

Some researchers have proposed that methylation changes can be driven by sequence changes [298] and while that may be true, there also exists the phenomenon of differential methylation between identical twins called 'metastable epialleles' [182]. Thus, not all methylation changes may be driven by the underlying genomic sequence. Gokhman and colleagues observed that only some but not all the human-specific methylation changes were influenced by the underlying genomic sequence [150].

Anatomically modern humans appeared on earth at least 300,000 years ago [218,219]. However, it is challenging to put an exact date on the emergence of superior mental abilities that define the modern *Homo sapiens*. In particular, anthropologists and archaeologists studying human evolution often cite the emergence of the superior intellectual abilities of *Homo sapiens* from about 70,000 years onwards [221]. This is the period from which there is irrefutable evidence of the emergence of art, religion [222,299] and possibly spoken language [227]. From an evolutionary perspective, it suggests a massive leap in the animal kingdom because *Homo sapiens* became the first to not only develop the capacity to think and imagine things that do not exist [222,299] but also to communicate the same ideas to other members of the species [227]. This aspect

would have been critical in the ability to coordinate and cooperate effectively with large groups numbering more than 150 individuals and even needed in keeping a group together [220,300].

This ability to cooperate and form bonds with other members of their species, united by a shared belief system may have allowed larger groups of humans to co-exist. This aspect gains significance from the recent work by Rogers et al. [268] that suggests Neanderthals, although spread far and wide as evidenced by the rich collection of their fossils, existed in small bands of individuals. One could thus speculate that although for most of the time in existence, humans were not able to displace the Neanderthal from their natural habitats, the 'intellectually-superior' humans, characterised by larger, well-coordinated groups may have driven the smaller bands of Neanderthals to extinction ca 40,000 years ago [301].

Using the data from Gokhman et al. [150], we gain an insight into the methylation variation that has potentially occurred since the last common ancestor of humans, Neanderthals and Denisovans diverged ca 750,000 years ago [268]. There thus remains a gap in our knowledge of the evolutionary events occurring in the human lineage from the period of ca 750,000 to 300,000 years when anatomically modern humans appeared. Assuming the superior intellectual abilities appeared ca 70,000 years, then there remains another gap in our knowledge of evolutionary events that allowed the massive leap in intellectual capacity.

Using the present study to determine when exactly in the period of the last 300,000 years [218,219] *Homo sapiens* developed their superior intellectual abilities or psychosis is therefore challenging. If the method used in the reconstruction of genomes of Neanderthals and Denisovans [150,302] could be implemented on samples of ancient *Homo sapiens* from different time periods [303–310] then theoretically it should be possible to reconstruct the methylomes of ancient humans [311]. Subsequently, a more 'time-series' analyses of change in methylation patterns of regions controlling neuro-

developmental processes implicated in schizophrenia and psychosis should be feasible. This idea has been further expanded upon by recent work from Gokhman et al. [182] and Hanghøj et al. [312].

Amongst the defining hallmarks of schizophrenia are hallucinations [313,314]- a phenomenon of imagining and experiencing things that do not exist. Also amongst the defining features of our species is the ability to think and imagine things that do not necessarily have a physical form of existence such as belief systems [222,223,299]. Given that abstract thinking including art and religion appeared at least 40,000 years ago [222,299], it may very well be the case then that the earliest psychotic patients may have belonged in this period and not in the *Homo sapiens* of ca 300,000 year period [218,219]. The *Homo sapiens* from ca 300,000 years, though physically similar to modern humans, may, in fact, have had sub-developed intellectual skills in working memory [225] that in turn is critical in creativity [315-317]. Indeed, the rapid expansion of Homo sapiens from ca 70,000 years onwards might have been spurred by a distinct advantage over earlier *Sapiens* through the origin of language or belief systems [220,224,227] that may have allowed larger bands of individuals to cooperate, migrate and colonise the world [220,225,300]. One could speculate that within this ability to bring together massive numbers of individuals through religion [220] and language [227] may be where psychosis originated. The answer therefore to the origins of psychosis may thus ultimately lie in the origins of creativity, language and religion that may be answered through evolutionary epigenomics of ancient Homo sapiens [182,312].

5.3 Conclusion & Future Perspectives



To recapitulate, we first tested if (a) regions of recent methylation changes (non-primate DMRs) are enriched for association with schizophrenia and other human traits (**Paper I**). We followed it up by (b) testing enrichment of association for ancient methylation changes (primate DMRs) for human traits (**Paper II**) and finally, (c) whether differentially methylated regions (DMRs) that contain significantly associated schizophrenia SNPs show variable methylation in patients with schizophrenia (**Paper II**).

Our original goal was to test T.J. Crow's evolutionary hypothesis of schizophrenia, but our results are not conclusive. Using evolutionary epigenetics datasets that together trace a period of development from ca 13 MYA to 750,000 YA, we find evidence of enrichment of recent, but not ancient methylation changes for schizophrenia associated SNPs. Our results in principle support the hypothesis that evolution may in part have contributed to schizophrenia risk. However, at present, we cannot ascertain whether the recent methylation changes harbouring schizophrenia markers are causative of the disorder or piggyback due to some hitherto unknown stochastic phenomenon. Furthermore, schizophrenia is a highly polygenic trait [266] that has shared pleiotropy with several traits [318–320]. Although we do not find enrichment of other trait-associated markers with evolutionary DMRs (with the possible exception of height), we cannot rule out that the enriched DMRs affect the pathophysiology of other traits.

Additionally, the hypothesis put forward by T.J. Crow stipulates a dysregulation of the language process being central in the aetiology of schizophrenia. Our current results neither confirm nor contradict this aspect of the hypothesis. This is partly due to the fact that the methods employed cannot test for language origin, proficiency or dysregulation. Furthermore, to utilise evolutionary methylation changes for language analysis, one would need much recent methylation data from a time where there is incontrovertible evidence of human civilisation and language flourishing [13].

In conclusion, while we find evidence to support the hypothesis that recent evolution may have played a role in modulating methylation in genomic regions associated in schizophrenia, the present methods lack the resolution to determine language dysregulation as a key component of human evolution and psychosis. As a consequence, there is much work that remains to be done to either prove or disprove T.J. Crow's evolutionary hypothesis that schizophrenia is the price humans pay for language. Future work should also investigate the human-specific DMRs using either an array technology with better probe resolution or whole-genome sequencing methods for measuring methylation variation in patients with schizophrenia.

6. References

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7. Papers I-III
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Recently evolved human-specific methylated regions are enriched in schizophrenia signals

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Abstract

Background: One explanation for the persistence of schizophrenia despite the reduced fertility of patients is that it is a by-product of recent human evolution. This hypothesis is supported by evidence suggesting that recently-evolved genomic regions in humans are involved in the genetic risk for schizophrenia. Using summary statistics from genome-wide association studies (GWAS) of schizophrenia and 11 other phenotypes, we tested for enrichment of association with GWAS traits in regions that have undergone methylation changes in the human lineage compared to Neanderthals and Denisovans, i.e. human-specific differentially methylated regions (DMRs). We used analytical tools that evaluate polygenic enrichment of a subset of genomic variants against all variants.

Results: Schizophrenia was the only trait in which DMR SNPs showed clear enrichment of association that passed the genome-wide significance threshold. The enrichment was not observed for Neanderthal or Denisovan DMRs. The enrichment seen in human DMRs is comparable to that for genomic regions tagged by Neanderthal Selective Sweep markers, and stronger than that for Human Accelerated Regions. The enrichment survives multiple testing performed through permutation (n = 10,000) and bootstrapping (n = 5000) in INRICH (p < 0.01). Some enrichment of association with height was observed at the gene level.

Conclusions: Regions where DNA methylation modifications have changed during recent human evolution show enrichment of association with schizophrenia and possibly with height. Our study further supports the hypothesis that genetic variants conferring risk of schizophrenia co-occur in genomic regions that have changed as the human species evolved. Since methylation is an epigenetic mark, potentially mediated by environmental changes, our results also suggest that interaction with the environment might have contributed to that association.

Keywords: Differentially methylated regions, Schizophrenia, Evolution, Epigenetics, Height, Neanderthal selective sweep score, Human accelerated regions

Background

Schizophrenia is a psychiatric disorder that has been reported throughout human history, possibly as far back as 5000 years [1, 2]. Family, twin and adoption studies estimate that schizophrenia has a high heritability of 60–90% [3–6]. Today, schizophrenia is estimated to have a prevalence of

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1%. It is associated with reduced fertility and increased mortality [7–11], and its persistence despite this heavy burden is paradoxical. Power et al. [11] leveraged Swedish registry data to demonstrate the reduced fecundity of patients with schizophrenia, despite the novel finding that sisters of individuals with schizophrenia had higher fitness than controls. They henceforth suggested hitherto unknown mechanisms for persistence of the disease. One explanation for this persistence is that evolution has indirectly selected the disease instead of eliminating it - the disease may co-segregate with creativity and intellectual prowess, providing selective advantages to the kin of affected individuals [9, 12]. Crow first

© The Author(s). 2018 **Open Access** This article is distributed under the terms of the Creative Commons Attribution 4.0 International License (http://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution, and reproduction in any medium, provided you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license, and indicate if changes were made. The Creative Commons Public Domain Dedication waiver (http://creativecommons.org/publicdomain/zero/1.0/) applies to the data made available in this article, unless otherwise stated. argued that language and psychosis may have common origins, which could explain the persistence of schizophrenia in human populations [12, 13]. This evolutionary hypothesis of the origins of schizophrenia can now be tested, thanks to the identification of genetic factors implicated in schizophrenia [14–16] and the availability of datasets that reflect recent genomic evolution in humans [17–19].

Large genome-wide association studies (GWAS) have identified thousands of variants that are associated with schizophrenia [14-16] but our mechanistic understanding of the candidate variants is poor. One approach to investigating the function of schizophrenia-associated variants is comparative genomics, which investigates the evolutionary relevance of certain genomic regions [20]. This field has introduced new datasets to test disease origins in humans, including Human Accelerated Regions (HARs) and Neanderthal Selective Sweep (NSS) scores [18, 19]. HARs are genomic regions that are highly conserved in non-human species, but have undergone rapid sequence change in the human lineage [20-24]. Xu et al. [18] showed that genes near HARs are enriched for association with schizophrenia. Neanderthals were hominids that co-existed and even bred with modern humans [25, 26]. Comparison of Neanderthal and human genome sequences [27, 28] has revealed genomic regions that have experienced a selective sweep in modern humans, presumably following a favorable mutation [28]. Negative NSS scores can be used to pinpoint mutations (usually single nucleotide changes) that were positively selected in humans as they diverged from Neanderthals. Srinivasan et al. [19] found that genomic regions tagged by negative NSS scores show enrichment of association with schizophrenia.

Using specific interpretation of genome sequencing in two recently extinct hominids, Neanderthals and Denisovans, Gokhman et al. [29] mapped genomewide methylation levels (i.e. the methylome) and compared them to modern humans. While 99% of the methylation maps were identical in the three hominids, nearly 2000 differentially methylated regions (DMRs) were identified, which give the first clues about the role of epigenomic evolution in generating anthropometric differences between modern humans and their ancient cousins [29]. These DMRs provide a dataset of evolutionary annotations complementary to pre-existing datasets. Unlike HARs and NSS scores, which are based on DNA sequence changes, DMRs provide information on the evolution of epigenomes. Since epigenomes can act as an interface with the environment [30, 31], these datasets provide the opportunity to investigate environmentally driven evolutionary changes. Keeping in mind the evolutionary hypothesis for schizophrenia proposed by Crow, we thus examined if these evolutionary DMRs are enriched for association with schizophrenia. We also examined a range of human traits to compare the possible enrichment in other traits. Using previously published methodologies [19, 32, 33] and publicly available GWAS datasets we systematically analyzed twelve diverse phenotypes to investigate the potential role of regions susceptible to epigenetic variation in the emergence of specific traits in the human lineage.

Results

SNPs in human-specific DMRs are enriched for association with schizophrenia.

The genomic locations of human-specific DMRs were obtained from data published by Gokhman et al. [29] (see Methods for full details). GWAS summary statistics for 12 common traits were obtained from published datasets: schizophrenia [14], bipolar disorder (BPD) [34], attention deficit hyperactivity disorder (ADHD) [35], rheumatoid arthritis [36], high density lipoprotein [37], low density lipoprotein [37], triglycerides [37], total cholesterol [37], systolic blood pressure [38], diastolic blood pressure [38], body mass index [39], and height [40]. The GWAS datasets are summarized in Additional file 1, Table S1. For each trait, we generated a list of single nucleotide polymorphisms (SNPs) within DMRs (positional annotation) and a list of SNPs in linkage disequilibrium (LD-based annotation) with markers within DMRs (Additional file 1, Table S1).

We used quantile-quantile (QQ) plots as described by Schork et al. [32] to test whether the DMR SNPs are enriched for association with the GWAS trait compared to the complete set of SNPs (see Methods for additional details). In such plots the baseline is the null line of no difference between expected distribution of *p*-values and observed *p*-values. Deviation of the observed data distributions from the expected data distribution indicates the presence of true associations. When the *p*-values for a set of selected markers show greater leftwards deflection, they are enriched for association compared to the overall GWAS set. For the schizophrenia GWAS, enrichment was observed both for SNPs in LD with markers in DMRs (Fig. 1, Additional file 1: Fig. S1) and for SNPs located within DMRs (Fig. 2). Although there was a slight leftward deflection in the higher p-values (smaller negative log₁₀ of *p*-values) in some other traits (e.g. height; Fig. 1, Additional file 2: Figure S1), the observed enrichment only crosses the genomewide significance level of 5×10^{-8} for the schizophrenia SNPs. The enrichment of disease-associated markers in DMRs is thus specific to schizophrenia and is independent of LD.



Human-specific DMR enrichment in schizophrenia is independent of the MHC region, other genomic annotations and total markers genotyped

could potentially bias our results because of long-range LD. The QQ plots show that the enrichment remains when the MHC is excluded (Fig. 1) or included (Fig. 2).

The Major histocompatibility complex (MHC) region harbors several significant schizophrenia markers and

The schizophrenia GWAS had the highest density of markers genotyped (~ 9.4 million) and thus had the most





SNPs in DMR regions (Additional file 1: Table S1), which could artificially inflate the enrichment. We normalized the total number of DMR SNPs with the total number of SNPs genotyped in each GWAS and found that the proportion of SNPs in DMRs is nearly identical for all traits (Additional file 1: Figure S3). To further eliminate the possibility that the enrichment is due to variation in the number of markers analyzed, we extracted ~ 2.4 million SNPs that were common across the twelve GWAS. Although not as strong as with the full set, the deflection observed for the schizophrenia GWAS remains higher than any other trait (Additional file 1: Figure S1), indicating the presence of significant disease markers in DMRs. These validations point to a true enrichment of association of the DMR SNPs with schizophrenia that is independent of the number of markers in a GWAS. It should be noted that we cannot rule out enrichment in the ADHD and BPD GWAS, because they are lacking in power (Additional file 1: Figure S1).

Additionally, we considered the distribution of schizophrenia-associated SNPs based on genomic annotations of 5' untranslated regions (5'UTRs), Exons, Introns and 3' untranslated regions (3'UTRs) [32]. Contrary to previously published findings [32], the enrichment was highest for intronic SNPs and lowest for 5'UTR SNPs (Additional file 1: Figure S4).

Only human-specific DMRs are enriched for association with schizophrenia

Next, we used QQ plots to test whether markers located in the Neanderthal- and Denisovan-specific DMRs are enriched for association with schizophrenia. Coordinates for these DMRs were obtained from data published by Gokhman et al., 2014 [29] (see Methods for details). Since we do not know the precise coordinates of the MHC for Neanderthals and Denisovans, the analysis for human DMRs included the MHC region. No enrichment was observed for Neanderthal or Denisovan DMRs (Fig. 2). It should be noted that this approach may not be appropriate for testing Neanderthal- and Denisovanspecific DMRs since (a) the schizophrenia GWAS was conducted in humans; (b) SNP and LD information is available only for humans; (c) the three hominids had variable number of DMRs, which affected the number of SNPs captured via positional annotation.

Comparison of human DMRs with other evolutionary annotations

We compared the enrichment observed for the human DMRs with the enrichment previously reported for NSS markers and HARs [18, 19] (see Methods for details). We first compared the enrichment via QQ plots and find that the enrichment of human DMRs in schizophrenia is comparable to that observed for NSS markers and far greater than that observed for HARs (Fig. 3).

In these analyses, it was important to check the extent of overlap of markers (SNPs) annotated to various genomic regions of DMRs, NSS markers and HARs. Reassuringly, the various evolutionary annotations do not share the same group of markers, indicating that we did not test the same regions or SNPs (Additional file 1: Figure S2). The overlap between NSS markers and DMR markers involved less than 0.5% of all NSS markers and less than 0.2% of all DMR markers (Additional file 1: Figure S2). The SNPs in the DMRs thus represent a different group of markers that have not been annotated or analyzed previously from an evolutionary standpoint (Additional file 2, Additional file 3).

Statistically-significant enrichment exists for human DMRs

To determine the statistical significance of the DMR enrichment in schizophrenia, we utilized the INRICH software pipeline. INRICH is a pathway analysis tool for GWAS, designed for detecting enriched association signals of LD-independent genomic regions within biologically relevant gene sets (in our case genes which contain DMRs). It performs permutation and bootstrapping procedures to determine the significance of association of markers in LD intervals while maintaining the SNP density and gene density of the original intervals [33]. INRICH confirmed significant (p < 0.05) enrichment of association for human DMRs with schizophrenia after correcting for multiple testing through bootstrapping at most p-value thresholds of LD intervals. Additionally, INRICH independently verified the previously reported enrichment of NSS markers with schizophrenia [19] (Fig. 4). Furthermore, INRICH identified gene-level enrichment of association for DMRs with height (Additional file 1: Figure S5), while at the SNP level the enrichment in height was seen only for smaller effects, i.e. the enrichment did not remain below $p < 10^{-8}$.

Pathway analysis

We utilized Ingenuity Pathway Analysis (IPA) to analyze DMR SNPs that show enrichment of association with schizophrenia (for details of the genes analyzed, please refer to the 'Pathway analysis' section in the Methods). We found 'CREB signaling in neurons' and 'Synaptic long term potentiation' amongst the top canonical pathways when analyzing pathways overrepresented in nervous system. Additionally, under physiological systems, 'Nervous system development and function' is also enriched (Additional file 1: Table S2). We repeated the same analysis for NSS markers as they also show enrichment of association with schizophrenia. 'CREB signaling in neurons' was also amongst the top canonical pathways





for enriched NSS markers (Additional file 1: Table S4). Additionally, we repeated the analyses with all organ systems and even then, 'CREB signaling in neurons' and 'Synaptic long term potentiation' emerged amongst the top canonical pathways for both enriched DMRs (Additional file 1: Table S3) and enriched NSS (Additional file 1: Table S5). This is an interesting result since there is very little marker overlap between the DMR and NSS SNPs (Additional file 1: Figure S2). Interestingly, genes containing enriched DMRs are also overrepresented in 'Hair and skin development' when considering all organ systems (Additional file 1: Table S3). This may suggest potential gene-by-environment interactions, modulated by methylation variation over human evolution (see Discussion below).

Discussion

Our results suggest that SNPs in regions of the human genome that have undergone recent changes in DNA methylation status are enriched for association with schizophrenia, and to a lesser extent with height. Amongst all the traits analyzed, the enrichment observed in QQ plots was strongest for schizophrenia and passed the genome-wide significance threshold of 5×10^{-8} when the MHC was both excluded (Fig. 1) and included (Fig. 2). INRICH analysis confirms significant enrichment (p < 0.01) in human DMRs that survived multiple testing through bootstrapping (Fig. 4) for association with schizophrenia, and also suggests a possible effect on height (Additional file 1: Figure S5).

Xu et al. [18] and Srinivasan et al. [19] respectively demonstrated that variants located in HARs and in regions containing NSS markers were enriched for association with schizophrenia. In our study, we compared the evolutionary enrichments of schizophrenia risk variants in DMRs, NSS markers and HARs. We validate the results of Srinivasan et al. [19] (Fig. 3 and Fig. 4). HARs do not show enrichment of disease markers by QQ plots and INRICH, unlike NSS markers and DMRs (Fig. 3 and Fig. 4). This difference with the report of Xu et al. could be due to a different freeze of the gene database used; it could also be because Xu et al. used a more stringent Hardy-Weinberg equilibrium (HWE) threshold to filter out markers from the schizophrenia GWAS [14], a step we could not replicate as the genotype data are not publicly available. We used the publicly available schizophrenia dataset that has a HWE *p*-value > 10^{-6} in controls and *p*-value > 10^{-10} in cases [14]. Interestingly, all the evolutionary annotations (DMRs, NSS markers and HARs) cover different sections of the genome with very little overlap between them (Additional file 1: Figure S2). Between the three evolutionary annotations, nearly 70,000 SNPs occur around regions with evolutionary significance (Additional file 1: Figure S2). Our results supply a wealth of information on genomic regions that are important for the evolution of humans and are also enriched for schizophrenia risk variants (NSS markers and DMRs, Additional file 3). In addition, our study provides genetic support from two independent datasets that regions which differ between modern and ancient hominids could be implicated in the development of schizophrenia. An interesting hypothesis to consider is the possibility that methylation patterns are potentially driven by the genomic sequence underneath. This hypothesis is supported by preliminary findings presented at the recently concluded World Psychiatrics Genetics Congress [41]. As such it is possible that the human specific DMRs analyzed here represent regions of the human genome where the underlying sequence might have diverged from Neanderthals and Denisovans. This hypothesis may be partially true as Gokhman et al. [29] observed that some, but not all of the methylation changes were indeed driven by sequence changes. On the other hand, there also exist metastable epialleles where there are methylation differences in genetically identical individuals [42]. As such, this would suggest that not all methylation differences are driven by the underlying genomic sequence alone. We did not test whether the schizophrenia markers are human-specific or not and therefore should be investigated in future research.

Neanderthal- or Denisovan-specific DMRs showed no enrichment of association (Fig. 2). This suggests that SNPs conferring vulnerability to schizophrenia occur in genomic regions whose methylation levels were altered in the modern human lineage but not in the ancestral lineages. It is possible that the evolutionary changes driving the variation in methylation status could also have made the human lineage more vulnerable to schizophrenia. A caveat to this result is that the LD structure in archaic genomes is unknown, so we cannot test LD-based enrichment in Neanderthal or Denisovan genomes. Our inter-lineage analyses with enrichment plots were thus restricted to SNPs occurring exclusively within DMRs. The other limitation to this comparative approach is that the GWAS data is specific to modern humans.

In previous studies [32], it was reported that 5'UTRs are the functional annotation harboring the most association with a given trait. However, the DMRs enriched for association with schizophrenia tended to localize in intronic regions (Additional file 1: Figure S4), which is in agreement with the expectation that methylation regions should not be localized in exons and UTRs. This shows that using more information to label some genomic regions in greater detail, such as potential regulatory regions in introns, might give a more precise annotation of regions of association.

Despite the genetic overlap between bipolar disorder and schizophrenia, we do not find evidence of enrichment of association of DMRs with bipolar disorder either at the SNP level (Fig. 1, Additional file 1: Figure S1) or the gene level (data available on request). This could possibly be due to lack of sufficient power in the bipolar disorder GWAS [34]. Additionally, the gene-level approach utilized by INRICH depicts enrichment of association of human DMRs with height (Additional file 1: Figure S5). This evidence is lacking at the SNP level as depicted by QQ plots (Fig. 1, Additional file 1: Figure S1). We speculate that this could be due to the difference in testing DMR-localized SNPs compared to genes flanking human DMRs.

Although the DMRs utilized here were obtained from bone samples, Gokhman et al. [29] assert that the DMRs refer to species-specific methylation differences and not tissue-specific variations [43]. Similarly, Hernando-Herraez et al. [44] noted that species-specific DMRs tend to be conserved across tissues and as such should not represent tissue-specific variations. Other studies also showed that neurological systems were enriched for methylation differences even when the tissue samples analyzed were not neurological [45-47]. Therefore, we believe that our results are valid for a 'brain' phenotype even though the DMRs were derived from non-brain tissues. The enrichment seen for schizophrenia also corroborates the results of Gokhman et al. [29] who reported that DMRs were more enriched around genes implicated in the nervous system amongst all the organ systems tested for evolutionary changes in methylation patterns. Hernando-Herraez et al. [44] also found that methylation differences between humans and great apes were located around genes controlling neurological and developmental features. It is therefore possible that the methylation differences were mediated by evolution of genomic regions controlling neurodevelopmental processes. The results of pathway analysis are consistent with this. Both the DMR and NSS regions that are enriched for association with schizophrenia contain genes that are overrepresented in 'CREB signaling in neurons' and 'Synaptic long term potentiation'.

Our results hint that epigenomic evolution has taken place in genomic regions implicated in the aetiology of schizophrenia. Furthermore, these regions harbor markers that are involved in the regulation of various neurodevelopmental pathways. The fact that methylation changes also took place in these very same regions suggests a complex gene-by-environment interaction in the evolution of humans, especially for pathways that led to the development of our brain. While it is known that various factors from the environment can make longlasting changes in DNA methylation patterns that can be subsequently inherited at a population level [30, 31, 48], the true significance of our findings from an evolutionary standpoint suggests that the superior mental abilities of our species may in part have been driven by environmental factors during the past 300,000 years [49, 50].

It is difficult to put an exact date on the emergence of the superior mental abilities that define the modern Homo sapiens. Anthropologists often date the onset of the advanced intellectual abilities of Homo sapiens from about 70,000 years onwards [51], a period which saw the emergence of art, religion [52, 53] and possibly spoken language [54]. From an evolutionary perspective, it suggests a massive leap in the animal kingdom because Homo sapiens became the first species not only to develop the capacity to think and imagine things that do not exist [52, 53], but also to communicate these ideas to other members of the species [54]. This ability would have been critical for effective coordination and cooperation within large groups and may even have been needed to keep a group together [55, 56]. The genomic approach to analyze mental disorders used in the present study and other studies can interrogate the effect of changes which appeared in the last 300,000 years [49, 50], but it will clearly be interesting to trace mores recent changes. If a similar method used in the reconstruction of Neanderthal and Denisovan genomes [29, 57] could be implemented on samples of ancient Homo sapiens from different time periods [58-65], then theoretically it should be possible to reconstruct the methylomes and regions of recent evolution from ancient humans [66]. Subsequently, more detailed 'time-course' analyses of changes in methylation patterns and in other regions of recent evolution and their implications in schizophrenia will surely result in more detailed elucidation of the evolutionary hypothesis of schizophrenia. This is the promise of the novel field of paleoepigenetics that seeks to infer past environmental cues that affected the epigenomes of ancient individuals [42, 43].

Conclusions

In summary, we have demonstrated that human genomic regions whose methylation status was altered during evolution are enriched in markers that show association with schizophrenia. Our results concur with previous genomic studies demonstrating that methylation changes in *Homo sapiens* have had the greatest impact on the nervous system and provide evidence that epigenomic evolution plays a role in conferring a high risk of schizophrenia on humans. Future research should attempt to perform a finer temporal resolution of the origins of psychosis through the prism of evolutionary epigenomics. To explore the period of evolution before the *Homo* lineage, it would also be interesting to determine whether methylation signatures from primates are enriched for schizophrenia markers. Future research should also investigate the influence of human-specific DMRs on height.

Methods

Differentially methylated region data

Coordinates for DMRs were obtained from data publicly available in Supplementary Table S2 of Gokhman et al., 2014 [29]. This file contained DMRs inferred by comparing genome sequence of fossilized Neanderthal and Denisovan limb samples with methylation data from osteoblasts of modern humans. From the genomes of the Neanderthal and Denisovan samples, Gokhman et al. inferred methylation by utilizing the natural degradation of methylated cytosine (C) to thymine (T) to create a $C \rightarrow T$ ratio [29]. The methylation information, in the form of $C \rightarrow T$ ratio, was then compared with each of the three species and classified according to the hominid in which the methylation change occurred, i.e. humanspecific, Neanderthal-specific and Denisovan-specific DMRs. These DMRs do not represent tissue-specific methylation but species-specific methylation [29]. The human-specific DMRs comprise regions that have both gained and lost methylation in comparison to Neanderthal- and Denisovan-specific DMRs. DMRs that could not be classified reliably in any of the three species (unclassified DMRs) [29] were not used. Full methodological details for assigning DMRs are in the Additional file of the original paper [29].

HAR data

Genomic coordinates were obtained from publicly available data (docpollard.com/2x) for three classes of human accelerated region: HARs, in which regions conserved in mammals are accelerated in humans; PARs, in which regions conserved in mammals are accelerated in primates; and pHARs, in which regions conserved in primates (but not other mammals) are accelerated in humans. Conversion to hg19 assembly was performed using the liftOver tool from the UCSC Genome Browser.

NSS data

NSS data was obtained as a list of markers with corresponding NSS values from Srinivasan et al. [19]. Markers with negative values, indicating positive selection in humans, were filtered out and used for analysis.

GWAS data

Summary statistics from GWAS of 12 common traits were obtained from published datasets: schizophrenia (SCZ) [14], bipolar disorder (BPD) [34], attention deficit hyperactivity disorder (ADHD) [35], rheumatoid arthritis (RA) [36], blood lipid markers (high density lipoprotein (HDL), low density lipoprotein (LDL), triglycerides (TG), total cholesterol (TC)) [37], blood pressure (systolic blood pressure (SBP), diastolic blood pressure (DBP)) [38], body mass index (BMI) [39], and height [40]. For studies published with hg18 coordinates (BPD, SBP, DBP, HDL, LDL, TG, TC, ADHD, RA), conversion to hg19 was performed using the command line version of the liftOver tool from the UCSC Genome Browser (http:// hgdownload.cse.ucsc.edu/downloads.html#utilities_

downloads). For BMI and height SNPs, the genomic coordinates were obtained by mapping them to the assembly of 1000 Genomes Project Phase 1 reference panel SNPs [67].

SNP assignment to DMRs

SNPs were assigned to DMRs with LDsnpR [68] using positional binning and LD (linkage disequilibrium)based binning in R [69]. We used both methods because DMR-localized SNPs that were not genotyped in a specific GWAS would be missed if we used positional binning alone [68] (Additional file 1: Table S1). The LD file utilized in HDF5 format was constructed on the European reference population of 1000 Genomes Project and can be publicly downloaded at: http://services.cbu.uib. no/software/ldsnpr/Download.

Enrichment analyses with stratified quantile-quantile (QQ) plots

QQ plots are an effective tool to visualize the spread of data and any deviations from the expected null distributions. They are frequently utilized in GWAS to depict enrichment of true signals. When the observed distribution of data matches the expected distribution, there is a lack of enrichment and a line of equality is obtained that depicts the null hypothesis. A distribution such as this reflects no enrichment of observed over expected data distribution. However, if the observed and expected distributions differ, there will be deviation from this null line. As described in detail by Schork et al. [32], leftwards deflections from this null line represent enrichment. The higher the leftward deflection, the greater is the enrichment of true signals. In GWASs, due to the extremely low *p*-values of SNPs, it is common to depict *p*-values by converting them to negative \log_{10} values so that smaller *p*-values give higher negative logarithmic values. We plotted the negative log₁₀ of the observed pvalues of SNPs against the expected negative log₁₀ of a normal distribution. The distributions were corrected for genomic inflation by λ_{GC} . This method of enrichment was used to show for example [32] that specific genomic regions are enriched for trait-associated SNPs and are much more likely to associate with a given trait than SNPs distributed across a genome. In other words, when SNPs are stratified according to specific genomic regions, there is a greater enrichment of true signals than what is observed in the GWAS. Using a similar

approach, we binned SNPs that fall in DMR regions and plotted the stratified *p*-value distribution.

Enrichment analyses with INRICH

The stratified QQ plots are a useful visual tool for observing the presence or absence of enrichment of true signals in a given set of SNPs. However, to quantify the enrichment visually observed, we used the INterval En-RICHment Analysis (INRICH) tool. It is a robust bioinformatics pipeline to determine enrichment of genomic intervals implicated by LD with predefined or custom gene sets [33]. It takes into account several potential biases that can otherwise lead to false positives. It is well suited for testing GWAS-implicated SNPs for association with gene sets as it controls for variable gene size, SNP density, LD within and between genes, and overlapping genes with similar annotations. We followed the procedure described by Xu et al. [18], with the extended MHC region (chr6:25-35 Mb) masked and SNPs with minor allele frequency (MAF) < 0.05 excluded. Full details may be found in Additional file 1.

Pathway analysis

Pathway analysis was performed using Ingenuity Pathway Analysis (IPA) from QIAGEN (https://www.giagen. com/no/shop/analytics-software/biological-data-tools/ingenuity-pathway-analysis/, last accessed 26th August 2016). The reference set was Ingenuity Knowledge Base (Genes). Both direct and indirect relationships were analyzed. All data sources were included with the confidence parameter set to experimentally observed and highly predicted pathways for Human. Under 'Tissues & Cell Lines, we performed the analysis once with all organ systems and once with only the nervous system. 5338 enriched DMR SNPs in 329 enriched DMRs (Additional file 3) were mapped to 349 unique RefSeg genes and 446 RefSeq genes in LD using the method of Schork et al. [32]. Genes in LD blocks containing enriched NSS markers were determined in a similar manner. 4276 enriched NSS markers mapped to 648 overlapping RefSeq genes and 1363 RefSeq genes in LD. IPA was performed on these gene lists.

Additional Files

Additional file 1: Additional Method, Figures and Tables (DOCX 475 kb) Additional file 2: Annotation of all DMRs with schizophrenia-associated SNPs. This file contains annotation of all the human-lineage specific DMRs that are associated with schizophrenia markers. Details of the various markers present within each DMR is provided, along with the marker with most significant *p*-value. (XLSX 263 kb)

Additional file 3: Annotation of enriched DMRs with genes, promoters, CpG islands and enhancers. This file contains detailed annotation of those human-lineage specific DMRs that are enriched for association with schizophrenia markers (except those in the MHC region). Compared to Additional file 2, these DMRs represent those that are enriched and whether they are present in any genes, promoters, enhancers or CpG islands. (XLSX 26 kb)

Abbreviations

3'UTR: 3' untranslated region; 5'UTR: 5' untranslated region; ADHD: Attention deficit hyperactivity disorder; BMI: Body mass index; BPD: Bipolar disorder; CpG: 5' Cytosine-phosphate-Guanine 3'; CREB: Cyclic adenosine monophosphate responsive element binding protein; DBP: Diastolic blood pressure; DMR: Differentially methylated region; DNA: Deoxyribonucleic acid; GWAS: Genome-wide association studies; HARs: Human Accelerated Regions; HDL: High density lipoprotein; HWE: Hardy-Weinberg equilibrium; INRICH: Interval enRICHment analysis tool; IPA: Ingenuity Pathway Analysis; LD: Linkage disequilibrium; LDL: Low density lipoprotein; MAF: Minor allele frequency; MHC: Major histocompatibility complex; NSS: Neanderthal Selective Sweep; QQ: Quantile-quantile; RA: Rheumatoid arthritis; SBP: Systolic blood pressure; SCZ: Schizophrenia; SNP: Single nucleotide polymorphism; TC: Total cholesterol; TG: Triqlycerides

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Availability of data and materials

The code supporting the results of this article is available in the Zenodo repository at https://doi.org/10.5281/zenodo.198451. GWAS datasets, DMR data and HAR data are publicly available as described in the Methods section.

Authors' contributions

NB carried out the bioinformatics analyses, contributed to the design of the study and drafted the manuscript. TP, SG, FB contributed to statistical and LD analyses. OAA and VMS critically revised the manuscript. SLH conceived of the study, participated in its design and coordination, and helped to draft the manuscript. All authors read and approved the final manuscript.

Competing interests

The authors declare that they have no competing interests.

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Enrichment Analysis with INRICH

To assess enrichment for SNPs with different disease significance thresholds in various gene sets, we generated a range of LD-implicated regions through LD clumping in PLINK for index SNPs with *p*-values from 1×10^{-3} to 1×10^{-8} . LD Clumps were formed at $r^2=0.5$ with the clump range limited to 250kb. INRICH was run on all the sets of LD intervals using default parameters described by Lee *et al* (2012).

All GENCODE V19 genes were used as the background set. The various gene sets tested included genes within a 100 kb flanking region of DMRs, HARs, PARs and NSS markers similar to the procedure described by Xu *et al*, (2015). For NSS markers, genes were assigned via LD blocks of $r^2 \ge 0.8$ since NSS markers are single-base markers unlike the HARs and DMRs that are interval regions. GENCODE v19 gene database (last accessed 5th February 2016) was used to map the genes to DMRs, NSS markers and HARs. In their analysis, Xu *et al* had 893 genes within 100 kb of pHARs, 326 genes within 100 kb of mHARs (regions conserved in all mammals which are accelerated in humans) and 305 genes within 100 kb of PARs. In our study, using GENCODE v19, we had 3700, 1316 and 1268 genes within 100 kb of pHARs, mHARs and PARs respectively.

INRICH merges overlapping genes and overlapping LD-implicated intervals to prevent potentially inflated results due to multi-counting of the same genes/intervals. A total of 2510, 1015, 445, 207, 108 and 68 LD-implicated intervals were analyzed respectively for SNPs with *p*-values from 1×10^{-3} to 1×10^{-8} in the schizophrenia GWAS. Similarly, a total of 4321, 2498, 1596, 1130, 892 and 704 intervals were analyzed for the height GWAS. INRICH employs a two-stage procedure for assigning the statistical significance of enrichment of a given interval set with a given gene set. The first stage employs 10,000 permutations to empirically derive the null distribution of the overlap of intervals with gene sets. The second stage employs multiple testing correction via 5000 rounds of

bootstrapping. Enrichment of a given interval is then determined by the likelihood of a chance overlap with a gene set over the empirically observed distribution. The final output from INRICH lists gene sets with an empirical p-value at a default of P = 0.1. This is not the threshold at which INRICH performs the statistical tests. It is only the threshold to control which gene sets are displayed in the output. The corrected *p*-value obtained via bootstrapping is also displayed alongside. Since bootstrapping is a very robust procedure and causes many gene sets that would otherwise be significant at an empirical level to lose significance, an empirical *p*-value default of 0.1 adjusts what gene sets are visible at the end of the analyses. INRICH also outputs global enrichment of unique genes in gene sets at three thresholds that describes an excess of enriched genes at nominal gene-set P = 0.001, 0.01 and 0.05 (Lee et al (2012)).

Additional Figures



Figure S1: Enrichment plots for common SNPs shared by all 12 GWAS

Different numbers of SNPs were genotyped in the different GWAS, which could potentially bias our results. To test this, we generated a common set of ~2.4 million SNPs that was determined by intersecting the SNP lists across all twelve GWAS including all SNPs from the ADHD GWAS (~1.2 million SNPs). ADHD, attention deficit hyperactivity disorder; BPD, bipolar disorder; BMI, body mass index; DBP, diastolic blood pressure; HDL, high density lipoprotein; LDL, low density lipoprotein; RA, rheumatoid arthritis; SBP, systolic blood pressure; SCZ, schizophrenia; TC, total cholesterol; TG, triglycerides. We find that the number of SNPs does not influence our results for SCZ, as maximum enrichment is seen for SCZ even when the common set of SNPs is used. The common set of SNPs did not include MHC SNPs, so the MHC was not represented in this analysis.



Figure S2: Overlap of SNPs between various evolutionary annotations

The figure shows that the overlap between the SNPs analysed for enrichment in various evolutionary annotations is very small. SNPs depicted here are those in LD with the respective regions at $r^2 \ge 0.8$. The biggest overlap is between the SNPs in the areas demarcated pHAR (regions conserved in primates that are accelerated in humans) and HAR (regions conserved in mammals that are accelerated in humans), where >50% of SNPs in LD with HARs are also in LD with pHARs. dmrH, human DMRs; NSS, NSS markers; PAR: regions conserved in mammals that are accelerated in primates.



Figure S3: Proportion of DMR SNPs per GWAS

The figure depicts the normalization performed to determine if the varying number of markers genotyped in different GWAS influences the number of SNPs in DMRs. The total number of SNPs obtained for DMRs in each trait was divided by the total number of SNPs present in the respective GWAS and multiplied by 100 to obtain the normalized percentage of SNPs in DMRs. Blue bars depict the normalized percentage for SNPs in LD with DMRs while yellow bars depict the normalized percentage for SNPs that are physically located within DMRs. We observe that the total number of SNPs genotyped in a GWAS does not influence the proportion of SNPs that are physically within the DMR regions. The same largely holds true for SNPs in LD with DMR regions except for ADHD, possibly because the GWAS was underpowered.



Figure S4: SCZ SNPs in DMRs stratified by genome annotation

The figure depicts (a) SCZ SNPs in linkage disequilibrium (LD) with DMRs (blue) and (b) SCZ SNPs within DMRs (blue) stratified according to the following genomic annotations: 5'UTR (magenta), Exon (dark green), Intron (red), 3'UTR (orange). The light green line shows all SNPs from the SCZ GWAS.



Figure S5: INRICH test for enrichment of association of DMRs, NSS and Accelerated
Regions with height

Corrected *p*-values based on performing multiple testing with bootstrapping 5000 times and p=0.1 as threshold. LD clumps of height markers from *p*-value $1e^{-3} - 1e^{-8}$ were tested for enrichment in: DMR, human-specific DMRs; NSS, Neanderthal Selective Sweep; HAR, mammalian conserved regions that are accelerated in humans; PAR, mammalian conserved regions that are accelerated in primates; and PrimateHAR (pHAR), primate-conserved regions that are accelerated in humans.

Additional Tables

Phenotype	Total Study Size (n)	Number of SNPs (hg19)	Reference	SNPs within DMRs	SNPs in LD with DMRs
Schizophrenia	150,064	9,444,320	PGC2 (2014)	3930	29,954
Bipolar Disorder	63,766	2,426,991	Sklar <i>et al</i> (2011)	938	6711
Attention Deficit	5,415	1,206,332	Neale <i>et al</i> (2010)	542	3970
Hyperactivity					
Disorder					
Rheumatoid	41,282	2,553,357	Stahl <i>et al</i> (2010)	884	8187
Arthritis					
High Density Lipoprotein	99,900	2,620,435	Teslovich <i>et al</i> (2010)	1006	7603
Low Density	95,454	2,620,568	Teslovich <i>et al</i>	1006	7608
Lipoprotein			(2010)		
Triglycerides	96,598	2,620,567	Teslovich <i>et al</i> (2010)	1006	7663
Total Cholesterol	100,184	2,620,450	Teslovich <i>et al</i> (2010)	1006	7663
Systolic Blood Pressure	200,000	2,461,102	ICBP GWAS (2011)	894	7157
Diastolic Blood Pressure	200,000	2,461,102	ICBP GWAS (2011)	894	7157
Body Mass Index	339,224	2,551,876	Locke <i>et al</i> (2015)	902	7364
Height	253,288	2,545,021	Wood <i>et al</i> (2011)	964	7567

Table S1: Summary of GWAS and DMR SNPs

For each GWAS, the table shows the sample size, marker density, the reference to the specific study, the number of SNPs located within DMRs, and the numbed of SNPs in LD with DMRs.

Top Canonical Pathways	P-value (Fisher's Exact test)
Wnt/Ca+ pathway	1.34E-05
P2Y Purigenic Receptor Signalling Pathway	1.04E-04
Thioredoxin Pathway	1.07E-04
CREB Signalling in Neurons	1.45E-04
Synaptic Long Term Potentiation	1.49E-04
Top Physiological System Development and Function	
Nervous System Development and Function	4.41E-02 - 2.23E-02
Tissue Morphology	2.23E-02 - 2.23E-02

Table S2: Pathway analysis results for genes in LD with enriched SNPs in DMRs (Nervous System only).

Top Canonical Pathways	P-value(Fisher's Exact test)
Wnt/Ca+ pathway	1.58E-05
P2Y Purigenic Receptor Signaling Pathway	1.14E-04
CREB Signaling in Neurons	1.49E-04
Synaptic Long Term Potentiation	2.05E-04
Thioredoxin Pathway	2.11E-04
Top Physiological System Development and Function	
Nervous System Development and Function	4.42E-02 - 1.41E-02
Cardiovascular System Development and Function	4.42E-02 - 2.24E-02
Connective Tissue Development and Function	4.42E-02 - 2.24E-02
Hair and Skin Development and Function	2.24E-02 - 2.24E-02
Hematological System Development and Function	2.24E-02 - 2.24E-02

Table S3: Pathway analysis results for genes in LD with enriched SNPs in DMRs (AllOrgan Systems)

Top Canonical Pathways	P-value(Fisher's Exact test)
CREB Signalling in Neurons	1.38E-04
IGF-1 Signalling	6.05E-04
T Cell Receptor Signalling	1.26E-03
Prolactin Signalling	1.27E-03
AMPK Signalling	1.31E-03
Top Physiological System Development & Function	
Organismal Development	4.70E-03 - 4.70E-03
Tissue Development	4.70E-03 - 4.70E-03
Nervous System Development and Function	4.41E-02 - 1.35E-02
Tissue Morphology	4.41E-02 - 4.41E-02

Table S4: Pathway analysis results for genes in LD with enriched NSS markers (NervousSystem only)

Top Canonical Pathways	P-value(Fisher's Exact test)	
CREB Signalling in Neurons	1.53E-04	
Protein Kinase A Signalling	3.02E-04	
Synaptic Long Term Potentiation	8.90E-04	
IGF-1 Signalling	9.67E-04	
ERK/MAPK Signalling	1.57E-03	
Top Physiological System Development & Function		
Organismal Development	2.32E-02 - 4.23E-03	
Tissue Development	2.32E-02 - 4.23E-03	
Nervous System Development and Function	4.81E-02 - 1.21E-02	
Connective Tissue Development and Function	2.32E-02 - 2.32E-02	
Embryonic Development	2.32E-02 - 2.32E-02	

 Table S5: Pathway analysis results for genes in LD with enriched NSS markers (All Organ Systems)

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II

- 1 Title:
- 2
- 3 Analysis of differentially methylated regions in primates and non-primates
- 4 provides support for the evolutionary hypothesis of schizophrenia
- 5
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33 Abstract

34

35	Introduction: The persistence of schizophrenia in human populations separated by
36	geography and time led to the evolutionary hypothesis that proposes schizophrenia as
37	a by-product of the higher cognitive abilities of modern humans. To explore this
38	hypothesis, we used here an evolutionary epigenetics approach building on
39	differentially methylated regions (DMRs) of the genome.
40	Methods: We implemented a polygenic enrichment testing pipeline using the
41	summary statistics of genome-wide association studies (GWAS) of schizophrenia and
42	12 other phenotypes. We investigated the enrichment of association of these traits
43	across genomic regions with variable methylation between modern humans and great
44	apes (orangutans, chimpanzees and gorillas; primate DMRs) and between modern
45	humans and recently extinct hominids (Neanderthals and Denisovans; non-primate
46	DMRs).
47	Results: Regions that are hypo-methylated in humans compared to great apes show
48	enrichment of association with schizophrenia only if the major histocompatibility
49	complex (MHC) region is included. With the MHC region removed from the analysis,
50	only a modest enrichment for SNPs of low effect persists. The INRICH pipeline
51	confirms this finding after rigorous permutation and bootstrapping procedures.
52	
53	Conclusion: The analyses of regions with differential methylation changes in humans

and great apes do not provide compelling evidence of enrichment of association with
schizophrenia, in contrast to our previous findings on more recent methylation
differences between modern humans, Neanderthals and Denisovans. Our results

further support the evolutionary hypothesis of schizophrenia and indicate that the
origin of some of the genetic susceptibility factors of schizophrenia may lie in recent
human evolution.
Key Words: schizophrenia; evolutionary hypothesis; epigenetics; differentially
methylated regions; primates; Neanderthals.

72 1. Introduction

73

74	Schizophrenia is a psychiatric disorder with a prevalence rate of 2.7-8.3/1,000 persons
75	(Messias et al., 2007) and heritability estimated between 60-90% (Cardno et al., 1999;
76	Lichtenstein et al., 2009; Skre et al., 1993; Sullivan et al., 2003). It occurs at quite
77	similar rates across populations worldwide (Ayuso-Mateos, 2002; Brüne, 2004;
78	WHO, 1973) and written records describing its symptoms exist dating back 5,000
79	years (Jeste et al., 1985). This consistent persistence of the disease despite reduced
80	fecundity (Brüne, 2004; Nichols, 2009) and increased mortality is a paradox (Bassett
81	et al., 1996; Brown, 1997; Larson and Nyman, 1973), since the reduced fecundity of
82	patients afflicted with schizophrenia does not appear to eliminate the disease from the
83	population (Power et al., 2013) Part of the reason may be due to afflicted individuals
84	reproducing prior to the onset of the disease (Markow, 2012). Another contributing
85	factor could be that schizophrenia risk variants may have provided an advantage to
86	the kin of the affected by conferring superior creative and intellectual abilities upon
87	them (Kyaga et al., 2011; Nichols, 2009). To explain the constant occurrence of the
88	disease, TJ Crow (Crow, 1997, 1995) proposed the so-called evolutionary hypothesis
89	of schizophrenia, which suggests that the disease is a consequence of human
90	evolution: the higher cognitive abilities of modern-day humans, including language,
91	may predispose to psychiatric illnesses such as schizophrenia (Crow, 2008, 2000,
92	1997).
93	
94	In the post-genomic era (Lander et al., 2001; Venter et al., 2001), emerging lines of
95	evidence are lending support to this hypothesis. Crespi et al. (Crespi et al., 2007) were

96 amongst the first to show that genes with evidence of recent positive selection in

97	humans are also implicated more frequently in schizophrenia. More evidence has
98	been provided by studies based on comparative genomics (Pollard et al., 2006;
99	Srinivasan et al., 2015; Xu et al., 2015), a field in which genomes of progressively
100	older species are compared to identify substitutions and mutations that help estimate
101	divergence between the species. For instance, a group of regions defined by negative
102	Neanderthal selective sweep (NSS) scores describe the selective evolution of genomic
103	regions in modern-day humans over Neanderthals (Burbano et al., 2010; Green et al.,
104	2010). These regions were shown by Srinivasan et al. (2015) to be enriched for
105	schizophrenia risk markers, in line with the evolutionary hypothesis of schizophrenia.
106	Other regions known as human accelerated regions (HARs) (Gittelman et al., 2015;
107	Pollard et al., 2006; Xu et al., 2015), first described by Pollard et al. (2006), show
108	accelerated evolution in humans compared to primates or mammals. HARs have also
109	provided some evidence of enrichment of association with schizophrenia (Xu et al.,
110	2015), but these findings may have been driven by a few genes since they were not
111	replicated using a polygenic approach (Srinivasan et al., 2017, 2015) .
112	
113	While several studies have looked at the evolution of the genome (Bird et al., 2007;
114	Bush and Lahn, 2008; Gittelman et al., 2015; Paaby and Rockman, 2014; Pollard et
115	al., 2006), there are reports that the epigenome is evolving as well (Gokhman et al.,
116	2014; Hernando-Herraez et al., 2015, 2013; Mendizabal et al., 2014; Molaro et al.,
117	2011). This provides new insights into events leading to the speciation and divergence
118	of modern humans. The epigenome refers to the layer of chemical modifications, such
119	as methylation and histone modifications, to the genome that regulate gene expression
120	(Bernstein et al., 2007; Kundaje et al., 2015; Rivera and Ren, 2013). For instance,
121	Gokhman et al. (2014) compared the methylomes of humans with Neanderthals and

122	Denisovans. They reported that while 97% of the methylome was comparable
123	between humans, Neanderthals and Denisovans, some regions showed differential
124	methylation between the three hominids. Previously (Banerjee et al., 2017), we
125	analysed the differentially methylated regions (DMRs) identified for Neanderthals,
126	Denisovans and modern humans by Gokhman et al. (2014), and found evidence that
127	the regions of the genome with human-specific DMRs harbour relatively more genetic
128	variants associated with schizophrenia than the rest of the genome, i.e. the DMRs
129	were enriched for SCZ markers both at the single-nucleotide polymorphism (SNP)
130	level and at the gene level. These human-specific DMRs thus provide evidence of
131	enrichment of methylation changes in regions harbouring genetic variants associated
132	with schizophrenia, at least since the divergence from Neanderthals and Denisovans
133	(Banerjee et al., 2017).

134

135 Here, we sought to determine if evolutionarily older methylation differences can 136 provide a further timeframe for the origin of schizophrenia risk markers in the human 137 lineage. We asked whether we can find epigenetic evidence that the origin of 138 schizophrenia risk markers predates the origins of the Homo genus, i.e. before the 139 divergence of chimpanzees and humans around 6-8 million years ago (MYA) (Glazko 140 and Nei, 2003; Langergraber et al., 2012). We tested this hypothesis by analysing 141 primate DMRs that trace an evolutionary history of at least 13 million years (Glazko 142 and Nei, 2003; Hasegawa et al., 1985; Rannala and Yang, 2003). We used the same 143 statistical analyses as described by Lee et al. (2012), Schork et al. (2013), and 144 Srinivasan et al. (2015) to test for polygenic enrichment of a set of markers from 145 genome-wide association studies (GWAS). We interrogated regions of the human 146 genome which are hypo- or hyper-methylated in comparison to the corresponding
- 147 ones in chimpanzees, gorillas and orangutans for enrichment of genetic variants
- 148 associated with schizophrenia or other human traits.

150 2. Materials and methods

151

152 <i>2.1</i>	. GWAS data
----------------	-------------

- 153 Summary statistics for thirteen different phenotypes were obtained from their
- 154 respective published GWAS studies: schizophrenia (SCZ) (Ripke et al., 2014), bipolar
- disorder (BPD) (Sklar et al., 2011), attention deficit hyperactivity disorder (ADHD)
- 156 (Demontis et al., 2017), rheumatoid arthritis (RA) (Stahl et al., 2010), blood lipid
- 157 markers (high density lipoprotein (HDL), low density lipoprotein (LDL), triglycerides
- 158 (TG), total cholesterol (TC)) (Teslovich et al., 2010), blood pressure (systolic blood
- 159 pressure (SBP), diastolic blood pressure (DBP)) (Ehret et al., 2011), body mass index
- 160 (BMI) (Locke et al., 2015), height (Wood et al., 2014) and intelligence (Sniekers et
- al., 2017). For studies published with hg18 coordinates (BPD, SBP, DBP, HDL, LDL,
- 162 TG, TC, RA), conversion to hg19 was performed using the command line version of

the liftOver tool from the UCSC Genome Browser (Karolchik et al., 2014)

- 164 (http://hgdownload.cse.ucsc.edu/downloads.html #utilities_downloads). For BMI and
- 165 height SNPs, the genomic coordinates were obtained by mapping them to the
- assembly of 1,000 Genomes Project (1KGP) Phase 1 reference panel SNPs (Durbin et
- 167 al., 2012).
- 168

169 2.2. Human hypo- and hyper-methylated regions from primate DMRs

170 These methylated regions were retrieved from the study by Hernando-Herraez et al.

- 171 (2015), who identified them by comparing the methylation profile of DNA from
- 172 peripheral blood samples of orangutans, chimpanzees and gorillas to that of humans.
- 173 Since the DMRs are determined by comparing humans with other primates, we refer
- 174 to this set collectively as primate DMRs. Both hypo- and hyper-methylated DMRs

175	from humans were analysed. As these DMRs are identified in the same tissues in all
176	samples, they are considered to represent species-specific methylation differences, not
177	tissue-specific methylation differences (Gokhman et al., 2014). Altogether, the human
178	hypo- and hyper-methylated DMRs can be used to represent an evolutionary course of
179	history spanning from at least 13 MYA (Glazko and Nei, 2003; Langergraber et al.,
180	2012), when orangutans diverged from the common ancestors, to 6 MYA, when the
181	chimpanzees and humans diverged from each other (Glazko and Nei, 2003;
182	Langergraber et al., 2012). Since our interest was in human-specific enrichment, we
183	focused the analyses on human hypo- and hyper-methylated DMRs.
184	
185	2.3. Differentially methylated regions (DMRs) from Neanderthals, Denisovans and
186	modern humans
187	As previously described (Gokhman et al., 2014), these methylated regions have been
188	identified by comparing the methylomes of osteoblasts from modern-day humans
189	with those from Neanderthals and Denisovans. We refer to them in this paper as non-
190	primate DMRs. Gokhman et al. (2014) devised a strategy utilizing information in the
191	form of cytosine (C) to thymine (T) ratios to decipher the ancient methylomes of
192	Neanderthals and Denisovans. Subsequently, they compared the methylomes of
193	Neanderthals, Denisovans and modern humans and inferred the species in which the
194	methylation variation likely took place; this information was used to classify the
195	DMRs as Neanderthal-specific, Denisovan-specific and human-specific. These DMRs
196	represent species-specific methylation (Gokhman et al., 2014).
197	

198 2.4. Neanderthal selective sweep (NSS) data

We obtained NSS marker data from Srinivasan et al. (2015). Negative scores for NSSmarkers indicate positive selection in humans. Markers with such scores were used in

201 the downstream analyses.

202

203 2.5. SNP assignment with LDsnpR

204 The previously published R-based software package LDsnpR (Christoforou et al.,

205 2012) was utilized for assigning SNPs to the respective DMRs using LD (linkage

206 disequilibrium)-based binning at $r^2 \ge 0.8$ in R (R Core Team, 2017). LD-based binning

207 makes it possible to determine whether SNPs from a specific GWAS are in LD with

208 the DMR of interest. Using LD allows the capture of a greater number of relevant

209 SNPs in comparison to an approach where only physically overlapping SNPs are

210 considered. The LD file utilized was in HDF5 format and was constructed from the

211 European reference population of 1KGP and can be publicly downloaded at:

212 http://services.cbu.uib.no/software/ldsnpr/Download.

213

214 2.6. Enrichment analyses based on stratified quantile-quantile (QQ) plots

215 QQ plots are an essential method used in GWASs to depict the presence of true 216 signals. They help to visually observe the spread of data and deviations from the null 217 distribution. Under the null hypothesis, no difference is expected between the 218 observed and expected distributions of data. As such, a line of no difference or null 219 line is obtained that is equidistant from both X and Y axes. However, if the null 220 hypothesis were to be false, there would be a deviation of the observed data 221 distribution from the expected data distribution. As described in depth by Schork et al. 222 (2013), a leftward deflection of the observed distribution from the null line represents 223 enrichment – the greater the leftward deflection, the stronger the enrichment of true 224 signals. This method has been used recently not only to show how specific genomic 225 annotation affects the distribution of disease SNPs with true signals (Schork et al., 226 2013), but also to demonstrate that regions of recent evolution are enriched for 227 schizophrenia markers (Banerjee et al., 2017; Srinivasan et al., 2015). We took the 228 SNPs that are in LD with the DMR regions and plotted their *p*-value distributions 229 from various GWASs. The observed *p*-value distributions were then determined to be 230 enriched or not using conditional Q-Q plots as described by Schork et al. (2013). 231 Genomic inflation was corrected by λ_{GC} .

232

233 2.7. INRICH-based enrichment analysis

234 The stratified OO plots provide a visual depiction of data distributions and enrichment 235 of true signals within a stratum of data, but they do not quantify this enrichment. 236 Therefore, we used the INterval EnRICHment (INRICH) analysis tool to statistically 237 quantify the enrichment observed. This pipeline performs permutation and 238 bootstrapping procedures to determine with statistical confidence whether LD-239 implicated genomic intervals are enriched in specific gene sets (Lee et al., 2012). The 240 INRICH analysis takes into account several potential biases that can otherwise lead to 241 false positives, such as variable gene size, SNP density within genes, LD between and 242 within genes, and overlapping genes in the gene sets. We used the same procedure 243 reported previously (Banerjee et al., 2017; Xu et al., 2015) with SNPs in the extended 244 MHC region and SNPs with MAF <0.05 excluded from the analysis. Additional 245 details can be found in the Supplementary Information.

246

247 3. Results

249 3.1. Co-localisation of human hypo-methylated regions and genetic variants

250 associated with schizophrenia in the MHC.

251 We ascertained whether there is any enrichment of human hypo- and hyper-

- 252 methylated regions in schizophrenia-associated SNPs. Using previously published
- 253 methodology (Christoforou et al., 2012), we mapped schizophrenia markers to human
- 254 hypo-methylated regions (hypo-DMRs) and hyper-methylated regions (hyper-DMRs).
- 255 Out of a total of ~9.4 million SCZ markers obtained from the GWAS, 10,165 markers

tagged hypo-DMRs and 4,503 tagged hyper-DMRs.

257

258 Figure 1A shows the conditional QQ plots for schizophrenia markers (all markers, the

259 hypo-DMR set and the hyper-DMR set) including those in the MHC region. For

260 hypo-DMR markers (Supplementary Dataset 1), we observed a significant enrichment

261 as depicted by the leftward deviation. No enrichment was observed for hyper-DMR

262 markers. Since the MHC region is a region of extended linkage disequilibrium, which

263 can bias the enrichment estimates, and since it is the main region of association with

264 schizophrenia, we also tested the enrichment with the MHC region removed (Figure

265 1B). Under these conditions there is a trend for enrichment of hypo-DMR markers at

266 higher *p*-value thresholds, but this enrichment is substantially less than when the

267 MHC is included (Figure 1A).

268

269 3.2. Enrichment of markers is not seen for other human traits

Next, we tested if the human hypo- and hyper-methylated regions are enriched for
other human traits and phenotypes. We tested a total of thirteen different phenotypes,
full details of which can be found in section 2.1. Each GWAS had been performed
with a different number of genotyped SNPs, and this difference could potentially bias

274 our results. To circumvent this, we created a list of ~2.4 million common SNPs that

275 were genotyped across all the phenotypes investigated in the present study. Only

276 SNPs on this list were used for enrichment analysis.

277

278 As can be seen in Fig. 2, no enrichment was observed in any of the traits, with the

279 possible exception of height at higher *p*-value threshold markers. The common list of

280 markers did not contain the MHC region and as such no enrichment is observed for

281 schizophrenia either.

282

283 3.3. Evidence of enrichment for hypo-methylated regions with SNPs at high p-values

284 The enrichment plots allowed us to visually ascertain enrichment in the datasets.

285 However, they did not give any indication of the statistical robustness of the

286 enrichment. To ascertain if the human hypo- and hyper-methylated regions are

287 statistically enriched for schizophrenia and height markers, we implemented the

288 INRICH pipeline, which performs 10,000 permutations and 5,000 bootstrapping

289 calculations, to determine with statistical confidence the enrichment observed (Lee et

290 al., 2012).

291

292 The INRICH analysis confirmed a significant (p<0.05) enrichment of association for

293 human hypo-DMRs, but not hyper-DMRs, with schizophrenia at SNPs of higher p-

value thresholds (*p*<10e-3 to *p*<10e-4) (Fig. 3). This enrichment was at the gene level,

and complemented the enrichment observed at the SNP level for higher *p*-value

296 thresholds (Fig. 1B). Importantly, this enrichment persisted upon testing a pruned

297 schizophrenia dataset (Supplementary Fig. 1). The enrichment was however not

298 significant at the genome-wide threshold (p < 5x10e-8) and was much weaker than that

299 observed for non-primate DMRs (Fig. 3). We also observed a similar trend for height 300 where there was enrichment at SNPs of higher but not lower *p*-value thresholds. This 301 enrichment was similarly less pronounced than for non-primate DMRs 302 (Supplementary Fig. 2). 303 304 305 4. Discussion 306 307 In our study, we investigated if regions of the human genome whose methylation has 308 evolved since the divergence of modern humans from great apes are enriched for 309 markers of schizophrenia. We found evidence that there is enrichment for hypo-310 methylated DMRs driven by the MHC locus, a known risk region that harbours the 311 most significant schizophrenia GWAS markers (Ripke et al., 2014). When the MHC 312 region was excluded from the analysis, there remained a trend towards enrichment of 313 hypo-DMRs driven by SNPs of higher *p*-value thresholds. This finding was 314 complemented by the INRICH analyses that indicated significant enrichment among 315 SNPs of higher *p*-value thresholds. When analysing a global SNP list common to 316 GWAS of several traits, we failed to find evidence of enrichment of any trait with the 317 possible exception of height at higher SNP *p*-value thresholds. We tested this further 318 with the INRICH pipeline, which revealed gene-level enrichment of LD intervals for 319 height markers below the genome-wide threshold (p < 5x10e-8). Compared to our 320 previous study, in which we demonstrated enrichment of association with 321 schizophrenia for non-primate DMRs that were derived by comparing human, 322 Neanderthal and Denisovan methylomes (Banerjee et al., 2017), the primate DMRs 323 tested here show far less enrichment. The primate and non-primate DMRs have very

little overlap, which suggests that the methylation changes that took place since the
divergence of modern humans from Neanderthals and Denisovans occurred in
different regions of the genome compared to those that took place since divergence
from great apes.

328

329 The central role of the MHC region in the enrichment of human hypo-methylated 330 regions poses interesting questions. The MHC region is known for its complex LD 331 architecture, which renders the interpretation of genetic signals very challenging. 332 Other groups have previously reported that the MHC region is one of the fastest 333 evolving regions of the human genome (Meyer et al., 2017) and have implicated it in 334 mate preference (Bernatchez and Landry, 2003; Kromer et al., 2016; Potts and 335 Wakeland, 1990; Roberts et al., 2008; Winternitz et al., 2017), odour perception 336 (Roberts et al., 2008; Santos et al., 2005) and immune response (Benacerraf, 1981; 337 Horton et al., 2004). Recently it was shown that a large proportion of the association 338 of the region with schizophrenia can be explained by complement C4 haplotypes that 339 include C4 copy number variation (Sekar et al., 2016). Nevertheless, there remains a 340 part of the association in this region that is unexplained (Gejman et al., 2011) and will 341 need further investigation. It is interesting to consider the possibility that the MHC 342 region and the immune system in general play a central role in evolution at the 343 epigenomic as well as at the genomic level (Meyer et al., 2017; Potts and Wakeland, 344 1990; Sommer, 2005; Traherne, 2008). The mechanisms by which hypo-methylation 345 could influence the aforementioned processes are open to speculation since the MHC 346 region has more than 200 genes in close physical proximity and LD with one another 347 (Beck et al., 1999). This makes it hard to interpret the exact biological consequences 348 of our findings.

349

350	Interestingly, the gene-level analysis via INRICH seems to suggest enrichment of
351	SNPs of higher <i>p</i> -value thresholds in primate DMRs for both schizophrenia and
352	height. This enrichment is far lower than what we found for non-primate DMRs for
353	both schizophrenia and height (Banerjee et al., 2017) and which persisted for
354	schizophrenia even with pruned datasets.
355	

356 The very small overlap between primate and non-primate DMRs might suggest that 357 the divergence from Neanderthals and Denisovans brought about more significant 358 methylation changes in regions implicated in the aetiology of schizophrenia and 359 height than the divergence from great apes. In other words, our results might suggest 360 that the evolutionary factors that regulate methylation variation acted on different 361 segments of the genome at different time points. So while the methylation variation 362 since the divergence from Neanderthals and Denisovans may mark a genome-wide 363 increase of schizophrenia susceptibility (Banerjee et al., 2017), the methylation 364 variation from the time period between 13 and 6 MYA appears not to have 365 significantly increased the risk for schizophrenia (except possibly for some markers in 366 the MHC region), 367

Our results are also in line with the findings of Srinivasan et al. (2017), who failed to
find evidence of enrichment of schizophrenia using genomic markers of evolution
dating back to 200 MYA. The same authors also reported enrichment of association
for regions of more recent evolution in modern humans (Srinivasan et al., 2015).
Interestingly, one of the evolutionary proxies used by Srinivasan and colleagues
(2017), namely HARs, also showed enrichment for height, similar to our recent study

374 (Banerjee et al., 2017). This suggests that regions controlling both genomic and

375 epigenomic variation in height may also be driven by recent evolution. Finally, our

results agree well with the observation by Srinivasan et al. (2017) of some

377 involvement of the MHC in an early evolutionary context.

378

379 Although our results are in line with several findings in the field, the current methods 380 have some limitations. Highly polygenic traits such as schizophrenia have a large 381 number of genetic loci contributing to the aetiology of a disease (Bulik-Sullivan et al., 382 2015; Schork et al., 2016). The ability to detect these large numbers of genetic loci is 383 dependent on the sample size and adequate statistical power (Schork et al., 2016). 384 Consequently, the polygenic enrichment methods may be limited by the statistical 385 power of the respective GWAS and trait polygenicity. Furthermore, in the INRICH 386 analysis that uses LD-clumping of SNPs at p<10e-3 to p<10e-8, higher p-value 387 thresholds (e.g. p < 10e-3) still include SNPs of lower p-values, even though they 388 become progressively smaller minorities. Thus, although higher p-values increase the 389 number of LD-clumps tested, we do not expect this to increase the Type I error rate 390 (Lee et al., 2012).

391

In conclusion, our results suggest that methylation markers tracing an evolutionary
period dating back to 13 MYA (primate DMRs) are not enriched for schizophrenia
markers, unlike methylation markers from a recent timeframe (non-primate DMRs)
(Banerjee et al., 2017). Taken in consideration with previous studies of genomic
markers of evolution dating back 200 MYA (Srinivasan et al., 2017), our results
support the hypothesis that the origins of schizophrenia lie in more recent

- 398 evolutionary events, possibly after the divergence of modern-day humans from
- 399 Neanderthals and Denisovans.

400

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402 Appendix A. Supplementary data

- 403 Supplementary Information: Additional Methods, Figures and Tables
- 404 Supplementary Dataset 1: Annotation of human hypo-methylated regions with
- 405 markers of schizophrenia

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768 Figure legends

769	Fig. 1: Enrichment plots of hypo-DMR and hyper-DMR SNPs in schizophrenia
770	Quantile-quantile (QQ) plots of GWAS SNPs for Schizophrenia (SCZ) with the
771	extended MHC region (chr6: 25-35Mb) unmasked (A) and masked (B). Expected -
772	$\log_{10} p$ -values under the null hypothesis are shown on the X-axis. Observed $-\log_{10} p$ -
773	values are on the Y-axis. The values for all GWAS SNPs are plotted in dark green
774	while the values for SNPs in linkage disequilibrium (LD) with hypo-methylated
775	DMRs are plotted in blue and SNPs in LD with hyper-methylated DMRs are plotted
776	in pink. A leftward deflection of the plotted <i>p</i> -values from the line for all GWAS
777	SNPs indicates enrichment of true signals - the greater the leftward deflection, the
778	stronger the enrichment. Genomic correction was performed on all SNPs with global
779	lambda.
700	
/80	
780	Fig. 2: Enrichment plots of hypo-DMR and hyper-DMR SNPs across
781 782	Fig. 2: Enrichment plots of hypo-DMR and hyper-DMR SNPs across multiple traits
780 781 782 783	Fig. 2: Enrichment plots of hypo-DMR and hyper-DMR SNPs across multiple traits Thirteen different GWASs were analysed using a common set of ~2.4 million
780 781 782 783 784	Fig. 2: Enrichment plots of hypo-DMR and hyper-DMR SNPs across multiple traits Thirteen different GWASs were analysed using a common set of ~2.4 million SNPs. The <i>p</i> -values for the common set of GWAS SNPs are plotted in dark
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781 782 783 784 785 786 786 787 788 789	Fig. 2: Enrichment plots of hypo-DMR and hyper-DMR SNPs across multiple traits Thirteen different GWASs were analysed using a common set of ~2.4 million SNPs. The <i>p</i> -values for the common set of GWAS SNPs are plotted in dark green; <i>p</i> -values for SNPs that tag hypo-methylated DMRs are plotted in blue; and <i>p</i> -values for SNPs that tag hyper-methylated DMRs are plotted in pink. ADHD, attention deficit hyperactivity disorder; BMI, body mass index; BPD, bipolar disorder; DBP, diastolic blood pressure; HDL, high density lipoprotein; LDL, low density lipoprotein; RA, rheumatoid arthritis; SBP, systolic blood
781 782 783 784 785 786 786 787 788 789 790	Fig. 2: Enrichment plots of hypo-DMR and hyper-DMR SNPs across multiple traits Thirteen different GWASs were analysed using a common set of ~2.4 million SNPs. The <i>p</i> -values for the common set of GWAS SNPs are plotted in dark green; <i>p</i> -values for SNPs that tag hypo-methylated DMRs are plotted in blue; and <i>p</i> -values for SNPs that tag hyper-methylated DMRs are plotted in pink. ADHD, attention deficit hyperactivity disorder; BMI, body mass index; BPD, bipolar disorder; DBP, diastolic blood pressure; HDL, high density lipoprotein; LDL, low density lipoprotein; RA, rheumatoid arthritis; SBP, systolic blood pressure; SCZ, schizophrenia; TC, total cholesterol; TG, triglycerides. The

793 Fig. 3: INRICH test for enrichment of association of DMR gene sets and NSS

794 genes with SCZ, MHC masked

- 795 A visual heatmap depicting *p*-values from bootstrapping with 5,000 iterations. The
- 796 various evolutionary annotations compared are as follows. HypoDMR human hypo-
- 797 methylated DMRs; HyperDMR human hyper-methylated DMRs. HypoDMR and
- 798 HyperDMR were taken from the study by Hernando-Herraez et al. (2013). dmrH -
- human-specific DMRs (Gokhman et al, 2014), which are referred to as non-primate
- 800 DMRs in this manuscript. NSS Neanderthal selective sweep. Datasets marked with *
- 801 have been previously reported by Banerjee et al. (2017) and are presented here for
- 802 comparison only.

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Figure 2



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Figure 3



Analysis of differentially methylated regions in primates and non-primates provides support for the evolutionary hypothesis of schizophrenia

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Vidar M. Steen, Ole A. Andreassen, Stephanie Le Hellard

SUPPLEMENTARY MATERIAL

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Supplementary Methods

Enrichment Analysis with INRICH

Before using INRICH to assess enrichment, it is necessary to generate genomic intervals to test for. For our purpose, we generated LD-implicated genomic intervals with PLINK (Purcell et al., 2007), using a procedure similar to that described by Lee et al. (2012). We generated intervals from SNPs at different disease significance thresholds through LD clumping in PLINK for index SNPs with *p*-values 1×10^{-3} to 1×10^{-8} . LD clumps were formed at $r^2=0.5$ with the clump range limited to 250 kb. INRICH was run on all the sets of LD intervals using the default parameters described by Lee et al. (2012). The various gene sets tested were obtained using a procedure similar to that described by Xu et al. (2015), and included genes within a 100 kb flanking region of human-specific DMRs (dmrH), HARs, PARs, primate HARs, hypomethylated DMRs, hyper-methylated DMRs, and NSS markers. For NSS markers, genes were assigned via LD blocks of $r^2 \ge 0.8$ since NSS markers are single-base markers unlike the HARs and DMRs, which are interval regions. GENCODE v19 gene database (last accessed 5th February 2016) was used to map the genes to DMRs, NSS markers, HARs, hypo-methylated DMRs and hyper-methylated DMRs.

To avoid counting the same region of the genome more than once and potentially inflating the test statistics, INRICH combines overlapping genes and overlapping LD-implicated intervals. In this study, a total of 2480, 1010, 444, 206, 107 and 68 LD-implicated intervals were analysed respectively for SNPs with *p*-values $\leq 1 \times 10^{-3}$, 1×10^{-4} , 1×10^{-5} , 1×10^{-6} , 1×10^{-7} and 1×10^{-8} in the schizophrenia GWAS. For the same p-values, a total of 4097, 2395, 1536, 1089, 860 and 678 intervals were analysed for the height GWAS, and a total of 711, 254, 96, 56,29 and 15 intervals were analysed for the

pruned SCZ GWAS (see below). Statistical significance in INRICH is determined via a two-stage procedure utilizing empirical null distributions and bootstrapping procedures. In the first step, a user-defined number of permutations is used to determine the background null distribution of chance overlap between intervals and gene sets. This is then followed by multiple testing procedures via bootstrapping in the second step. We used the default INRICH parameters of 10,000 permutations and 5,000 rounds of bootstrapping (Lee et al., 2012).

LD Pruning

In GWAS studies, due to the phenomenon of LD, many SNPs end up providing similar information in terms of statistics. To avoid this redundancy and increase the robustness further, we also performed INRICH on the LD-implicated intervals of pruned sets of SNPs. We generated 100 randomly pruned sets for all SCZ GWAS SNPs and 100 randomly pruned sets for SCZ GWAS SNPs annotated to DMR regions. We mapped all SNPs to 1000 Genomes genotypes and computed pairwise correlations for all markers. For 8,572,136 GWAS SNPs and 26,975 DMR SNPs that were mapped to the 1000 Genomes genotypes, we repeated the LD pruning protocol from Schork et al. (2013). In that analysis, all non-SNP signals were excluded (for example, insertions and deletions). For further analysis, we masked the extended MHC region in the SCZ GWAS (chr6: 25Mbp-35Mbp, containing 52,903 markers). SNPs were pruned randomly to approximate independence ($r^2 < 0.2$) 100 times. Finally, using PLINK, LD clumping was performed as described previously to generate LD intervals from ~180,000 pruned SNPs.

Supplementary Figures



Supplementary Fig. 1: INRICH test for enrichment of association of DMR gene sets and NSS gene sets with pruned sets of SCZ GWAS SNPs

A visual heatmap depicting the *p*-values obtained from 5,000 bootstrap iterations. The various evolutionary annotations compared are as follows. HypoDMR – human hypo-methylated DMRs; HyperDMR – human hyper-methylated DMRs. HypoDMR and HyperDMR are taken from the study by Hernando-Herraez et al. (2013). dmrH - human-specific DMRs, which are referred to as non-primate DMRs in the manuscript of Gokhman et al. (2014). NSS - Neanderthal Selective Sweep markers. Datasets marked with * have been previously reported by Banerjee et al. (2017) and are shown here for comparison only.



Supplementary Fig. 2: INRICH test for enrichment of association of DMR gene sets and NSS gene with height GWAS SNPs

A visual heatmap depicting the *p*-values obtained from 5,000 bootstrap iterations. The various evolutionary annotations compared are as follows. HypoDMR – human hypo-methylated DMRs; HyperDMR – human hyper-methylated DMRs. HypoDMR and HyperDMR are taken from the study by Hernando-Herraez et al. (2013). dmrH – human-specific DMRs, which are referred to as non-primate DMRs in the manuscript of Gokhman et al. (2014). NSS – Neanderthal Selective Sweep markers. HAR – mammalian conserved regions that are accelerated in humans. PAR - mammalian conserved regions that are accelerated in primates. PrHAR (primate HAR) – primate-conserved regions that are accelerated in humans. Datasets marked with * have been previously reported by Banerjee et al. (2017) and are presented here for comparison only.

Supplementary Tables

	Gokhman DMR	Neanderthal DMR	Denisovan DMR
	(n = 891)	(n = 307)	(n = 295)
Human	5	0	1
hypoDMR			
(n = 360)			
	primate HAR	mammalian HAR	PAR
	(n = 1928)	(n = 556)	(n = 577)
Human	1	0	0
hypoDMR			
(n = 360)			

Supplementary Table 1 Table describing the overlaps of various previously defined evolutionary annotations with human hypo-methylated DMRs. The cells show the number of regions of the respective annotations that overlap with at least one human hypo-methylated DMR.

	Gokhman DMR	Neanderthal DMR	Denisovan DMR
	(n = 891)	(n = 307)	(n = 295)
Human	2	2	2
hyperDMR			
(n = 210)			
	primate HAR	mammalian HAR	PAR
	(n = 1928)	(n = 556)	(n = 577)
Human	0	0	0
hyperDMR			
(n = 210)			

Supplementary Table 2 Table describing the overlaps of various previously defined evolutionary annotations with human hyper-methylated DMRs. The cells show the number of regions of the respective annotations that overlap with at least one human hyper-methylated DMR.

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Supplementary Dataset 1: Annotation of human hypo-methylated regions with markers of schizophrenia

This dataset may be downloaded for review at <u>https://www.dropbox.com/s/g48nubbem7v66nb/Banerjee_Supplementary_</u> Dataset_forPhD_Dissertation_xlsx?dl=0





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