# Supplemental reports

## **Contents**







**Supplemental figures and legends**



**Figure S1. Workflow of the data analysis.**



Figure S2, SCD exome map quality. A, the Venn diagram shows the overlap of variants between three variant caller methods used, gatk, samtool and freebayes. B, Overall depth distribution of SCD exome map. C, overall percentage of variant functions from 8,458,386 variants. D, Number of heterozygous by allele frequency. E, Substitution types. F, Ts/Tv by allele frequency.



Figure S3. Comparison of SCD exome map with recently 1000 Genomes release. A, principal component analysis of the three Cameroonian SCD sub-groups ("Random", "Stroke" and "Survival"), and continental samples from 1000 Genomes phase 3 release. Both components show a close relationship between the SCD and Africans than non-Africans. B, overall percentage of exonic variant functions of 8,458,386 variants. C, principal component analysis of the three SCD groups ("random", "Stroke" and "Survival"), showing a slight departure of survival to the rest of other SCD patients. D, the Venn diagram shows the overlap of SCD exome map and 1000 Genomes release phase3.



**Figure S4. Biological sub-network of the identified candidate mutations in 'long survivor" SCD patients.** A, sub-networks of the identified candidate mutation in the survival. B, diagram of the top significant pathways associated with the identified candidate mutations.



**Figure S5. Biological sub-network of the identified candidate gene mutations in SCD patients with stroke.** A, sub-networks of the identified candidate mutation in SCD with stroke. B, diagram of the top significant pathways associated with the identified candidate mutations.



**Figure S6. Biological sub-network of the identified candidate mutations in "random" SCD patients' group**. A, sub-networks of the identified candidate mutation in the normal SCD. B, diagram of the top significant pathways associated with the identified candidate mutations.



Table: Pathways Associated to the network formed with genes interacting with identified mutation genes in<br>SCD DRC (see Extended Table 2).



Figure S7. Biological sub-network of the identified candidate gene mutations in SCD patients a replication cohort of 29 SCD patients from DRC. A, sub-networks of the identified candidate mutation. B, diagram of the top significant pathways associated with the identified candidate mutations.



Figure S8. Circular Manhattan plot of gene-specific signal of unusual difference in SNPs frequencies. A, unusual gene-specific frequency difference between SCA with stroke, and the rest of SCA patients. B, gene-specific signal of unusual genetic difference between "long survivor" patients and the rest of SCA patients. C, unusual differentiation between SCA with stroke and "long survivor" SCA patients. **Table S3** displays the results of Cameroun control versus each the above SCA group.

#### Α. Significant human pathways associated to genes of large departure of unusual gene-specific difference between survival, and other SCD patients.



#### Significant human biological process associated to genes shown unusual gene-specific difference between survival, and other SCD patients.





C.

**Figure S9. Significant pathways and Biological processes associated to gene-specific difference in SNPs frequency between "**long survivor**" and other SCD patients**. A. Significant pathways associated to genes exhibited a large unusual gene-specific difference between "long survivor" group and other SCD patients. B. diagram of the top significant pathway in panel A. C. Significant biological processes associated to genes with unusual departure of gene-specific exome wide difference between "long survivor" and other SCD patients.

**Supplemental Tables**

**Table S1. Genes with mutations in SCD patients from Cameroon. The Z-score is obtained from aggregating the SiPhy (29-way) score based on identified mutants SNPs within gene (See details in Table S4 of mutation in polymorphisms within reported genes).** The reported Homozygous; heterozygous, compound heterozygous**,** cDNA change, Protein change, and all ExAc frequencies are from the polymorphism with top SiPhy (29-way) score.

	# SV	CHR Max Max $#$ <b>Patients</b>	<b>Region</b>	<b>Genotypes</b>	Gene	Gene name	cDNA Change	Protein Change	<b>ExAC</b> <b>AFR</b>	<b>ExAC</b> <b>EUR</b>	"Random" <b>SCD</b> Z-score	<b>SCD</b> with stroke Z-score	"Long Survivor" <b>SCD</b> Z-score
2	11	69/105	2q34	Hom	CPS1	Carbamoyl-phosphate synthetase 1, mitochondrial	c.C1086G	p.V362V	$\overline{0}$	0.01	20.86	20.86	20.86
$\overline{2}$	$\overline{7}$	82/105	2p13.1	Hom	SLC4A5	Solute carrier family 4, sodium bicarbonate cotransporter, member 5	c.C2790T	p.T930T	0.0003	$\overline{0}$	15.65	15.65	15.65
11	12	83/105	11q13.4	Hom	<b>NADSYN1</b>	NAD synthetase 1	c.G256A	p.V86M	$\overline{0}$	$\mathbf{0}$	15.15	15.5	15.15
16	$\overline{3}$	79/105	16p13.3	Hom	<b>CACNA1H</b>	Calcium channel, voltage-dependent, T type, alpha 1H subunit	c.G93A	p.E31E	$\overline{0}$	$\mathbf{0}$	15.05	15.18	15.05
20	$\overline{2}$	76/105	20p11.21	Het	PYGB	Phosphorylase, glycogen; brain	c.G907T	p.A303S	$\overline{0}$	$\mathbf{0}$	$18 - 71$	$18 - 71$	18.71
	3	47/82	1q25.1	Het	<b>SERPINC1</b>	Serpin peptidase inhibitor, clade C, member 1	c.A1011A	p.Q337Q	$\overline{0}$	$\overline{0}$	19.75	19.75	$\overline{a}$
$\mathbf{1}$	14	68/82	1q24.2	Het	F5	Coagulation factor V	c.2247_2249del p.749_750del			$\overline{a}$	17.62	17.62	÷,
$\overline{c}$	8	41/82	2q32.2	Het	<b>PMS1</b>	PMS1 postmeiotic segregation increased 1	c.T141C	p.Y47Y	$\overline{0}$	$\overline{0}$	19.13	18.06	$\overline{\phantom{a}}$
10	6	58/82	10p14	Het	GATA3	GATA binding protein 3	c.T606C	p.R202R			18.28	18.28	
11	2	49/82	11p13	Het	PAX6	Paired box 6	c.C1139T	p.S380L			20.86	20.86	L,
19	5	67/82	19q13.11	Het	<b>GPI</b>	Glucose phosphate isomerase	c.G7A	p.A3T	$\overline{0}$	$\mathbf{0}$	15.39	15.39	÷,
19	3	53/79	19p13.2	Het	<b>INSR</b>	Insulin receptor	c.C3255T	p.H1085H	$\overline{0}$	$\mathbf{0}$	15.83	$\sim$	15.83
$7\phantom{.0}$	$7\phantom{.0}$	66/79	7q36.1	Het	NOS3	Nitric oxide synthase 3	c.341_348del	p.S114fs	$\overline{0}$	$\mathbf{0}$	15.73	$\sim$	15.73
5	3	40/79	5q13.2	Het	MCCC2	Methylcrotonoyl-Coenzyme A carboxylase 2 (beta)	c.T969C	p.A323A		ä,	18.04	$\overline{\phantom{a}}$	18.04





£Exonic. nonsynonymous variants that were considered damaging according to 21 different functional scores from the annotation databases, including SIFT, Polyphen2\_HDIV, Polyphen2\_HVAR, Likelihood ratio test, MutationTaster, MutationAssessor, FATHMM, fathmm-MKL, RadialSVM, LR, CADD, PROVEAN, MetaSVM and MetaLR, as previously reported.<sup>8</sup> Abbreviations: Hom: Homozygous; Het: heterozygous; cHet: compound heterozygous; #SV: nonsynonymous variants; SNP: Single Nucleotide Polymorphism; ExAC: Exome Aggregation Consortium; AFR: African; EUR: European.



**Table S2. Description of the replication study cohort (SCA patients from the Democratic Republic of Congo)**

<b>CHR</b>	<b>Max</b>	#	<b>Region</b>	Gene	<b>Gene Name</b>	<b>CDNA</b>	Protein	<b>EXAc</b>	<b>ExaC</b>
		# SNPs Patients				<b>Change</b>	Change	<b>AFR</b>	<b>EUR</b>
$\mathbf{1}$	11	12/29	1p21.1	COLIIAI	Collagen Type XI Alpha 1 Chain	c.G4025A	p.G1342D	$9.617e-05$ 0	
$\overline{1}$	6	9/29	1p36.13	ALDH4A1	Aldehyde Dehydrogenase 4 Family Member A1	c.C852A	p.F284L	$\overline{0}$	$1.505e-05$
$\overline{1}$	$\overline{4}$	17/29	1p36.22	CLCN6	Chloride channel 6	c.C2436A	p.F812L		
$\mathbf{1}$	8	12/29	1p36.33	ATAD3C	ATPase Family, AAA Domain Containing 3C	c.G425C	p.G142A	0.0014	$\mathbf{0}$
$\mathbf{1}$	$\mathbf{1}$	11/29	1q25.1	<b>SERPINC1</b>	Serpin peptidase inhibitor, clade C, member 1	c.G167A	p.R56H	$\overline{0}$	$\boldsymbol{0}$
$\overline{2}$	$\mathfrak{Z}$	11/29	2p23.1	CAPN13	Calpain 13	c.G838A	p.A280T	0.9181	0.6884
$\overline{2}$	3	23/29	2q14.3	MYO7B	Myosin VIIB	c.G5764A	p.G1922R	$\boldsymbol{0}$	$2.609e-05$
$\overline{2}$	$\mathfrak{Z}$	19/29	2q22.1	LRPIB	LDL Receptor Related Protein 1B	c.A4487G	p.N1496S	$\mathbf{0}$	$1.5e-0.5$
$\sqrt{2}$	$7\overline{ }$	16/29	2q37.3	COL6A3	Collagen, type VI, alpha 3	c.A3290G	p.Q1097R	$\sim$	$\Box$ =
$\overline{4}$	9	11/29	4p16.3	SLC26A1	Solute Carrier Family 26 Member 1	c.G1060A	p.A354T	$\mathbf{0}$	$9.686e-05$
$\overline{4}$	$\overline{4}$	8/29	4q31.3	${\it LRBA}$	LPS Responsive Beige-Like Anchor Protein	c.G3914C	p.R1305P	$\overline{0}$	$\boldsymbol{0}$
$\overline{7}$	$\mathfrak{Z}$	15/29	7q21.11	HGF	Hepatocyte growth factor	c.C58A	p.L20I	0.0003	$\mathbf{0}$
$\overline{7}$	5	17/29	7q31.33	GRM8	Glutamate Metabotropic Receptor 8	c.C1534G	p.P512A	0.0648	0.0001
$\overline{7}$	1	21/29	7q36.1	NOS3	Nitric oxide synthase 3	c.C1801A	p.Q601K	÷.	٠.
8	$\mathbf{1}$	11/29	8p21.2	$NKX2-6$	NK2 Homeobox 6	c.G464T	p.R155L	0.0004	0.0001
8	$\overline{4}$	13/29	8q24.12	SNTB1	Syntrophin, beta 1	c.G19A	p.A7T	0.0278	$\mathbf{0}$
10	6	8/29	10q11.23	<b>OGDHL</b>	Oxoglutarate dehydrogenase-like	c.C1259T	p.T420M	$\overline{0}$	$4.502e-05$
11	$\mathbf{1}$	11/29	11q13.3	IGHMBP2	Immunoglobulin Mu Binding Protein 2	c.G2857A	p.G953S	0.0003	$\mathbf{0}$

**Table S3 | Gene with mutations in SCD patients from Democratic Republic of Congo (DRC)£ .**



£Exonic. nonsynonymous variants that were considered damaging according to 21 different functional scores from the annotation databases, including SIFT, LRT, MutationTaster, MutationAssessor, FATHMM, fathmm-MKL, RadialSVM, LR, PROVEAN, MetaSVM, MetaLR, CADD, GERP++, DANN, M-CAP, Eigen, GenoCanyon, Polyphen2 HVAR, Polyphen2 HDIV, PhyloP, and SiPhy, as previously reported.<sup>8</sup> Abbreviations: Max #SNPs: Maximum number of nonsynonymous variant observed among the 3 SCD groups; SNP: Single Nucleotide Polymorphism; ExAC: Exome Aggregation Consortium; AFR: African; EUR: European.



**Table S4 | Gene-specific signal of unusual difference in SNPs frequencies between Cameroun Control versus All SCA, "randomly selected", "stroke" and "long survivor" SCD patients**.

![](_page_19_Picture_617.jpeg)

![](_page_20_Picture_146.jpeg)

. \*Abbreviations: CHR: chromosome; SNPs: Single Nucleotide Polymorphism.

![](_page_21_Picture_463.jpeg)

![](_page_22_Picture_533.jpeg)

![](_page_23_Picture_537.jpeg)

![](_page_24_Picture_550.jpeg)

![](_page_25_Picture_550.jpeg)

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![](_page_31_Picture_529.jpeg)

#### **Supplemental methods**

#### **1. Introduction**

The African continent harbours the greatest genetic and environmental diversity<sup>1, 2</sup> and has the highest health burden per capita<sup>3</sup>, yet there is a scarcity of large-scale disease-specific genome studies of African populations<sup>4, 5</sup>. Sickle cell disease (SCD) has its highest burden in Africa, particularly in Central and West Africa. Here, we report the first study on deleterious variants in deep whole exome sequencing of 192 individuals. This is the first data on whole exome sequencing landscape of SCD in Africa, which has generated a novel database of candidate modifier genes. The exome data provided will serve the global community as it represents the first step of a series of studies on the genomic architecture of SCD, which will be enhanced by the establishment of major NIH-funded research consortia for the study of SCD in Africa<sup>6</sup>. Figure S1 describes the overall pipeline used for data generation and analyses.

#### **2. Sample Collection**

#### **2.1** *Ethics Statement*

The study was performed in accordance with the guidelines of the Helsinki Declaration. Ethical approval was given by the National Ethical Committee Ministry of Public Health, Republic of Cameroon (No 033/CNE/DNM/07) and the University of Cape Town, Faculty of Health Sciences Human Research Ethics Committee (HREC RE: 132/2010). Written and signed informed consent was obtained from the adult participants who were 18 years or older, and for the children consent was obtained from parents/guardians with an assent from the participants older than seven years of age.

#### **2.2** *Patients and assessment of clinical events*

The recruitment for the discovery group was conducted in Cameroon at the Yaoundé Central Hospital and Laquintinie Hospital in Douala, as previously described<sup>7</sup>. Briefly, socio-demographic and clinical data were collected by means of a structured questionnaire. Anthropomorphic variables were measured in the outpatient setting. Routine blood counts of patients and haemoglobin (Hb) electrophoresis were conducted on arrival at the hospital. In the present study, three sub-groups of SCD patients were included: 1) the "stroke" group made of SCD patients with at least one clinical episode of overt stroke, a devastating complication of SCD, occurring in 11% of patients before age 20 years and considered to be a proxy of severity<sup>8</sup>, influenced by genetic modifiers<sup>9</sup>; 2) the "long survivor" SCD group made of patients older than 40 years considered here as the most genetically fit; whose cut off was based on life expectancy of 43 years for SCD-HbSS in the cooperative study conducted four decades ago in the USA8; 3) the "random" group made of SCD patients randomly selected among clinical stable patients without incidence of any cerebrovascular disease by clinical criteria and younger than 40 years.

The replication cohort consisted of adult SCD patients recruited at the Haematology Clinic, Groote Schuur Hospital in Cape Town, that are mostly recent migrants from other sub-Saharan African countries where SCD is prevalent<sup>10</sup>. In order to have a similar genetic background for this replication group, only patients from Demographic Republic of Congo (DRC) were included in the present study. Details of sample information are in **Table S2**

#### *2.3 Control participants*

A total of 58 ethnically matched Cameroonian controls were randomly recruited from healthy blood donors in Yaoundé<sup>11</sup> and volunteered their participation in the study. Only individuals, without HbS mutation and that were homozygous HbAA as confirmed by molecular analysis, were included.

#### **3. Library Construction and Sequence**

### *3.1 Molecular methods: Sickle cell anaemia mutation, β-globin gene cluster haplotypes, and 3.7 kb α-globin gene deletion*

DNA was extracted from peripheral blood following the manufacturer's instructions (Puregene Blood Kit; Qiagen, Hilden, Germany). Molecular analysis was performed to determine the presence of the sickle mutation and was carried out on 200 ng DNA by polymerase chain reaction (PCR) to amplify a 770 bp segment of the β-globin gene. This was, followed by DdeI restriction analysis of the PCR product<sup>12,13</sup>. Using published primers and

methods, five restriction fragment length polymorphism (RFLP) sites in the β-globin gene cluster were amplified to analyse the XmnI (5'Gγ), HindIII (Gγ), HindIII (Aγ), HincII ( $3\psi\beta'$ ) and HinfI (5' $\beta$ ) for the HBB haplotype background<sup>11</sup>. The 3.7 kb α-globin gene deletion was successfully screened, using the expand-long template PCR (Roche Diagnostics, Basel, Switzerland), as previously published $^{11,14}$ .

#### *3.2 Whole Exome Sequencing and Accuracy of exome variant detection*

DNA samples underwent sequencing at the Omega Bioservices, Omega Bio-tek, Inc, Emory University USA. DNA concentrations were accurately determined using a picogreen fluorescent detection method (Quant-iT; Invitrogen). Equal amounts of DNA from each sample constituting a pool were manually combined before WES. The Roche Nimblegen SeqCap EZ MedExome v2.0 (~47Mb target) were used for sequence capture. The MedExome Kit was designed to provide sequencing coverage for gene annotations from several sources (i.e. Refseq, Ensemble and GENCODE) as well as miRBase, and enhanced coverage of medically relevant genes such as those in GeneTests, OMIM, ClinVar. All protocols for shotgun library construction for exome capture have been automated on a Perkin-Elmer Janus II liquid handling robot or multi-channel pipettors. After shotgun library construction, library concentrations and molecular weight distributions are determined in parallel on an Agilent Bioanalyzer in order to flag low-quality libraries prior to exome capture. Samples passing quality control, library preparation and exome capture are sequenced on an Illumina HiSeq 4000 sequencer. WES was generated on the HiSeq X.

#### **4. Reads Mapping and Alignment**

To insure the forward and reverse reads are of high quality and appropriate length, we evaluate these using used both FastQC<sup>15</sup> and SolexaQA++<sup>16</sup>. From the UCSC database<sup>17</sup>, we obtained the human reference genome, version hg19 (build37), together with its gene annotation. The reads were aligned to the UCSC hg19 (build37) complete reference genome using BWA<sup>18,19</sup>. Using the Picard tool kit<sup>20</sup>, the duplicate reads were marked, and after alignment, the BAM files were sorted by coordinates, indexed and read groups were added via Picard<sup>20</sup>. BAM files were re-ordered according to UCSC hg $19^{17}$ . Insertions and deletions at the end of the reads can misguide the aligners into mis-aligning with mismatches. This artificial mismatch can

mislead base quality score recalibration and variant detection. To address this issue, we used the Genome Analysis Toolkit (GATK) software<sup>20</sup> for local realignment along all reads at a problematic locus to create a cleaned version of the BAM file and found a best consensus sequence that, together with the reference, best fits the reads in a pile. We used the 1000 genomes phase 1 INDELs and Mills and 1000 genomes gold standard INDELs<sup>21</sup> to drive the process. Using these known sites improves the accuracy. After INDEL realignment we applied Picard "FixMateInformation" to recalculate read pair information to see if it has changed. At this stage all 192 samples have  $> 79\%$  of target bases covered to  $\sim 35x$ .

#### **5. Variant Calling**

As different calling methods produce a large number of differing variants and previous studies have demonstrated that these methods have differing advantages<sup>22,23,24</sup>, we adopted an ensemble approach implemented in VariantMetaCaller<sup>25</sup> in each data set of subjects group and the all dataset of 192 subjects. To detect SNPs and short indels, we combined information generated from three independent variant caller pipelines (**Figure S1**): (1) An incremental joint variant discovery implemented in GATK 3.0 HaplotypeCaller<sup>20</sup>, which calls samples independently to produce gVCF files and leverages the information from the independent gVCF file to produce a final call-set at the genotyping step; (2) FreeBayes<sup>26</sup> and (3) samtools via mpileup<sup>27</sup> variant callers (**Figure S1**). The best practice specific to each caller were adopted<sup>28</sup>.

#### **6. Variant Calling Quality Control and Final Call-set**

Before applying the ensemble approach from the resulting variant sets per subject group and all subjects from each these three callers respectively, we filtered each resulting VCF files using the GATK tool "VariantFiltration".

#### *6.1 Flagging Variants*

We added additional filter levels to each call set as follows: (1) If 3 SNPs are detected within a window of 10 base-pairs, the site will be flagged as a "SNPCluster" in the FILTER column (2) if 4 or more alignments having a mapping quality of  $MO = 0$  (which means it maps to different locations equally well) and the number of alignments that mapped ambiguously are more than a tenth of all alignments, it is difficult to decipher artefacts and true

differences. These sites will be flagged as "HARD\_TO\_VALIDATE", (3) SNPs which are covered by less than 5 reads may be potential artefacts and these sites was flagged as "LowCoverage", (4) SNPs having a SNP quality below 30 are typically artefacts, were flagged as "VeryLowQual", (5) SNPs having a quality score between 30 and 50 are potential artefacts, flagged as "LowQual", (6) SNPS having a OD score  $\lt 1.5$  are indicative of false positive calls and artefacts, flagged as "LowQD" (7) and SNPs covered only by sequences on the same strand are often artefacts, was flagged as "StrandBias".

#### *6.2 Variants Quality Control Assessment Prior Final Call-set*

Variants flagged "VeryLowQual", "LowQual", "LowQD" and "StrandBias" were removed in each VCF files. Exomes VCF files were assessed according to the total reads, coverage distribution, raw error rates, transition/transversion (Ti/Tv) ratios (3.2), comparison of genomic sex to recorded sex, distribution of known variants (relative to dbSNP), CytoSNP array fingerprint concordance > 99%, homozygosity, heterozygosity, and sample contamination validation. Additionally, variant sites that strongly deviate from Hardy-Weinberg equilibrium (p-value  $\lt 5x$  10-5) were flagged. These criteria reduce the inclusion of false-positive variant calls during the ensemble of the VCF files.

The final call-set from each subjects group, were produced from VariantMetaCaller<sup>25</sup>, a support vector machines approach that combined the hardfiltered VCF files obtained from these three variants callers.

#### **7. Variant Annotation and Mutation Prioritization**

After high confidence variants were called using VariantMetaCaller from each dataset include 3 Cameroonian SCD categories; namely 56 moderate SCD patients, 26 stroke SCD patients, 23 survival SCD individuals for the discovery analysis, 58 Cameroon control samples and 29 SCD patients from the DRC for replication analysis. We used ANNOVAR<sup>29</sup> to independently perform gene-based annotation in each final VCF data set to determine whether SNPs cause protein coding changes and produce a list of the amino acids that are affected. We used ANNOVAR "2016Dec18" setting, where the population frequency, pathogenicity for each variant was obtained from 1000 Genomes exome<sup>21</sup>, Exome Aggregation Consortium<sup>30</sup> (ExAC), targeted exon datasets and COSMIC<sup>31</sup>. Gene functions were obtained from RefGene<sup>32</sup> and different functional predictions were obtained from ANNOVAR's

library, which contains up to 21 different functional scores including  $SIFT^{33,34}$ , LRT<sup>35</sup>, MutationTaster<sup>36</sup>, MutationAssessor<sup>37,38</sup>, FATHMM<sup>39</sup>, fathmm-MKL<sup>39</sup>, RadialSVM<sup>40</sup>, LR<sup>40</sup>, PROVEAN<sup>40</sup>, MetaSVM<sup>40</sup>, MetaLR<sup>40</sup>, CADD<sup>41</sup>, GERP++<sup>42</sup>, DANN<sup>29</sup>, M-CAP<sup>29</sup>, Eigen<sup>29</sup>, GenoCanyon<sup>29</sup>, Polyphen2  $HVAR<sup>43</sup>$ , Polyphen2 HDIV<sup>43</sup>, PhyloP<sup>44</sup> and SiPhy<sup>44</sup>. We additionally included conservative and segmental duplication sites, dbSNP code and clinical relevance reported in dbSNP<sup>45</sup>. From each resulting functional annotated data set, we independently filtered for predicted functional status (of which each predicted functional status is of "deleterious" (D), "probably damaging" (D), "disease\_causing\_automatic" (A) or "disease\_causing" (D). $^{46,47,49}$ ) from SIFT, LRT, MutationTaster, MutationAssessor, FATHMM, fathmm-MKL, RadialSVM, LR, PROVEAN, MetaSVM, MetaLR, CADD, GERP++, DANN, M-CAP, Eigen, GenoCanyon, Polyphen2 HVAR, Polyphen2 HDIV, PhyloP, and SiPhy.

We used a casting vote approach, by retaining only a variant if it had at least 17 predicted functional status "D" or "A"out of 21. Second, the retained variants from each data set were further filtered for rarity, exonic variants, and nonsynonymous mutations and with high quality call as describe above, yielding a final candidate list of predicted mutant variants in each subject group, including the replication group. To compare the results from the above strategy, we re-applied FATHMM<sup>22</sup>, a disease-specific weighting scheme, which uses a Hidden Markov Models prediction algorithm capable of discriminating between disease-causing mutations and neutral polymorphisms. We report on the aggregated SiPhy score from all identified mutants SNPs within gene.

#### **8. Network and Enrichment Analysis**

#### *8.1 Reconstruction of Sub-network*

To identify sub-networks of interactive mutant variant genes (**section 7** above) or from gene-specific difference in SNPs frequencies genes (**section 13** below) from each SCD category occurred, we used a comprehensive human Protein-Protein Interaction (PPI) network<sup>50,51,52,53,54,55</sup> to analyse how each set of variant genes are layered and interact within a biological network, thus extracting a sub-network. A clustering script in R's (R Core Team, 2016) igraph package was used to determine a network plot that would allow us to identify the hub proteins in the sub-networks.

#### *8.2 Enrichment of genes within Sub-network*

We examined these candidate variants genes from either mutation prioritization (**section 7** above) or gene-specific difference in SNPs frequencies (see **section 13** below) are interact with other genes and how in the formed sub-network they can be associated with human phenotypes and what are their pathways, biological processes and molecular functions. To address this, we used a custom script and adopted to compare our results with different tools including DAVID<sup>56</sup> and PANTHER<sup>57</sup>. We additionally conducted an enrichment analysis using the Enrichr software<sup>58</sup>. The most significant pathway enriched for genes in the networks were selected from  $KEGG^{59}$ , Panther<sup>57</sup>, Biocarta<sup>60</sup> and Reactome<sup>61</sup>, and gene ontologies from the Gene Ontology Consortium<sup>62</sup> were defined for cellular component, biological process and molecular function.

#### **9. Further Characterization of Enriched Sub-networks.**

To identify the association between each sub-network Sj,  $(j=1,...,T)$  within  $n_1,..., n_T$  genes to human pathway,  $P_k \in$  Pthe set of human pathways. We obtained 1,547 annotated pathways<sup>51,52,53,54,55</sup> and collected more than 107 annotated pathways from the KEGG<sup>59</sup>, BioCarta<sup>60</sup> and Ambion GeneAssistTM Pathway Atlas pathway databases. We downloaded genomic co-ordinates for all genes from the NCBI ftp-server<sup>45</sup> and retained only entries for the human reference sequence. We assigned the SNPs located within a gene or in LD within less than 40kb distance up/downstream of the gene using dbsnp database<sup>45</sup>. Let a number of genes in the intersection between genes within Sj and genes within pathway  $P_k$ . Let b be the number of genes in the intersection between genes within Sj and those in the union of all pathways  $P_{k(k=1,\dots,K)}$ . Let n be the number of genes in the intersection between genes in the  $P_j$  pathway and those in the union of all pathways  $P_{k(k=1,\dots,K)}$  with  $k \neq j$ , and m be the total number of genes in all pathways  $P_{k(k=1,\dots,K)}$ . We computed the statistic of significance of overlap between sub-network S<sub>j</sub>, of n<sub>t</sub> genes and a given pathway  $P_k$  using the z-score (ZS), which employs the binomial proportion test,

$$
Z_S = \frac{\left(\frac{a}{n} - \frac{b}{m}\right)}{\sqrt{\frac{1 - \frac{b}{m}}{m}}}
$$

#### **10. Procedure to Aggregating SNPs Summary Statistics at the Gene level.**

From each subject group, we estimated the statistical significance at gene level from the list of resulting genes associated to predict mutant variants (**section 7** above) or from the list of candidate gene-specific difference in SNP frequencies (**section 13** below). In doing so, we aggregated the P-values from SNPs 40kb downstream and upstream gene region (exon) as per gene-based annotation file in our exome datasets. Under the null hypothesis, pvalues  $p_k$  (k = 1,...,L) for a test-statistic with a continuous distribution are uniformly distributed in the interval [0,1]. It follows that a parametric cumulative distribution function F can be chosen and  $p_k$  can be transformed into quantiles according to  $q_k = F^{-1}(p_k)$ . The combined test statistic  $C^p = \frac{\sum_{k=1}^{L} q_k}{\sqrt{L}}$  is a sum of independent and identically distributed random variables  $q_k$ . To account for the independence assumption given correlation among neighbouring genomic markers, we implement the Stouffer-Liptak method accounting for spatial correlations among SNPs within a gene or SNPs within a given sub-network. The overall statistic can be obtained by  $p = \Phi(C^p)$ , in which  $\Phi$  is the cumulative distribution function of the standard normal distribution. We apply the Benjamini-Hochberg false-discovery correction method to control the type I error rate and account for gene/subnetwork differences in the numbers of associated SNPs. From each subject group, we reported on the overall statistical significance of gene mutational burden gene, p-values after the Benjamini-Hochberg false-discovery correction.

#### **11. Phased and Haplotypes Inference**

From the VCF file resulted from joint variant calling (section VI above), a merged dataset of all 192 samples (58 Hb AA Cameroon controls, a replication cohort of 29 SCD patients from DRC, 56 random, 26 Stroke, and 23 survival SCD patients and 58 controls from Cameroon. We further conducted quality control to remove all structured, indel, multi-allelic variants and those with low minor allele frequency (MAF < 0.05) prior to phasing. We first phased and inferred the haplotypes using Eagle<sup>66</sup> from the resulting curated data.

Second, we extracted and re-phased samples from the 1000 Genomes Project<sup>21</sup>. To merge our exomic haplotypes to those from 1000 Genomes, we computed a cross-imputation using impute2<sup>67</sup>. We performed further quality control after the imputation, which consisted of removal of variants with low minor allele frequency (MAF < 0.05); low genotypes call ( $\leq$  95%) and imputation accuracy ( $\leq$  955) prior to re-phasing using Eagle66. We performed a post-phasing quality control in which we checked the switch-error between our exomic haplotypes panel and the exomic haplotypes merged to 1000 Genomes panel<sup>21</sup>, where 99.7% and 97,05% of the sites were with no phase switch-error in both panels, respectively. We further compared sites discordance between these haplotype panels and independently with their original VCF file prior phasing. The only site with phase switch-errors showed discrepancies in MAF and were therefore removed.

#### **12. Fine-scale Population Structure**

Population structure analyses were performed to characterize the genetic contributions to our 192 patient samples. We first tested whether populations conform to an isolation-by-distance model or whether there is strong heterogeneity among populations relative to geographic distance. To this end, we have merged our 192 samples with data from 1000 Genomes Projects in which we performed principal component analysis using smartpca in the EIGENSOFT package<sup>68,69</sup> and included all SNP haplotypes shared between the populations analysed. Population-specific pair-wise genetic distance (F\_ST) and a phylogeny tree was computed from smartpca. All the 192 samples, including the SCD from DRC were observed to cluster together,

indicating geographic and genetics proximity. Table below displays the population-specific F\_ST, indicating close genetic relatedness between SCD groups from Cameroon as well as relatedness between SCD patients from DRC and the Control Cameroon group. The data suggests an isolation-bydistance model.

**Table S3** Pair-wide Population genetic distance among 58 Hb AA Cameroon controls, a replication cohort of 29 SCD patients from DRC, 56 random, 26 Stroke and 23 survivor SCD patients from Cameroon.

![](_page_41_Picture_156.jpeg)

### **13. Unusual Genetic Difference: SNP-specific differences in allele frequency**

Similarly, to<sup>70,71</sup>, and assuming the population evolved under the Wright-Fisher model, selective neutrality and with an expected number of mutations, we used a step-wise constant effective population size<sup>70</sup> to compute allele frequency spectrum. We secondly computed the pair-wise group frequency

spectrum difference at SNP level, thus SNP allele frequency spectrum difference are assigned to a given gene if they are located within the gene's 40kb downstream or upstream using dbsnp database, thus aggregating SNPs allele frequency difference into genes<sup>51,52,53,54,55</sup>. To this end, let  $f_i^1$  and  $f_i^2$  be the allele frequency spectrum in group 1 and group 2, respectively. To minimize deviation from the normality assumption, SNPs with minor allele frequencies < 0.05 are excluded. Thus, at a given locus i, the difference  $f_i = (f_i^1 - f_i^2)$  between observed variant allele frequencies of two groups 1 and 2. Let gene j (j = 1,.., N) has  $n_j$  associated SNPs, thus  $d_j = \frac{\sum_{i=1}^{n_j} f_i}{n_j}$  is gene j (j=1,..,N) frequency difference from group 1 and 2, and can be approximated as a normal distribution under neutral drift with mean 0 and variance<sup> $71,72$ </sup>

$$
d(1-d)\left(2\mathrm{F}_{\mathrm{ST}}+\frac{1}{n_j}\right)
$$

where  $F_{ST}$  is the genetic distance between the group 1 and 2

$$
d = \frac{\sum_{i=1}^{n_j} (f_i^1 + f_i^2)}{2}
$$

total variant allele counts in each population, and p is the overall gene-specific ancestral frequency that is approximated as the average of the two observed variant allele frequencies from  $n_j$ SNPs associated to gene j. Similar to<sup>70,71</sup>, we test unusual gene-specific difference U<sub>12</sub> from groups 1 and 2 as follows

$$
U_{12}^{j} = \frac{(d_j)^2}{d(1-d)\left(2F_{ST} + \frac{1}{n_j}\right)}
$$

This equation is  $\chi^2$  distributed with 1 degree of freedom (d.o.f). An excess of large values of the  $\chi^2$  statistic indicates deviations from the null model, suggesting the action of natural selection<sup>71,72</sup>. We applied this method to each group-pair from the three groups of SCD. Finally, SNP-specific unusual allele frequency summary statistics of SNPs within gene region can be aggregated (**see section** 10 above) to obtain gene-specific differences in SNP frequencies.

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