# Support Figure 1.10.1072/2020 Gonzalez-Garay et al. 10.1073/pnas.1315934110

#### SI Materials and Methods

Cohort Description. The cohort consists of members and spouses in the Houston Chapter of the Young Presidents Organization (YPO). Criteria for membership into the YPO includes corporate and community leadership (1). This cohort is well educated and of higher socioeconomic status. All 450 YPO members were invited to attend an 8-h educational program incorporating technology, human genetics, anticipated outcomes, ethical considerations, discussion groups, and technology demonstrations and printed materials. Of the 150 attendees, 81 volunteered to participate in this study: 46 men and 35 women, with an average age of 54 y. All 81 elected under the terms of the University of Texas Health Science Center at Houston's institutional review board to receive "need to know" genomic disease risk results. Each volunteer provided a detailed medical and drug use history reviewed by our physician-researcher (C.T.C.). A three-generation medical pedigree was acquired on each volunteer. One volunteer could provide no family history.

Whole exome sequencing (WES) Sequencing. Genomic DNA was extracted using a DNA kit (Promega wizard genomic DNA purification kit) following Promega's instructions (2). The cohort was sequenced twice: the first whole exome sequencing experiment (2011) was performed using Illumina's HiSeq and the Genome Analyzer IIx system (3) after enrichment with Nimblegen V2 kit (44 Mb) (4) (outsourced to the national center for genome resources). Our second WES experiment (2013) was performed using Illumina's newest machines HiSEq. 2500 (3) after enrichment with Agilent SureSelect target enrichment V5+UTRs (targeting coding regions plus UTRs) (5) (outsourced to Axeq Technologies). Genome sequencing of a small subset (24 subjects) for validation purposes was carried out by Complete Genomics Inc. (CGI) (6).

Sequencing Analysis. Our analysis pipeline consists of Novoalign (7), Samtools (8), Picard (9), and The Genome Analysis Toolkit (GATK) (10), followed by variant annotation (11–14) using multiple databases from the University of California Santa Cruz (UCSC) Genome bioinformatics site (15). Fig. 1 illustrates our pipeline. Fig. 2 describes our pipeline to detect known pathogenic variations. We detected known variants associated with human diseases using the Human Genome Mutation Database (HGMD) database from Biobase (16, 17) and genes known to be associated with human disorders from Online Mendelian Inheritance in Man (OMIM) (18, 19) and GeneTests (20). Functional effects of each nonsynonymous coding variant were evaluated using three different functional prediction algorithms [Polyphen 2.0 (21), Sift (22–27), and MutationTaster (28)] using the Database of Human Non-synonymous SNVs and their functional predictions and annotations (dbNSFP) (29). Filtration of common polymorphisms was accomplished using frequencies from the National Heart, Lung, and Blood Institute (NHLBI) exome sequencing project (ESP) (30), 1,000 Genomes (31, 32), and internally by removing any variant that appeared more than three times in our cohort. In addition, a group of candidate genes was obtained from OMIM (18, 19) for each volunteer after a careful analysis of the family and personal health history of each volunteer. Variations in those OMIM (18, 19) candidate genes were identified and submitted to the same frequency and functional effects filter as described before.

Variant Validation. Every variant identified in our pipeline was evaluated for quality control, and the variant's read alignments in

the BAM file [Binary version of a SAM (Sequencing Alignment Map) file] file were visualized using Integrative Genomics Viewer (IGV) (33). The purpose of this step was to try to remove the remaining false positives.

Each genetic variant was validated using the following steps:  $(i)$ retrieve reads over variant sites for each individual;  $(ii)$  make SamTools (8) genotype calls (an alternate calling algorithm); (*iii*) retrieve quality scores for all reads; (*iv*) keep track of the directional depth and require at least two variant reads in the 5′ and 3<sup>'</sup> orientation for a variant to be considered true; and  $(v)$ filter out variants if the SamTools (8) genotype call disagrees with the GATK (10) call or if the quality scores or directional depth values do not exceed minimum values.

Establishing Criteria for Highly Reliable Variant Calling from Exome Sequencing. Our first objective was to define the methods needed to identify a set of "highly reliable" variants from the Illumina sequencing and apply these methods to variant calling on all of our samples. To meet our definition of a highly reliable variant, each variant had to be detected under two independent orthogonal sequencing technologies and been considered as high quality. Because there is not a common definition of what a highquality variant is, we decided to take advantage of the confidence category scores provided from complete genomics; variants with a score of VQHIGH are consider high quality (masterVarbeta files version 2.0) and develop an equivalent value in our illumina sequencing data. To accomplish our first objective, a dataset of variants was generated from a set of 24 samples that we sequenced using Illumina (3) and an orthogonal sequencing technology (CGI) (6). CGI has their own proprietary workflow from alignment to data annotation (34), Fig. 1 describes our analysis workflow for exome sequencing data. Fig. S2A shows the intersection between the nonsynonymous coding variants (NSCVs) detected by CGI (6) and Illumina (3) exome sequencing. We extracted variants from CGI with a score of VQHIGH and that were also detected in the corresponding illumina's vcf file (Fig. S2B). This subset of highly reliable variants represents an average of 72% of the variants detected by CGI. By using our dataset, we were able to systematically test for conditions and software setting in our pipeline that generate the majority of the highly reliable variants and reduce the probability of selecting variants not present in our dataset. We reached the conclusions that by using two variant callers tools, GATK UnifiedGenotyper and mplileup/bcftools (samtools), and selecting an overlapping set of variants, we obtained variants of the highest quality. In addition, a postcalling filter enforces that each variant has to have a mapping quality  $>30$ , a base quality  $>20$ , and a coverage ≥10, with at least a 3:7 ratio of variant to reference (Het) and the presence of the variant in reads from both orientations. By using these postcalling filters, we eliminated the majority of falsepositive calls (FP).

Counseling. Genome counseling was conducted by a board-certified internist and a medical geneticist by both individual meetings and two written summaries over a period of 12 mo. The summary reports were prepared and jointly endorsed by a bioinformatician and a physician. Additional counseling was conducted by phone calls and appointments with their physician as requested by the volunteers.

Counseling of Results. Both causative and problematic alleles were reported verbally and in two written reports over an 18-mo period.

The first comprehensive report was updated  $\sim$ 1 y after (i) larger control databases downgraded some problematic alleles with more than a  $1\%$  frequency; (*ii*) private consultation with disease experts; and (iii) validation with original publications and small disease center databases. Several new disease–gene associations were discovered for the reported familial diseases found by pedigree and personal medical histories. Volunteers were informed that these were research results and instructed to consult with their personal physician so that they could have the results validated in a Clinical Laboratory Improvement Amendments (CLIA)-certified laboratory. Volunteers whose family members warranted genetic study were referred to the Baylor College of Medicine genetics program as a medical referral because this function was outside the institutional review board scope and Baylor College of Medicine offered both clinical genetic and CLIA Laboratory expertise. Our study preceded the publication of the incidental findings guidelines in clinical WES and whole genome sequencing (WGS) of the American College of Medical Genetics and Genomics (ACMG) (35). However, we have reviewed their list of 57 genes and 24 actionable conditions, and we found that we included all their genes in our analysis.

#### Poststudy Survey

We conducted an online survey to assess volunteers' experiences of participating in this project under a Baylor College of Medicine instituational review board. The survey consisted of 82 items and focused on how the volunteers felt about taking part in the research project, as well as their perspectives on genetic information in health care and genomic research in general. Study participants were told the survey was completely voluntary and that they could skip any question they preferred not to answer and could end their participation at any time.

All 81 study volunteers were invited via e-mail to participate in the anonymous online survey within 12 mo after receiving their individual genome reports. Forty-two participants responded to the online survey (response rate, 51.9%; 38 responses were complete). Of those who responded, 59% were men, 41% were women, and 95% had biological children. Ninety-seven percent described their race as white, and 5% chose "other" (participants could choose all that applied); 5% also identified themselves as Hispanic or Latino. All participants had earned a college degree, and 63% had completed at least some graduate work. All participants reported having had a routine medical check-up within the last 2 y, and when asked how they would rate their health, 58% reported excellent, 29% reported very good, 11% reported good, and 3% reported fair.

Poststudy survey results. This study had as its objective to deliver helpful medical genetic information. The mandatory education program informed volunteers that unexpected risks were to be expected.Our institutional review board required volunteers to have the options of declining this information. None chose that option.

- 1. Anonymous Membership criteria YPO. Available at [http://www.ypo.org/join-ypo/.](http://www.ypo.org/join-ypo/) Accessed September 19, 2013.
- 2. Anonymous Wizard. Available at [http://www.promega.com/resources/protocols/technical](http://www.promega.com/resources/protocols/technical-manuals/0/wizard-genomic-dna-purification-kit-protocol/)[manuals/0/wizard-genomic-dna-puri](http://www.promega.com/resources/protocols/technical-manuals/0/wizard-genomic-dna-purification-kit-protocol/)fication-kit-protocol/. Accessed September 19, 2013.
- 3. Anonymous Illumina. Available at<http://www.illumina.com>. Accessed September 19, 2013.
- 4. Anonymous NimbleGen Roche. Available at [http://www.nimblegen.com/products/seqcap/ez/](http://www.nimblegen.com/products/seqcap/ez/v2/index.html) [v2/index.html](http://www.nimblegen.com/products/seqcap/ez/v2/index.html). Accessed September 19, 2013.
- 5. Agilent Technologies Agilent SureSelect array. Available at [http://www.genomics.agilent.](http://www.genomics.agilent.com/en/Exome-Sequencing/SureSelect-Human-All-Exon-Kits/?cid=cat240002%26tabId=AG-PR-1204) [com/en/Exome-Sequencing/SureSelect-Human-All-Exon-Kits/?cid](http://www.genomics.agilent.com/en/Exome-Sequencing/SureSelect-Human-All-Exon-Kits/?cid=cat240002%26tabId=AG-PR-1204)=cat240002&tabId=AG-PR-[1204.](http://www.genomics.agilent.com/en/Exome-Sequencing/SureSelect-Human-All-Exon-Kits/?cid=cat240002%26tabId=AG-PR-1204) Accessed September 19, 2013.
- 6. Anonymous Complete Genomics Inc. Available at [http://www.completegenomics.com.](http://www.completegenomics.com) Accessed September 19, 2013.
- 7. Novocraft.com (2012) Available at [http://www.novocraft.com.](http://www.novocraft.com) Accessed September 19, 2013.
- 8. SAMtools. Available at<http://samtools.sourceforge.net/>. Accessed September 19, 2013.
- 9. Picard. Available at<http://picard.sourceforge.net/>. Accessed September 19, 2013.

The results of the anonymous online survey showed that, overall, participants were motivated to take part in the project to receive their genetic results and learn about their personal risk of disease. Seventy-nine percent of respondents reported that the opportunity to receive their personal genetic results was the most important factor in their decision to take part in the project, whereas another 10% cited a personal interest in genetics in general. When asked to choose which factor was most important in their decision to receive their personal genetic results, most respondents (52%) reported that their interest in finding out their personal risk for diseases was the most important factor; other important factors included the desire to get information about risk of health conditions for their children (17%), the desire to learn more about the medical conditions in their family (10%), and curiosity about their genetic makeup (10%).

Ninety-seven percent of respondents agreed or strongly agreed that they were glad that they decided to participate in this study and receive their personal results, leaving only 3% undecided. Most respondents (72%) spoke with their primary care provider about their results, and 50% reported that they spoke with other medical professionals, including cardiologists, oncologists, and obstetricians/gynecologists, among others; 22% reported that they had their twice-confirmed research results confirmed in a CLIA-certified laboratory.

Twenty-five percent of respondents reported that the test results motivated them to make changes to their health care (i.e., undergoing tests, seeing a specialist, taking vitamins or herbal supplements), exercise, medications, or insurance (Table S11).

Respondents generally felt that researchers should offer personalized results to research participants: 54% felt that researchers are obligated to offer results, 22% felt that researchers are obligated to offer results only if the researcher is a physician, and the remaining 24% did not think researchers were obligated to offer results. Respondents were pleased with the methods by which they were given their results in this study, with 95% agreeing or strongly agreeing that they were glad the researchers sent them a personalized results report, and 100% agreeing or strongly agreeing that they found the in-person consultation about their results very helpful. When asked, 94% said they would also want an electronic record of their entire genome if it were available.

When asked about genetic testing in health care, 83% reported that they felt that genetic testing should be a regular part of health care and 97% agreed or strongly agreed that they felt comfortable using these results to make decisions about their health. Nevertheless, respondents were evenly split when asked if they thought these results should be part of their medical record.

In summary, our poststudy surveys indicated that volunteers were motivated to gain personal and family health knowledge, satisfied with the translation of the genetic information, and had a divided opinion about incorporating their genetic information into their medical records.

- 10. McKenna A, et al. (2010) The Genome Analysis Toolkit: A MapReduce framework for analyzing next-generation DNA sequencing data. Genome Res 20(9):1297–1303.
- 11. Cingolani P snpEff: SNP effect predictor. Available at [http://snpeff.sourceforge.net/.](http://snpeff.sourceforge.net/) Accessed September 19, 2013.
- 12. Cingolani P, et al. (2012) A program for annotating and predicting the effects of single nucleotide polymorphisms, SnpEff: SNPs in the genome of Drosophila melanogaster strain w1118; iso-2; iso-3. Fly (Austin) 6(2):80–92.
- 13. San Lucas FA, Wang G, Scheet P, Peng B (2012) Integrated annotation and analysis of genetic variants from next-generation sequencing studies with variant tools. Bioinformatics 28(3):421–422.
- 14. Wang K, Li M, Hakonarson H (2010) ANNOVAR: functional annotation of genetic variants from high-throughput sequencing data. Nucleic Acids Res 38(16):e164.
- 15. Kuhn RM, Haussler D, Kent WJ (2013) The UCSC genome browser and associated tools. Brief Bioinform 14(2):144–161.
- 16. Stenson PD, et al. (2012) The Human Gene Mutation Database (HGMD) and its exploitation in the fields of personalized genomics and molecular evolution. Curr Protocol Bioinform.
- 17. Stenson PD, et al. (2009) The Human Gene Mutation Database: 2008 update. Genome Med 1(1):13.
- 18. Anonymous NCBI OMIM Online Mendelian Inheritance in Man. Available at [http://www.](http://www.ncbi.nlm.nih.gov/omim) [ncbi.nlm.nih.gov/omim.](http://www.ncbi.nlm.nih.gov/omim) Accessed September 19, 2013.
- 19. Anonymous Online Mendelian Inheritance in Man OMIM. Available at [http://omim.](http://omim.org) [org](http://omim.org). Accessed September 19, 2013.
- 20. Anonymous Genetic Testing Registry (GeneTests). Available at [http://www.genetests.](http://www.genetests.org) [org](http://www.genetests.org). Accessed September 19, 2013.
- 21. Adzhubei IA, et al. (2010) A method and server for predicting damaging missense mutations. Nat Methods 7(4):248–249.
- 22. Kumar P, Henikoff S, Ng PC (2009) Predicting the effects of coding non-synonymous variants on protein function using the SIFT algorithm. Nat Protoc 4(7):1073–1081.
- 23. Sim NL, et al. (2012) SIFT web server: predicting effects of amino acid substitutions on proteins. Nucleic Acids Res 40(Web Server issue):W452–W457.
- 24. Hu J, Ng PC (2012) Predicting the effects of frameshifting indels. Genome Biol 13(2):R9. 25. Ng PC, Henikoff S (2001) Predicting deleterious amino acid substitutions. Genome Res 11(5):863–874.
- 26. Ng PC, Henikoff S (2003) SIFT: Predicting amino acid changes that affect protein function. Nucleic Acids Res 31(13):3812–3814.
- 27. Ng PC, Henikoff S (2006) Predicting the effects of amino acid substitutions on protein function. Annu Rev Genomics Hum Genet 7:61–80.
- 28. Schwarz JM, Rödelsperger C, Schuelke M, Seelow D (2010) MutationTaster evaluates disease-causing potential of sequence alterations. Nat Methods 7(8): 575–576.
- 29. Liu X, Jian X, Boerwinkle E (2011) dbNSFP: a lightweight database of human nonsynonymous SNPs and their functional predictions. Hum Mutat 32(8):894–899.
- 30. Anonymous NHLBI Exome Sequencing Project (ESP) exome variant server. Available at <http://evs.gs.washington.edu/EVS/>. Accessed September 19, 2013.
- 31. Clarke L, Zheng-Bradley X, et al. (2012) The 1000 Genomes Project: Data management and community access. Nat Methods 9(5):459–462.
- 32. Abecasis GR, et al.; 1000 Genomes Project Consortium (2010) A map of human genome variation from population-scale sequencing. Nature 467(7319): 1061–1073.
- 33. Robinson JT, et al. (2011) Integrative genomics viewer. Nat Biotechnol 29(1):24–26.
- 34. Complete genomics (data file format standard pipeline version 2.0). Available at [http://www.completegenomics.com/customer-support/documentation/100357139.html.](http://www.completegenomics.com/customer-support/documentation/100357139.html) Accessed September 19, 2013.
- 35. Green RC, Berg JS, et al. (2013) ACMG recommendations for reporting of incidental findings in clinical exome and genome sequencing. Genet Med 15(7): 565–574.





Fig. S1. Grouping genes by occurrence. Frequency of genes with nonsynonymous coding mutations in our cohort. This graphic provides a summary of the number of times alleles were observed for an individual gene. In each of these cases, the allele was either part of HGMD or OMIM, rare, and carried a high polyphen2 score. An example of a gene with frequent risk alleles include Titin, the largest genes in our genome and recently reported to be causative of dilated cardiomyopathy. A second example of a smaller gene with a large number of variations is CFTR, where the disease database is deep, and it is known to be one of the most common autosomal recessive diseases in whites. This graphic supports that we did not select polymorphic genes but unique mutations in each volunteer.



Fig. S2. Variants detected using Complete Genomics Inc. (CGI) and Illumina. (Left) Comparison of nonsynonymous coding SNPs (NSCS) obtained from Complete Genomics (red) and Illumina (green). Twenty-four human samples were sequenced using both technologies, and NSCS were compared in each sample. The average results were calculated and graphed as a venn diagram. The intersection represents the set of NSCS detected by both technologies. On average, 73% of the NSCS detected by CGI were also detected by Illumina, while 82% of the NSCS detected by Illumina were also detected by CGI. (Right) Using the same samples we calculated that 96% of all the CGI NSCS are considered "High Quality" according to the CGI proprietary quality matrix. An average of 72% of all the NSCS detected by CGI was also detected by Illumina (blue). Since two orthogonal sequence technologies detected the same set of NSCS, this group of variants most likely represents a set of real variants which we refer to as "Highly reliable NSCS." The set of "Highly reliable NSCS" were used to establish quality criteria in our Illumina's variant detection pipeline.

#### Table S1. Disease associations with alleles



NA, not available.

PNAS PNAS





—, negative; IP, research in progress.

#### Table S3. Recessive disorders

PNAS PNAS



# Table S4. X-linked recessive



#### Table S5. Breast cancer risk



NA, not available.

#### Table S6. Colon cancer risk



NA, not available.

PNAS PNAS

## Table S7. Other cancer risk



NA, not available.

## Table S8. Cardiomyopathy-affected volunteers

PNAS PNAS



CAD, coronary artery disease; MI, myocardial infarction; NA, not available.

## Table S9. Cardiomyopathy unaffected but family history



## Table S10. Neurodegenerative risk

PNAS PNAS



#### Table S11. Percentage of survey respondents reporting having made behavioral changes specifically motivated by their test results

