

RESEARCH ARTICLE

“Morphology is the Link Between Genetics and Function”: A Tribute to Ewald R. Weibel

A systematic analysis of protein-altering exonic variants in chronic obstructive pulmonary disease

Matthew Moll,^{1,2}  Victoria E. Jackson,^{3,4,5} Bing Yu,⁶ Megan L. Grove,⁶  Stephanie J. London,⁷  Sina A. Gharib,⁸ Traci M. Bartz,^{9,10} Colleen M. Sitlani,¹⁰  Josée Dupuis,¹¹ George T. O'Connor,¹² Hanfei Xu,¹¹ Patricia A. Cassano,^{13,14} Bonnie Kaufmann Patchen,¹³  Woo Jin Kim,¹⁵ Jinkyong Park,^{1,16} Kun Hee Kim,¹⁷ Buhm Han,¹⁸ R. Graham Barr,¹⁹ Ani Manichaikul,²⁰ Jennifer N. Nguyen,²⁰ Stephen S. Rich,²⁰ Lies Lahousse,^{21,22} Natalie Terzikhan,²¹  Guy Brusselle,²¹ Phuwat Sakornsakolpat,²³  Jiangyuan Liu,¹  Christopher J. Benway,¹ Ian P. Hall,²⁴ Martin D. Tobin,^{3,25} Louise V. Wain,^{3,25} Edwin K. Silverman,^{1,26} Michael H. Cho,^{1,2,26*} and  Brian D. Hobbs^{1,2,26*}

¹Channing Division of Network Medicine, Department of Medicine, Brigham and Women's Hospital, Boston, Massachusetts;

²Division of Pulmonary and Critical Care Medicine, Department of Medicine, Brigham and Women's Hospital, Boston, Massachusetts; ³Department of Health Sciences, University of Leicester, Leicester, United Kingdom; ⁴Population Health and Immunity Division, The Walter and Eliza Hall Institute of Medical Research, Parkville, Victoria, Australia; ⁵Department of Medical Biology, University of Melbourne, Parkville, Victoria, Australia; ⁶School of Public Health, University of Texas Health Science Center, Houston, Texas; ⁷Epidemiology Branch, National Institute of Environmental Health Sciences, National Institutes of Health, Department of Health and Human Services Research, Research Triangle Park, Durham, North Carolina; ⁸Center for Lung Biology, Division of Pulmonary and Critical Care Medicine, Department of Medicine, University of Washington, Seattle, Washington; ⁹Department of Biostatistics, University of Washington, Seattle, Washington;

¹⁰Cardiovascular Health Research Unit, Department of Medicine, University of Washington, Seattle, Washington; ¹¹Department of Biostatistics, Boston University School of Public Health, Boston, Massachusetts; ¹²Division of Pulmonary, Allergy, Sleep, and Critical Care Medicine, Department of Medicine, Pulmonary Center, Boston University School of Medicine, Boston Medical Center, Boston, Massachusetts; ¹³Division of Nutritional Sciences, Cornell University, Ithaca, New York; ¹⁴Division of Epidemiology, Department of Population Health Sciences, Weill Cornell Medicine, New York, New York; ¹⁵Department of Internal Medicine, Kangwon National University, Chuncheon, South Korea; ¹⁶Department of Internal Medicine, Dongguk University Ilsan Hospital, Goyang-Si, Gyeonggi-do, South Korea; ¹⁷Department of Convergence Medicine and Asan Medical Center, University of Ulsan College of Medicine, Seoul, Korea; ¹⁸Department of Medicine, Seoul National University College of Medicine, Seoul, South Korea; ¹⁹Department of Medicine, Columbia University Medical Center, New York, New York; ²⁰Center for Public Health Genomics, University of Virginia, Charlottesville, Virginia; ²¹Department of Epidemiology, Erasmus University Medical Center, Rotterdam, The Netherlands; ²²Department of Bioanalysis, Ghent University, Ghent, Belgium; ²³Department of Medicine, Faculty of Medicine Siriraj Hospital, Mahidol University, Bangkok, Thailand; ²⁴NIHR Nottingham Biomedical Research Centre, Queen's Medical Centre, Nottingham, United Kingdom; ²⁵National Institute for Health Research Leicester Respiratory Biomedical Research Centre, Glenfield Hospital, Leicester, United Kingdom; and ²⁶Harvard Medical School, Boston, Massachusetts

Abstract

Genome-wide association studies (GWASs) have identified regions associated with chronic obstructive pulmonary disease (COPD). GWASs of other diseases have shown an approximately 10-fold overrepresentation of nonsynonymous variants, despite limited exonic coverage on genotyping arrays. We hypothesized that a large-scale analysis of coding variants could discover novel genetic associations with COPD, including rare variants with large effect sizes. We performed a meta-analysis of exome arrays from 218,399 controls and 33,851 moderate-to-severe COPD cases. All exome-wide significant associations were present in regions previously identified by GWAS. We did not identify any novel rare coding variants with large effect sizes. Within GWAS regions on chromosomes 5q, 6p, and 15q, four coding variants were conditionally significant ($P < 0.00015$) when adjusting for lead GWAS single-nucleotide polymorphisms. A common gasdermin B (*GSDMB*) splice variant (rs11078928) previously associated with a decreased risk for asthma was nominally associated with a decreased risk for

* M. H. Cho and B. D. Hobbs contributed equally to this work.

Correspondence: B. D. Hobbs (rebdb@channing.harvard.edu); M. H. Cho (remhc@channing.harvard.edu).

Submitted 11 January 2021 / Revised 15 April 2021 / Accepted 27 April 2021



COPD [minor allele frequency (MAF)=0.46, $P = 1.8\text{e-}4$]. Two stop variants in coiled-coil α -helical rod protein 1 (*CCHCR1*), a gene involved in regulating cell proliferation, were associated with COPD (both $P < 0.0001$). The *SERPINA1* Z allele was associated with a random-effects odds ratio of 1.43 for COPD (95% confidence interval = 1.17–1.74), though with marked heterogeneity across studies. Overall, COPD-associated exonic variants were identified in genes involved in DNA methylation, cell-matrix interactions, cell proliferation, and cell death. In conclusion, we performed the largest exome array meta-analysis of COPD to date and identified potential functional coding variants. Future studies are needed to identify rarer variants and further define the role of coding variants in COPD pathogenesis.

chronic obstructive pulmonary disease; exome; exon; functional; genomics

INTRODUCTION

Chronic obstructive pulmonary disease (COPD) is characterized by irreversible airflow limitation (1) and is one of the leading causes of morbidity and mortality worldwide (2). Genome-wide association studies (GWASs) have lent considerable insight into the genetic risk to COPD (3–7). Most GWAS variants are noncoding and are thought to affect COPD susceptibility through gene regulation (8). As such, identifying disease-causing variants in COPD GWAS regions remains challenging. Whereas coding regions make up only ~1% of the genome, ~10% of GWAS signals in complex diseases are attributable to nonsynonymous variants (8). Specific rare coding variants may confer a particularly high risk for complex diseases such as COPD. For example, α -1 antitrypsin deficiency (AATD) is associated with an ~15-fold increased odds for emphysema (9) and is most commonly caused by homozygosity for the Serpin Family A Member 1 (*SERPINA1*) Z allele (rs28929474), which is a missense variant found in ~2%–3% of the United States population (10). Exome sequencing of a French-Canadian family with early-onset emphysema identified a rare nonsynonymous causal variant in protein tyrosine phosphatase nonreceptor type 6 (*PTPN6*) (11). Germline mutations in telomerase genes have been observed in severe COPD cases (12). Thus, examining coding variants across the genome may identify important functional (protein-altering) variants associated with COPD.

Exome arrays were designed to allow genotyping of a large fraction of functional (nonsynonymous, splice, stop-gain) variants across the genome (13), and association analyses have been reported for COPD and lung function (14–16). However, several important questions regarding the utility of exome array studies in COPD remain unanswered. It is not known whether increasing sample size and power will identify novel rare coding variants that markedly increase COPD risk. There have since been several large-scale GWASs for lung function and COPD, yet GWASs have poor coverage of exonic variants and are not intended to identify rare coding variants; exome array results have not been directly compared with GWAS results, which may elucidate the functional variants being tagged by GWAS-identified single-nucleotide polymorphisms (SNPs). Although the *SERPINA1* Z allele (rs28929474) is a known risk factor for COPD—even in heterozygous individuals (17)—the largest GWASs to date (3, 4, 6, 7) did not identify an association of the *SERPINA1* Z allele with COPD or lung function; one reason for this result may be the smoking-dependent effects of the Z allele and/or imputation inaccuracies, as the Z allele is not present on most genotyping arrays. However, the Z allele is present on exome arrays, allowing for direct assessment of the

association of the Z allele with COPD risk. Further, many COPD case-control studies intentionally exclude ZZ individuals, which could introduce selection bias. A gene-by-environment interaction of cigarette smoking may be important for *SERPINA1* variants to contribute to COPD (18), which may affect the association of the Z allele on COPD in population-based cohorts (as opposed to COPD cohorts enriched for cigarette smoking).

We hypothesized that a larger exome array meta-analysis would provide increased power to detect rare and poorly imputed functional exonic variants associated with COPD and to identify the most likely causal variants in previously defined COPD GWAS regions. We also leveraged the exome array data to assess effect size heterogeneity of the Z allele across studies.

METHODS

Study Cohorts

We included 12 cohorts in our analysis: ARIC (Atherosclerosis Risk in Communities) study with African ancestry (Aa) and European ancestry (Ea) participants (19); CHS (Cardiovascular Health Study) including Ea and Aa participants (20); COPDGene (Genetic Epidemiology of COPD) with non-Hispanic White (NHW) and African American (AA) participants (21); EOCOPD/ICGN [Boston Early-Onset COPD (22, 23) and International COPD Genetics Network (24)] studies; the FHS (Framingham Heart Study) (25–27); HABC (Health, Aging, and Body Composition) study with Ea and Aa participants (28); KARE (Korean Association Resource) study (29); MESA (Multi-Ethnic Study of Atherosclerosis) including non-Hispanic African American, Chinese American, Hispanic, and non-Hispanic White subpopulations (30, 31); RS (Rotterdam Study) (32, 33); TCGS (Transcontinental COPD Genetics Study) from Poland and South Korea (34); UK COPD Exome Chip Consortium (UKECC) (16); and UK Biobank (35). Moderate-to-severe COPD was primarily defined by prebronchodilator forced expiratory volume in 1 s (FEV_1)/forced vital capacity (FVC) ratio < 0.7 and $\text{FEV}_1 < 80\%$ predicted; postbronchodilator measures were only performed in a minority of studies and were used when available. Individual study details, including genotyping methods, are available in the Supplemental Materials.

Statistical Analyses

Genetic association analysis was performed for case-control moderate-to-severe COPD status using an additive genetic model adjusted for age, sex, cigarette smoking pack-years, and principal components of genetic ancestry. In the

family-based studies, including FHS and EOCOPD/ICGN, we utilized logistic regression with generalized estimating equations to adjust for familial clustering. Quality control on summary statistics from all cohorts was performed with EasyQC (36) to ensure common variant names and reference strand across cohorts and minor allele count (MAC) > 10 within each cohort. In addition to these exome array results, we also included the subset of matching variants (MAC > 4) in a case-control association analysis of UK Biobank (4); models were adjusted for age, sex, pack-years of smoking, ever smoking (when available), and principal components of genetic ancestry.

Power calculations were performed using the genome association study (GAS) calculator available at http://csg.sph.umich.edu/abecasis/cats/gas_power_calculator/index.html (37), based on a COPD prevalence of 0.10 (38, 39). To account for relatedness among individuals, total effective sample size was calculated as previously described (40) and used in power calculations to approximate the number of independent individuals represented by our sample. The total effective sample size was 53,117.

We performed an inverse-variance fixed-effects meta-analysis of exome array results with METAL (41) and limited our analysis to putative functional (nonsynonymous, stop, and splice) variants, which were annotated using WANNVAR (42). Variants were considered for analysis if they were present in the UK Biobank and at least half of the other cohorts. Exome-wide significance was determined using Bonferroni adjustment ($P < 0.05/20,536$ variants $< 2.4 \times 10^{-6}$). Replication of signals from previously reported exome array studies (14–16) was defined as a consistent direction of effect and exome-wide statistical significance. Plink v1.9 (43) clump was used to choose a single “index” variant from all variants with $R^2 \geq 0.2$ in each significantly associated genetic locus. We also performed a targeted analysis of splice and stop variants, considering P values below a Bonferroni-adjusted threshold ($P < 0.05/\text{number-of-stop/splice-variants} < 0.05/257 < 0.00019$) to be nominally significant. We examined the relative association of exome-wide significant COPD variants with the spirometric parameters FEV₁ and FEV₁/FVC in the GWAS results from Shrine et al. (3). As genetic effects may vary with age, we examined whether age modifies the effect of exome-wide significant variants in the UK Biobank. In addition, we evaluated the association of alleles with age of COPD diagnosis in the COPDGene study. To examine the differential effects of associated variants based on smoking exposure, we performed stratified analyses in ever versus never smokers and heavy (>20 pack-years) versus light (≤ 20 pack-years) smokers in UK Biobank and compared effect sizes between strata.

To determine whether the exome signals were novel, or accounted for by previously described associations, index exonic variants from each locus were compared with prior COPD and lung function GWAS results (3, 4, 6, 7, 26) and were considered distinctly associated if outside of a 2-Mb window. For SNPs within this 2-Mb window, we assessed linkage disequilibrium (LD) between exonic variants and prior GWAS variants by calculating an R^2 value using a reference panel of 10,000 randomly selected UK Biobank participants (4). To determine if exonic SNPs were distinct from previously described lead GWAS variants, we used results

from GCTA-conditional and joint (COJO) analyses (44) from a prior GWAS, as exome arrays do not assay genome-wide variants (4). Being previously performed, this conditional and joint (COJO) analysis was necessarily limited to variants and cohorts present in the prior GWAS (i.e., all cohorts in the current analysis except HABC and UK COPD Exome Chip Consortium). We calculated a conditionally significant P value threshold by performing a Bonferroni correction for the total number of functional exonic variants genotyped within 2 Mb of the index GWAS variants in which exome-wide significant variants were found [$0.05/340$ variants (across all regions) = 0.000147].

To examine whether exonic SNPs explained the lead signal at previously reported GWAS loci, we examined whether the exonic variant was present within the 99% credible sets from a recent COPD GWAS (4), obtained using the method of Wakefield et al. (45). We also evaluated predicted functional consequences of amino acid mutations using PolyPhen 2.0 and scaled CADD (Combined Annotation-Dependent Depletion) scores (46, 47). Briefly, CADD scores are based on a support vector machine model predicting the relative deleteriousness of a mutation within a data set; scaling these scores on a rank order magnitude scale allows for external comparisons. For example, a scaled CADD score of 10 means the mutation is in the top 10% of deleterious mutations, a scaled CADD score of 20 means the mutation is in the top 1% of deleterious mutation, and so forth (46, 47). To gain insight into potential biological pathways affected by exonic variants, we also queried gene names at genetics.opentargets.org, which reports relevant biological pathways based on the Reactome Database of Pathways (48, 49).

We performed expression quantitative trait locus (eQTL) lookups for COPD-associated exonic variants, extracting eQTL-regulated genes (eGenes) with $P_{\text{eQTL}} < 1 \times 10^{-8}$ from prior publications and publicly available data. We queried four previously published eQTL data sources, including GTEx (www.gtexportal.org) (50, 51) analysis release V6, cis- and trans-eQTLs from Westra et al. (52), lung tissue eQTLs from the Hao et al. (53) study of asthma, and cis- and trans-eQTLs from the Vosa et al. (54) study in the eQTLGen Consortium. For all eQTL sources, a false discovery rate (FDR) of < 0.05 was considered a statistically significant eQTL association. Due to sparsity inherent to exome array association analyses, colocalization with eQTLs could not be performed. Therefore, for each COPD-associated exonic variant that was an eQTL for an eGene, we calculated R^2 values between the COPD-associated eQTL and the eGene's sentinel eQTL SNP using the UK Biobank as an LD reference panel, considering an $R^2 > 0.2$ to be indicative of a shared causal variant in the eQTL and exome array analyses. Sentinel eQTL SNPs for each eGene were defined as the eQTL SNP with the lowest P value. Protein QTL (pQTL) analyses were performed by querying SNP-regulated proteins from Sun et al. (56) and considering P values less than a Bonferroni-corrected threshold ($0.05/128,037$ SNP-protein pairs = 3.9×10^{-7}) to be statistically significant.

We also examined the association of the nonsynonymous SERPINA1 Z allele (rs28929474), the most common cause of α -1 antitrypsin deficiency, with COPD in our study. For the Z allele, we examined the impact of including Z allele homozygotes in a study. For COPD-associated functional exonic

variants and the Z allele, we constructed forest plots using the meta R package (57). To examine heterogeneity across studies, we performed meta-regression (57) of COPD-associated variant effect sizes across studies, evaluating the contribution of age, FEV₁% predicted, pack-years of smoking, and whether studies excluded ZZ homozygotes (for the Z allele) to individual variant effect sizes.

RESULTS

Characteristics of Cohorts

Characteristics of study participants in each cohort are shown in Table 1. In total, there were 218,399 controls and 33,851 moderate-to-severe COPD cases, which provided 99% power to detect variants with an MAF of 0.01 and an odds ratio of 1.3. (Supplemental Table S1; all Supplemental material is available at <https://doi.org/10.6084/m9.figshare.14538222.v1>). The cohorts were diverse with respect to case ascertainment, sex distribution, cigarette smoking history, and ancestry. For example, COPDGene, BEOCPD, ICGN, TCGS (Korea and Poland), and the UK COPD Exome Chip Consortium were COPD case-control studies, and thus, the participants were enriched for COPD cases, ever-smoking status, pack-years of smoking, and lower FEV₁% predicted compared with individuals in the population-based cohorts. TCGS-Korea had the highest percentage of males (>95%) in both case and control participants, whereas the lowest proportion of males was observed among cases in BEOCPD (39.9%) and controls (27.6%) in CHS Aa. Among COPD cases, there was a predominance of males, with 14 cohorts reporting over 55% of cases to be male. With respect to genetic ancestry, there were 7,493 African (including African Americans), 236,312 European, 7,771 East Asian, and 674 Hispanic participants. Not

surprisingly, with this sample size and the different cohort characteristics, all of the ANOVA or chi-squared *P* values across studies were significant ($P < 1 \times 10^{-3}$).

Exome Chip Meta-Analysis

An overview of the study design is shown in Fig. 1. Exome arrays containing 109,036 nonsynonymous, stop, and splice variants from International COPD Genetics Consortium (ICGC) ($n = 51,458$) and UK Biobank ($n = 200,792$) were meta-analyzed; 20,536 variants were reported in UK Biobank and $\geq 50\%$ of the other studies. The distribution of variant allele frequencies is shown in Supplemental Fig. S1. Of these, 80 variants reached exome-wide Bonferroni-adjusted level of significance ($P < 2.4 \times 10^{-6}$) (Fig. 2 and Supplemental Table S2). After clumping, these 80 variants were represented by 35 lead variants. All 35 lead variants were within 2Mb of previously reported GWAS SNPs (Table 2). Eight of these variants met the criteria (see METHODS) for replication of exonic signals from prior exome array and genome-wide studies (Supplemental Table S3). Twenty-one exonic variants were in low LD ($R^2 < 0.2$) with nearby GWAS variants.

Of the 35 exome-wide significant lead variants, we identified four novel conditionally significant exonic SNPs (Table 3), meaning that these SNPs were within 2Mb of COPD GWAS variants, though retained regional significance after conditioning on the lead COPD GWAS SNP using GCTA-COJO (Bonferroni P value = 0.05/340 variants = 0.000147; see MATERIALS AND METHODS). Seven of the 35 exonic variants were index variants, so conditional and joint analyses were not performed for these variants (rs721917, rs28929474, rs12373142, rs11205303, rs2571445, rs1800888, and rs1334576) (4). The rs2454206 variant in tet methylcytosine dioxygenase 2 (*TET2*) was significant

Table 1. Characteristics of cohorts in meta-analysis

Cohort	<i>n</i>		Age in Years, Mean \pm SD		Males, %		Pack Years of Smoking, Mean \pm SD		FEV ₁ (% Predicted)	
	Cases	Controls	Cases	Controls	Cases	Controls	Cases	Controls	Cases	Controls
ARIC AA	289	2,765	55.7 (5.84)	53.06 (5.73)	52.6	34.43	28.23 (29.4)	9.18 (16)	63.2 (13)	100.3 (12.5)
ARIC EA	1,284	7,405	56.33 (5.37)	53.73 (5.64)	56.15	44.09	37.73 (25.9)	11.83 (17.9)	65.5 (12.4)	100.7 (11)
BEOCPD	366	560	50.8 (8.2)	39.3 (12.2)	39.9	41.6	37.5 (16.5)	1.66 (14.2)	29.2 (22.6)	94.5 (8.5)
CHS AA	107	232	72.25 (4.91)	72.76 (5.25)	49.5	27.6	29.36 (24.4)	20.89 (20.4)	61.38 (13.4)	102.6 (15)
CHS EA	914	1,690	73.51 (5.72)	71.87 (5.11)	60.2	32.3	44.59 (28.9)	25.77 (23.7)	59.97 (15.6)	99.49 (13.6)
COPDGene AA	796	1,715	58.2 (6.6)	51.8 (3.8)	55.5	58.1	37.8 (13.8)	32.7 (11.1)	54 (13.1)	96.6 (9.4)
COPDGene NHW	2,777	2,507	65.2 (5.8)	59.3 (6.6)	55.7	49.4	49.8 (20.7)	35 (12)	50 (15.5)	95.5 (8.5)
FHS	625	4,959	61.96 (12.1)	51.63 (13.2)	51.04	44.69	37.22 (24.2)	15.47 (16.9)	66.4 (11)	102 (12)
HABC AA	126	817	73.3 (2.84)	73.43 (2.91)	67.46	42.59	38.99 (24.8)	27.34 (23.5)	59.83 (13.6)	101.6 (20.5)
HABC EA	213	1,259	73.53 (2.74)	73.75 (2.85)	56.34	52.9	49.71 (34.7)	33.36 (30.5)	62.79 (12.7)	97.7 (15.7)
ICGN	1,769	696	59.4 (4.2)	54.9 (5.8)	58.6	48.3	45 (19.5)	25.1 (13.7)	39.2 (13.5)	97.5 (10.5)
KARE	106	6,862	57.39 (8.14)	51.49 (8.64)	78.3	45.07	23.67 (25)	8.124 (14.7)	70.5 (8.6)	113.8 (16.3)
MESA Black	95	551	67.5 (8.95)	64.39 (9.39)	67.4	41.4	35 (25.5)	18.8 (17.8)	64.1 (13.9)	102.6 (14.4)
MESA Chinese	32	403	69.56 (9.09)	64.03 (9.34)	53.1	47.9	31.88 (21)	20.74 (18)	65.7 (13.4)	104.3 (14)
MESA Hispanic	61	613	67.74 (9.48)	62.82 (9.54)	63.9	43.2	33.73 (31.5)	15.82 (18)	65.3 (12.9)	100 (12.2)
MESA White	180	824	68.42 (8.87)	64.38 (9.61)	51.1	47	42.42 (33.2)	23.01 (22.7)	66.2 (12.1)	98.9 (11.7)
RS	60	415	80.1 (5.3)	79.6 (4.9)	70	52	30.3 (23.8)	14.3 (20.3)	66.5 (11.1)	111.6 (18.1)
TCGS Korea	149	219	69 (5)	53 (6)	99.3	96.8	40 (12)	25.5 (8.5)	33.2 (6.9)	93.6 (6.4)
TCGS Poland	304	307	62.2 (5.5)	58.3 (4.6)	70.1	67.4	40.3 (12.6)	32.3 (8.9)	28.7 (6.7)	102 (9)
UK Biobank	21,081	179,711	59.4 (7.3)	55.7 (8)	52	58	19.7 (23.9)	6.1 (12.5)	65.1 (11.8)	98.3 (11.4)
UK COPD Exome Chip Consortium	2,517	3,889	66.1 (7.74)	49 (6.08)	55.24	56.08	41.2 (24.4)	22.05 (15.6)	51.93 (10)	99.25 (10)

In total, there were 218,399 controls and 33,851 moderate-to-severe COPD cases. Aa, African ancestry; ARIC, Atherosclerosis Risk in Communities; CHS, Cardiovascular Health Study; COPD, chronic obstructive pulmonary disease; EOCOPD/ICGN, Early-Onset COPD study and International COPD Genetics Network; Ea, European ancestry; FHS, Framingham Heart Study; HABC, Health, Aging, and Body Composition; KARE, Korean Association Resource; MESA, Multi-Ethnic Study of Atherosclerosis; NHW, non-Hispanic White; RS, Rotterdam Study; TCGS, Transcontinental COPD Genetics Study; UKECC, UK COPD Exome Chip Consortium.

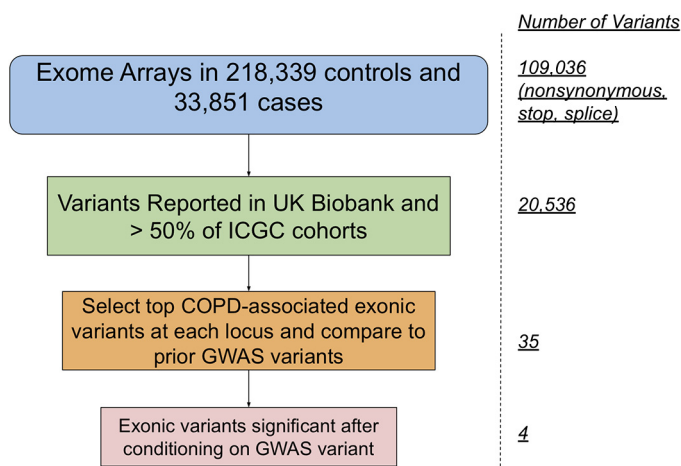


Figure 1. Overview of study design. COPD, chronic obstructive pulmonary disease; GWAS, genome-wide association studies.

after conditioning on the rs34712979 index variant, though this variant exists at a locus with two additional independent variants (rs2047409 and rs10516528) (5). We observed that the exonic rs2454206 variant association was no longer significant after conditioning on rs2047409 ($P = 0.24$). In stepwise joint modeling considering these four *TET2* locus variants, only rs2454206 and rs34712979 were selected for the final model.

We also evaluated the 35 exome-wide significant lead variants in the 99% credible sets for the COPD GWAS loci from Sakornsakolpat et al. (4) (Table 4); 18 lead exonic variants were present in the 99% credible sets. Three variants had a

posterior probability of association (PPA) > 10%, and 10 variants were in the top 20% of their respective credible sets (Supplemental Fig. S2), suggesting these are more likely to be causal variants. Only rs1334576 in *ras* responsive element binding protein 1 (*RREB1*) had a PPA > 10%, ranked within the top 20% of its credible set, and was predicted to be damaging by PolyPhen and CADD. The remaining 17 top exonic variants (Supplemental Table S4) were not present in their respective 99% credible set.

We also analyzed 257 stop or splice variants, of which two stop variants (rs3130453 and rs72856718) and one splice variant (rs11078928) reached Bonferroni-adjusted significance ($P < 0.00019$; see METHODS) (Supplemental Table S5). The stop variant rs3130453 (MAF = 0.49) in the coiled-coil α -helical rod protein 1 (*CCHCR1*) gene was associated with an odds ratio of 1.04 [95% confidence interval (CI) = 1.02–1.06, $P = 1.3 \times 10^{-5}$] for COPD. The rs72856718 stop variant (MAF = 0.09), also in the *CCHCR1* gene, was associated with an odds ratio of 1.08 (95% CI = 1.04–1.13, $P = 8.8 \times 10^{-5}$) for COPD. The splice variant, leading to an exon 6 deletion in gasdermin B (*GSDMB*), had an odds ratio of 1.04 (95% CI = 1.02–1.06, $P = 1.8 \times 10^{-4}$) in association with COPD. Forest plots for all exome-wide significant, stop, and splice variants are shown in Supplemental Fig. S3. Reactome pathways for the genes associated with conditionally significant, stop, and splice variants are shown in Supplemental Table S6. Twelve exonic variants (including stop/splice variants), many of which were highly correlated with each other (Fig. 3), are located within the complex human leukocyte antigen (HLA) region (hg19; chromosome 6:28477797–33448354).

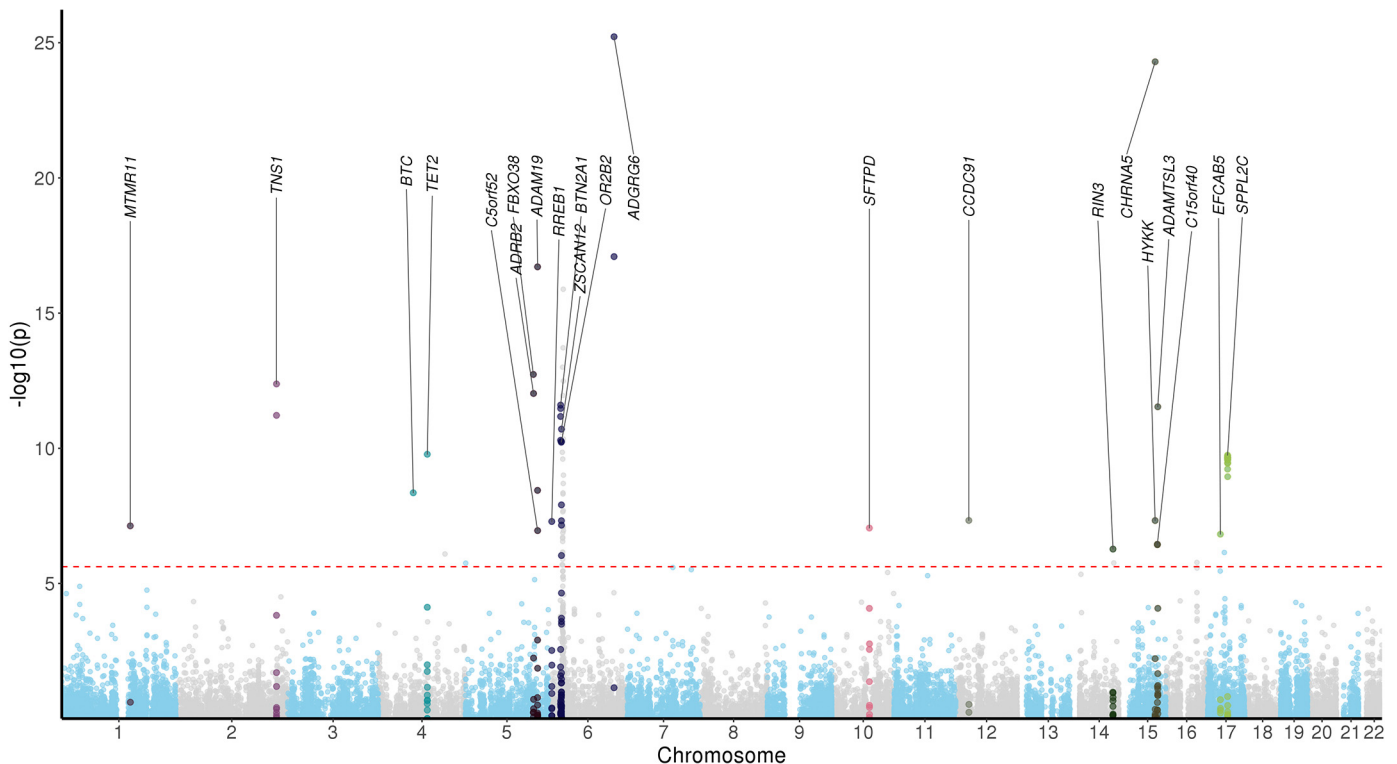


Figure 2. Manhattan plot of exome array variants. The horizontal red line indicates an exome-wide significance level of 2.4×10^{-6} . The exonic variants reaching exome-wide significance are annotated.

Table 2. Thirty-five lead exonic SNPs and nearby sentinel GWAS SNPs (within 2 Mb)

Exon rs No.	Chr	Position (hg19)	Risk Allele	Other Allele	Gene Name	Risk Allele Frequency	OR (95% CI)	P	GWAS rs No.	GWAS Closest Gene	R ²	Source	Trait
rs11205303	1	149906413	C	T	MTMR11	0.4	1.06 (1.03–1.08)	7.41E-08	rs11205354	C1orf54	0.0055**	Shrine (3)	PEF
rs2571445	2	218683154	A	G	TNS1	0.39	1.08 (1.05–1.1)	4.17E-13	rs2571445	TNS1	1	Shrine (3)	FEV ₁
rs11938093	4	75675841	A	T	BTC	0.74	1.07 (1.04–1.09)	4.44E-09	rs4585380	BTC	1	Sakornsakolpat (4)	Moderate COPD
rs2454206	4	106196951	G	A	TET2	0.38	1.07 (1.05–1.09)	1.67E-10	rs10516526	GSTCD	0.011**	Wain (6)	FEV ₁
rs10043775	5	147805120	T	C	FBXO38	0.73	1.09 (1.06–1.12)	1.86E-13	rs10037493	HTR4	0.31	Sakornsakolpat (4)	Moderate COPD
rs1800888	5	148206885	T	C	ADRB2	0.014	1.32 (1.22–1.42)	9.39E-13	rs1800888	ADRB2	1	Shrine (3)	FEV ₁
rs2287749	5	156918850	C	T	ADAM19	0.87	1.09 (1.06–1.12)	3.61E-09	rs72811310	ADAM19	0.8	Sakornsakolpat (4)	Moderate COPD
rs1422795	5	156936364	C	T	ADAM19	0.35	1.09 (1.07–1.11)	1.94E-17	rs1990950	ADAM19	0.31	Wain (6)	FEV ₁ /FVC
rs11740603	5	157098756	T	G	C5orf52	0.14	1.08 (1.05–1.11)	1.1E-07	rs1990950	ADAM19	0.029**	Wain (6)	FEV ₁ /FVC
rs1334576	6	7211818	A	G	RREB1	0.42	1.05 (1.03–1.07)	5.11E-08	rs1334576	RREB1	1	Sakornsakolpat (4)	Moderate COPD
rs13195509	6	26463660	A	G	BTN2A1	0.12	1.11 (1.08–1.15)	2.53E-12	rs2070600	AGER	0.0023**	Shrine (3)	FEV ₁ /FVC
rs61742093	6	27879982	G	A	OR2B2	0.11	1.11 (1.08–1.14)	5.98E-11	rs2070600	AGER	0.0026**	Shrine (3)	FEV ₁ /FVC
rs2232423	6	28366151	G	A	ZSCAN12	0.11	1.11 (1.08–1.15)	1.96E-11	rs2070600	AGER	0.0023**	Shrine (3)	FEV ₁ /FVC
rs3749971*	6	29342775	A	G	OR12D3	0.12	1.11 (1.08–1.14)	2.60E-11	rs2070600	AGER	0.003**	Shrine (3)	FEV ₁ /FVC
rs2523989*	6	30078275	T	C	TRIM31	0.17	1.09 (1.06–1.12)	1.40E-10	rs2070600	AGER	0.0012**	Shrine (3)	FEV ₁ /FVC
rs929156*	6	30139699	G	A	TRIM15	0.76	1.06 (1.04–1.09)	8.17E-08	rs2070600	AGER	0.044**	Shrine (3)	FEV ₁ /FVC
rs9262143*	6	30652781	T	C	PPR18	0.14	1.11 (1.08–1.15)	9.98E-14	rs2070600	AGER	0.0044**	Shrine (3)	FEV ₁ /FVC
rs2074506*	6	30890483	G	T	VARS2	0.65	1.06 (1.03–1.08)	2.79E-07	rs2070600	AGER	0.041**	Shrine (3)	FEV ₁ /FVC
rs7750641*	6	31129310	T	C	TCF9	0.15	1.11 (1.08–1.14)	1.1E-12	rs2070600	AGER	0.0078**	Shrine (3)	FEV ₁ /FVC
rs3101017*	6	31733466	C	T	VWA7	0.13	1.12 (1.09–1.15)	1.92E-14	rs2070600	AGER	0.0092**	Shrine (3)	FEV ₁ /FVC
rs2070600*	6	32151443	C	T	AGER	0.94	1.19 (1.15–1.25)	1.31E-16	rs2070600	AGER	1	Shrine (3)	FEV ₁ /FVC
rs7775397*	6	32261252	G	T	C6orf10	0.13	1.12 (1.08–1.15)	3.27E-13	rs2070600	AGER	0.011**	Shrine (3)	FEV ₁ /FVC
rs1129740*	6	32609105	A	G	HLA-DQA1	0.59	1.07 (1.04–1.09)	9.84E-10	rs2070600	AGER	0.033**	Shrine (3)	FEV ₁ /FVC
rs17280293	6	142688969	A	G	ADGRG6	0.97	1.32 (1.24–1.41)	8.13E-18	rs17280293	ADGRG6	1	Shrine (3)	FEV ₁ /FVC
rs1155242	6	142691549	A	C	ADGRG6	0.81	1.14 (1.11–1.17)	5.98E-26	rs9399401	ADGRG6	0.62	Sakornsakolpat (4)	Moderate COPD
rs721917	10	81706324	G	A	SFTPD	0.42	1.05 (1.03–1.07)	8.91E-08	rs721917	SFTPD	1	Shrine (3)	FEV ₁ /FVC
rs11049488	12	28412372	G	A	CCDC91	0.7	1.06 (1.04–1.08)	4.67E-08	rs11049386	PTH1H; CCDC91	0.83	Sakornsakolpat (4)	Moderate COPD
rs3829947	14	9318038	A	G	RIN3	0.45	1.05 (1.03–1.07)	5.35E-07	rs117068593	RIN3	0.18**	Wain (6)	FEV ₁
rs3885951	15	78825917	G	A	HYKK	0.096	1.09 (1.06–1.13)	4.71E-08	rs28534575	CHRNA4	0.026**	Sakornsakolpat (4)	Moderate COPD
rs16969968	15	78882925	A	G	CHRNA5	0.33	1.11 (1.09–1.14)	5.03E-25	rs28534575	CHRNA4	0.14**	Sakornsakolpat (4)	Moderate COPD
rs4842860	15	83680287	A	G	C15orf40	0.38	1.05 (1.03–1.07)	3.54E-07	rs1781169	BTBD1	0.44	Sakornsakolpat (4)	Moderate COPD
rs17361375	15	83680329	G	A	C15orf40	0.79	1.06 (1.04–1.09)	3.72E-07	rs1781169	BTBD1	0.33	Sakornsakolpat (4)	Moderate COPD
rs4842838	15	84582124	G	T	ADAMTS13	0.47	1.07 (1.05–1.09)	2.92E-12	rs1896797	SH3GL3	0.28	Shrine (3)	FEV ₁ /FVC
rs9897794	17	28296327	G	T	EFCAB5	0.48	1.05 (1.03–1.07)	1.51E-07	rs22444592	SSH2	0.71	Shrine (3)	FEV ₁ /FVC
rs12373142	17	43924200	G	C	SPPL2C	0.22	1.08 (1.05–1.1)	1.80E-10	rs12373142	SPPL2C	1	Sakornsakolpat (4)	Moderate COPD

*Variant location within HLA region (hg19; chromosome 6: 28477797–33448354). **R² < 0.2. Exonic variants were clumped prior to comparing with GWAS SNPs based on an R² > 0.2. References to GWAS variants are for the most recent publication. COPD, chronic obstructive pulmonary disease; GWAS, genome-wide association study; HLA, human leukocyte antigen; PEF, peak expiratory flow; SNPs, single-nucleotide polymorphisms.

Table 3. Conditionally significant exome array SNPs ($P < 0.000147$) within 2 Mb of GWAS SNPs identified in UK Biobank (4)

Chr	GWAS Index		Exonic Variant		B	SE	P	b (Conditional)	SE (Conditional)	P (Conditional)
	SNP	Exonic SNP	Gene Name	Risk Allele Frequency						
5	rs10866659	rs2287749	ADAM19	0.9	-0.089	0.014	1.00E-09	-0.057	0.014	4.30E-05
6	rs2284174	rs13195509	BTN2A1	0.069	0.12	0.015	7.80E-15	0.056	0.014	3.40E-05
15	rs10152300	rs17361375	C15orf40	0.81	-0.058	0.012	1.60E-06	-0.051	0.012	2.20E-05
15	rs10152300	rs4842860	C15orf40	0.65	0.043	0.0099	1.60E-05	0.04	0.0099	5.20E-05

Exonic variant effects were adjusted for the index SNPs indicated in the table. Chromosome positions based on build hg19. Note that the rs2454206 variant in *TET2* was significant after conditioning on the rs34712979 index variant, though this variant exists at a locus with two additional independent variants (rs2047409 and rs10516528) (5). We observed that the exonic rs2454206 variant was no longer significant after conditioning on rs2047409 ($P = 0.24$). Note that HLA imputation was not performed, so HLA region variants were not included in conditional and joint analyses. GWAS, genome-wide association study; HLA, human leukocyte antigen; SNPs, single-nucleotide polymorphisms.

Similar associations of variants in Table 2 were observed in a prior GWAS of FEV₁ and FEV₁/FVC, except that three variants (rs3885951, rs11078928, and rs28929474) did not reach our level of exome-wide significance for either GWAS phenotype (Supplemental Table S7). We also assessed for interactions of exome-wide significant variants in Table 2 with age in UK Biobank and found no significant interactions (all $P > 0.05$). Furthermore, we evaluated whether each of these variants was associated with earlier age of COPD diagnosis in the COPDGene cohort and observed that the smoking behavior-associated rs16969968 SNP in *CHRNA5* was associated with earlier age of COPD diagnosis ($P = 0.001$; Supplemental Fig. S4). Comparing ever with never smokers and heavy with light smokers, the effect sizes are generally similar between strata (Supplemental Fig. S5). The exceptions include rs1422795, rs2571446, and rs3829947 in ever versus never smokers and rs1422795 in heavy versus light smokers.

eQTL and pQTL analyses.

The correlations between the 35 lead exonic variants and sentinel eQTL SNPs (i.e., the eQTL SNP with the lowest P value of all eQTL SNPs assigned to an eGene) in which the LD R^2 is >0.2 are shown in Table 5, and the full set of eQTL-regulated SNPs are shown in Supplemental Table S8. Several exonic variants are associated with eQTL SNPs that regulate the same gene within lung tissue, including *FBXO38*, *ADGRG6*, *RREB1*, *C15orf40*, and *EFCAB5*. In pQTL analyses (56), 12 exonic variants were significantly associated with protein expression (Table 6).

SERPINA1 Z allele effects.

The *SERPINA1* Z allele rs28929474 was associated with a 1.18 odds ratio for COPD in the fixed-effects analysis (95% CI = 1.10–1.26, $P = 1.74\text{e-}6$) (Supplemental Table S5). In the

Table 4. Exome array variants identified in 99% credible sets derived from UK Biobank (4) using the method by Wakefield et al. (45) and wANNOVAR functional annotations

Chr	Exonic SNP	Gene Name	GWAS Index SNP		Rank	Percentile	Polyphen Prediction	Polyphen Rank	Amino Acid	Scaled CADD
			for Fine-Mapping*	PPA				Score	Change	
2	rs2571445	TNS1	218683154:A:G	0.58	1	100	Benign	0.013	W1197R	5.551
4	rs11938093	BTC	75673363:G:A	0.032	4	93	Probably damaging	0.739	L124M	24.4
5	rs10043775	FBXO38	148059519:G:A	0.00031	356	91	Benign	0.013	S592P	12.25
5	rs10043775	FBXO38	148203236:T:C	4.70E-05	471	84	Benign	0.013	S592P	12.25
5	rs10043775	FBXO38	148611623:C:A	7.60E-05	368	85	Benign	0.013	S592P	12.25
5	rs2287749	ADAM19	156948318:T:G	0.023	6	100	Possibly damaging	0.494	G660D	24.3
5	rs1422795	ADAM19	156937043:A:G	0.049	9	60	Benign	0.391	S284G	14.33
5	rs11740603	C5orf52	156948318:T:G	1.00E-05	3708	6.2	Possibly damaging	0.451	R45L	24.2
5	rs11740603	C5orf52	157002695:C:T	1.20E-05	1110	59	Possibly damaging	0.451	R45L	24.2
6	rs1334576	RREB1	7211818:G:A	0.14	1	100	Possibly damaging	0.594	G195R	12.63
6	rs17280293	ADGRG6	142814991:C:T	0.024	5	0	Possibly damaging	0.493	S123G	24.7
10	rs721917	SFTPD	81706324:A:G	0.23	1	100	Benign	0.013	M31T	0.003
12	rs11049488	CCDC91	28320536:T:A	0.0022	93	81	Benign	0.08	A36T	11.08
14	rs3829947	RIN3	92600798:G:T	5.20E-05	421	86	Benign	0.04	H215R	3.995
15	rs3885951	HYKK	78388464:C:T	6.60E-05	1189	67	Benign	0.104	K343E	18.98
15	rs3885951	HYKK	78923845:T:G	1.80E-05	944	66	Benign	0.104	K343E	18.98
15	rs16969968	CHRNA5	78898932:C:G	0.016	10	83	Benign	0.145	D398N	15.07
15	rs4842860	C15orf40	83693513:T:C	0.00088	70	78	Benign	0.013	C25R	0.029
15	rs17361375	C15orf40	83693513:T:C	0.00021	149	53	Benign	0.093	L11F	6.178
15	rs4842838	ADAMTSL3	84515943:C:G	3.30E-05	277	26	Benign	0.013	V661L	12.87
17	rs9897794	EFCAB5	28413129:T:C	0.0039	73	79	Benign	0.013	L237V	12.25
17	rs12373142	SPPL2C	43924200:C:G	0.03	1	100	Benign	0.139	P643R	0.117

PolyPhen and CADD were used to predict consequences of mutation. CADD scores are based on a support vector machine model predicting the relative deleteriousness of a mutation within a dataset; scaling these scores on a rank order magnitude scale allows for external comparisons. For example, a scaled CADD score of 10 means the mutation is in the top 10% of deleterious mutations, a scaled CADD score of 20 means the mutation is in the top 1% of deleterious mutation, and so forth (46, 47). Chromosome positions based on hg19. Percentile indicates the ranking of the exonic variant within the credible set of the GWAS index SNP. CADD, combined annotation dependent depletion; GWAS, genome-wide association study; PPA, posterior probability of association.

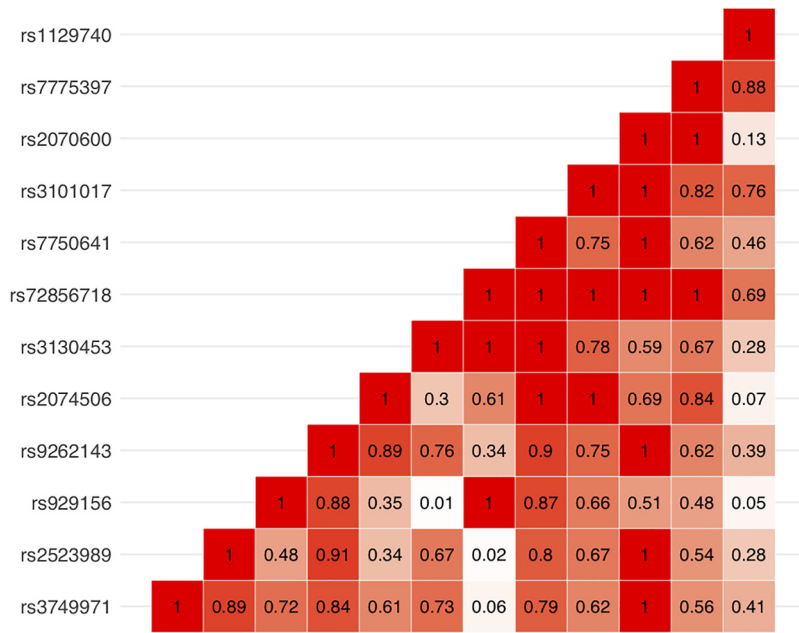


Figure 3. LD matrix (R^2) of exome array variants within the HLA region (hg19; 6:28477797-33448354). HLA, human leukocyte antigen; LD, linkage disequilibrium.

Z allele meta-analysis, there is evidence of heterogeneity ($I^2 = 0.6$), and the African Americans from the ARIC cohort exhibited an opposite direction of effect, which was not statistically significant (Fig. 4). Given the

observed Z allele effect size heterogeneity, we performed a random-effects meta-analysis, and the rs28929474 variant demonstrated association with a 1.43 odds ratio for COPD (95% CI = 1.17–1.74, $P = 0.0043$).

Table 5. Exon SNPs and sentinel eQTL SNPs with $R^2 > 0.2$ and P value (eQTL) $< 1e-8$

Chr	Exonic SNP	Gene Name	eQTL rs No.	eQTL-Regulated Gene	Direction of Effect	P Value	R^2	Source
5	rs10043775	FBXO38	rs6876982	FBXO38	+	2.00E-20	0.7	Hao et al. (53); lung cis-eQTL
6	rs11155242	ADGRG6	rs11155242	ADGRG6	–	5.20E-136	1	Vosa et al. (54); cis-eQTL
6	rs13195509	BTN2A1	rs35304979	BTN3A2	+	3.10E-82	0.84	GTEx lung
			rs3117425	BTN3A2	–	3.80E-45	0.59	Hao et al. (53); lung trans-eQTL
			rs149959	ZNF165	+	2.00E-09	0.27	Hao et al. (53); lung cis-eQTL
6	rs61742093	OR2B2	rs3117425	BTN3A2	–	3.80E-45	0.79	Hao et al. (53); lung trans-eQTL
			rs35304979	BTN3A2	+	3.10E-82	0.62	GTEx lung
			rs149959	ZNF165	+	2.00E-09	0.32	Hao et al. (53); lung cis-eQTL
6	rs2232423	ZSCAN12	rs3117425	BTN3A2	–	3.80E-45	0.85	Hao et al. (53); lung trans-eQTL
			rs35304979	BTN3A2	+	3.10E-82	0.58	GTEx lung
			rs149959	ZNF165	+	2.00E-09	0.31	Hao et al. (53); lung cis-eQTL
6	rs3749971*	OR12D3	rs3117425	BTN3A2	–	3.80E-45	0.92	Hao et al. (53); lung trans-eQTL
			rs35304979	BTN3A2	+	3.10E-82	0.5	GTEx lung
			rs149959	ZNF165	+	2.00E-09	0.26	Hao et al. (53); lung cis-eQTL
6	rs2523989*	TRIM31	rs3117425	BTN3A2	–	3.80E-45	0.54	Hao et al. (53); lung trans-eQTL
			rs35304979	BTN3A2	+	3.10E-82	0.28	GTEx lung
6	rs929156*	TRIM15	rs9261468	TRIM10	–	4.60E-11	0.89	Hao et al. (53); lung cis-eQTL
6	rs9262143*	PPP1R18	rs3117425	BTN3A2	–	3.80E-45	0.58	Hao et al. (53); lung trans-eQTL
			rs35304979	BTN3A2	+	3.10E-82	0.32	GTEx lung
6	rs7750641*	TCF19	rs114810457	AGER	+	4.20E-82	0.29	Vosa et al. (54); cis-eQTL
			rs3117425	BTN3A2	–	3.80E-45	0.41	Hao et al. (53); lung trans-eQTL
			rs35304979	BTN3A2	+	3.10E-82	0.22	GTEx lung
6	rs3101017*	VWA7	rs114810457	AGER	+	4.20E-82	0.37	Vosa et al. (54); cis-eQTL
			rs3117425	BTN3A2	–	3.80E-45	0.34	Hao et al. (53); lung trans-eQTL
6	rs7775397*	C6orf10	rs114810457	AGER	+	4.20E-82	0.39	Vosa et al. (54); cis-eQTL
			rs3117425	BTN3A2	–	3.80E-45	0.29	Hao et al. (53); lung trans-eQTL
6	rs1129740*	HLA-DQA1	rs9273500	HLA-DRA	–	2.60E-29	0.36	Vosa et al. (54); cis-eQTL
6	rs1334576	RREB1	rs2714341	RREB1	–	1.20E-86	0.34	Vosa et al. (54); cis-eQTL
15	rs16969968	CHRNA5	rs931794	PSMA4	+	5.60E-107	0.91	Vosa et al. (54); cis-eQTL
			rs12591557	PSMA4	–	3.30E-20	0.37	Hao et al. (53); lung cis-eQTL
15	rs4842860	C15orf40	rs6603041	C15orf40	+	3.10E-110	0.64	Vosa et al. (53); cis-eQTL
			rs6603041	C15orf40	+	9.70E-11	0.64	GTEx lung
17	rs9897794	EFCAB5	rs7501472	CORO6	+	3.00E-61	0.78	Vosa et al. (54); cis-eQTL
			rs4567782	EFCAB5	+	2.30E-09	0.97	Hao et al. (53); lung cis-eQTL
			rs3936006	EFCAB5	–	5.10E-74	0.93	Vosa et al. (54); cis-eQTL

*Indicates HLA region. eQTL, expression quantitative trait locus; HLA, human leukocyte antigen; SNPs, single-nucleotide polymorphisms.

Table 6. Exonic genes associated with pQTL-regulated proteins at Bonferroni-corrected significance level ($P < 3.9 \times 10^{-7}$)

Marker	Exon rs No.	Exon HGNC Symbol	Effect	P Value	pQTL-Regulated Protein
6:26463660	rs13195509	<i>BTN2A1</i>	0.3635	1.90E-10	MICB
6:27879982	rs61742093	<i>OR2B2</i>	-0.4214	1.40E-13	MICB
			-0.3019	2.20E-07	PDE4D
6:28366151	rs2232423	<i>ZSCAN12</i>	-0.4332	2.50E-14	MICB
			-0.333	8.40E-09	PDE4D
6:29342775	rs3749971	<i>OR12D3</i>	0.4299	1.20E-14	MICB
			0.3077	6.60E-08	PDE4D
6:30078275	rs2523989	<i>TRIM31</i>	0.2574	3.80E-07	GRIA4
			0.4292	1.80E-18	MICB
			0.2725	6.80E-08	PDE4D
6:31124849	rs3130453	<i>CCHCR1</i>	-0.2171	1.60E-08	PRSS3
6:31125257	rs72856718	<i>CCHCR1</i>	-0.7092	3.10E-22	CREB3L4
6:31129310	rs7750641	<i>TCF19</i>	0.3488	4.30E-11	C4A
			0.3216	1.50E-09	CD96
			0.4254	3.60E-16	GRIA4
			0.5975	3.30E-32	MICB
			0.4388	3.50E-17	PDE4D
6:31733466	rs3101017	<i>VWA7</i>	-0.4409	2.10E-15	C4A
			-0.4089	2.40E-13	CD96
			-0.305	8.50E-08	DEFB119
			-0.5098	1.70E-20	GRIA4
			-0.3301	5.70E-09	HLA-DQA2
			-0.3009	1.30E-07	IL21
			-0.6693	5.00E-36	MICB
			-0.5366	9.90E-23	PDE4D
6:32151443	rs2070600	<i>AGER</i>	0.3086	5.50E-08	PRSS3
			0.5749	8.40E-15	AGER
			0.5391	2.90E-13	PRSS3
6:32261252	rs7775397	<i>C6orf10</i>	0.5014	1.90E-11	RACGAP1
			-0.4155	1.70E-13	C4A
			-0.3764	3.20E-11	CD96
			-0.3222	1.90E-08	DEFB119
			-0.4735	2.20E-17	GRIA4
			-0.3798	2.10E-11	HLA-DQA2
			-0.5861	1.00E-26	MICB
			-0.5085	5.10E-20	PDE4D
			0.315	3.90E-08	PRSS3
14:94844947	rs28929474	<i>SERPINA1</i>	-1.1964	1.20E-21	ACP2
			-0.7288	1.90E-08	DNAJB9
			-1.7387	8.60E-48	MRPL33
			-1.0455	1.40E-16	NCF2
			-1.0295	4.40E-16	PIM1
			-0.9825	1.10E-14	SNAP25
			-0.7328	1.60E-08	TXNDC5
			-0.7449	8.80E-09	WISP3
			-1.3836	3.20E-29	ZNF175

*Indicates variant is in HLA region. pQTL, protein quantitative trait locus; HGNC, HUGO Gene Nomenclature Committee; HLA, human leukocyte antigen; SNPs, single-nucleotide polymorphisms.

Meta-regression.

For each exome-wide significant variant, we performed meta-regression to examine the cohort-specific effects of FEV₁% predicted and pack-years of smoking; for the Z allele (rs28929474), we also examined the effects of inclusion of Z allele homozygotes on the reported variant effect sizes (Supplemental Table S9). Mean differences in FEV₁% predicted from individual cohorts did not account for the observed heterogeneity, nor did whether a study excluded Z allele homozygotes. Heterogeneity of effect sizes was at least partially attributable to mean differences in pack-years of smoking for several variants (rs-12373142, rs1334576, rs16969968, rs2523989, rs3130453, and rs7750641).

DISCUSSION

In this study, we meta-analyzed exome array data from 33,851 moderate-to-severe COPD cases and 218,399 controls. We report four exonic variants on chromosomes 5q, 6p, and 15q, as well as two stop variants and one splice variant associated with COPD. We also examined the association of the *SERPINA1* Z allele (rs28929474) with COPD and heterogeneity of effect sizes across cohorts. These results lend further insight into the potential pathogenesis of this disease and identify potential loci for laboratory-based validation.

Compared with prior studies, this exome array meta-analysis includes significantly more participants and extends prior findings by providing an in-depth characterization of

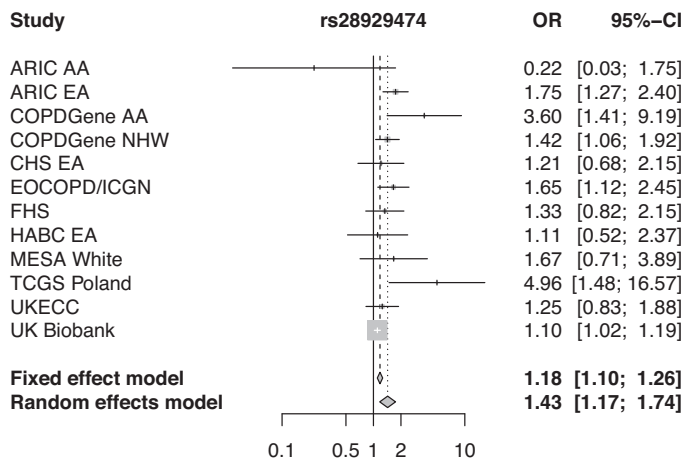


Figure 4. Forest plot of the *SERPINA1* Z allele (rs28929474). The Z allele was associated with a 1.18 odds ratio for COPD in fixed-effects analysis (95% CI = 1.10–1.26, $P=1.74 \times 10^{-6}$) and 1.43 odds ratio for COPD in random-effects analysis (95% CI = 1.17–1.74, $P=0.0043$) ($I^2=0.60$). See METHODS for cohort abbreviations. Aa, African ancestry; ARIC, Atherosclerosis Risk in Communities; CHS, Cardiovascular Health Study; CI = confidence interval; COPD, chronic obstructive pulmonary disease; EOCOPD/ICGN, Early-Onset COPD study and International COPD Genetics Network; Ea, European ancestry; FHS, Framingham Heart Study; HABC, Health, Aging, and Body Composition; MESA, Multi-Ethnic Study of Atherosclerosis; NHW, non-Hispanic White; TCGS, Transcontinental COPD Genetics Study; UKCC, UK COPD Exome Chip Consortium.

exonic variants. Using the criteria that exome-wide significance is reached and the direction of effect and risk allele are the same in both the current and prior studies, eight exonic variants from prior genome-wide and exome array studies were replicated (3, 4, 6, 7, 14–16, 58). Of these, multiple lines of evidence suggest that rs1334576 in *RREB1* is likely a functional variant; *RREB1* is a zinc-finger transcription factor that binds to Ras-related elements in gene promoters and has been implicated in cell differentiation (59–61). Smoking history was associated with the *CHRNA5* variant in meta-regression, which is not surprising given the well-established role of this locus in smoking behavior (62). This variant was also associated with early age of COPD diagnosis. Although we had adequate power to detect variants with an MAF of 0.01 with an effect size of 1.3 or greater, we did not identify any novel rare variants with large effect sizes. These data suggest that low-frequency protein-coding variants (down to 1%) with large effect sizes do not play a substantial role in COPD pathogenesis. However, this study was not powered to assess the impact of very rare variants ($MAF < 0.01$), nor the effects of low frequency and common protein-coding variants on COPD subtypes.

Although all variants were near previously identified COPD GWAS loci, applying a more relaxed multiple testing threshold (63, 64) led to the identification of four independently associated exonic variants that remained significant after conditioning on the lead nearby GWAS variant. The rs2287749 variant may be a causal variant based on conditional, credible set, and PolyPhen analyses and is located within *ADAM19*, a metalloproteinase (65) involved in cell-matrix interactions and invadopodia formation in cancer cells (49) and previously implicated in COPD risk (4, 66). Three independent variants have been previously reported

at the *TET2* 4q24 locus (5). Conditional and joint analyses suggest that rs2047409 and rs34712979 account for the signal observed at this locus. *TET2* is involved in DNA demethylation and regulation of gene expression, and variants have been associated with extremes of FEV_1 (5) and linked to age-associated clonal hematopoiesis and self-reported COPD and/or asthma (67). Our results further highlight the importance of *TET2* in COPD risk. Two novel variants, rs4842860 and rs17361375, in *C15orf40* were identified. In eQTL analyses, the former SNP was correlated with eQTL SNP rs6603041 in both lung and blood. Neither variant was found in their respective 99% credible sets from a COPD GWAS. This finding might indicate that these variants are not causal or could indicate that this locus was not adequately characterized by GWAS. A deeper characterization of this locus could help clarify its role in COPD pathogenesis.

Examining only the most deleterious (stop and splice) variants, we identified three nominally significant associations. We found two stop variants in the *CCHCR1* gene. *CCHCR1* has a role in regulating cell proliferation and differentiation, both of which are important in the pathogenesis of emphysema. The splice variant rs11078928 encodes a polymorphism at a splice acceptor site in gasdermin B (*GSDMB*) on chromosome 17q21 (67). *GSDMB* is important in pyroptosis, a type of programmed cell death that releases inflammatory mediators. Pyroptosis is activated by caspase-mediated cleavage of the inhibitory C-terminus of gasdermin B, releasing the functional N-terminus (68–70). The rs11078928 variant leads to a deletion of exon 6 in the N-terminus, rendering gasdermin B unable to activate pyroptosis (71). The minor allele (C) has been associated with lower asthma risk (71) and was associated with lower COPD risk in our study. This finding is consistent with the notion that subpopulations of individuals have features of both asthma and COPD; indeed, childhood asthma is associated with lower lung function and increased risk for COPD in adulthood (72, 73). Thus, *GSDMB* may contribute to the pathobiology of asthma-COPD overlap.

Prior investigations into the Z allele association with COPD have been conflicting. Many prior lung function and COPD genetic association studies (GWASs and exome-wide) have not reported associations with the *SERPINA1* Z allele (3–6, 14–16). Yet, the Z allele has also been associated with severe COPD (74) and lung function (75) at genome-wide significance in cohorts enriched for COPD and heavy smoking, potentially with a gene-by-smoking interaction (76). We evaluated the effect of a directly genotyped (rather than imputed) Z allele and applied a random-effects meta-analysis. The Z allele was associated with a 1.17–1.74 odds ratio for COPD.

We observed an asymmetric distribution of effect sizes and standard errors for the Z allele across cohorts, suggesting that there may be cohort-specific selection bias with regard to the inclusion of individuals with the Z allele. The combination of the exclusion of homozygous Z allele individuals (PiZZ) from many COPD case-control studies and the inclusion of a large number of individuals with little to no smoking history in population-based cohorts likely diminished the power to detect an overall effect for the Z allele. To explore this issue, we used meta-regression to assess the impact of intentional exclusion of ZZ individuals, lung

function severity, and cigarette smoke exposure on Z allele effect size heterogeneity. None of these factors clearly explained the observed Z allele effect size heterogeneity across studies.

This study has several strengths and limitations. The primary strengths of this study are the large sample size and the direct assessment of protein-coding variant associations with COPD in the context of GWAS findings. We were not well powered to detect variants with an MAF < 0.01, so we are unable to assess the impact of very rare protein-coding variants on COPD risk. Larger studies are needed to replicate our findings and assess the impact of very rare variants. Exome array data provide sparse coverage of variants across the genome, making colocalization analyses between COPD exonic variant associations and eQTLs or pQTLs impossible. However, we attempted to address this limitation by identifying eQTLs and pQTLs in the highest LD with COPD exonic variants. Finally, we used a limited set of bioinformatic prediction tools to identify functional variants, but the accuracy of such tools for predicting biologically important changes in protein structure and function is not clear (77). Laboratory-based validation is critical to understanding the causal influence of the exome array variants reported here.

In conclusion, we performed the largest exome array meta-analysis of moderate-to-severe COPD to date. We were unable to identify any protein-altering coding variants at exome-wide significance in regions not previously identified by GWAS. However, at previously described GWAS loci, we report multiple coding variants associated with COPD, including four conditionally significant nonsynonymous variants, two stop variants, and a splice variant. These variants exist in genes important in cell-matrix interactions, cell proliferation, DNA demethylation, regulation of proteases, and regulation of cell death. We further identify the heterogeneity of effects of the *SERPINA1* Z allele across cohorts. Future studies will be needed to replicate and validate these identified exonic variants, identify rarer variants, and further describe the role of coding variants in COPD pathogenesis.

GRANTS

This work was supported by Grant T32HL007427 (to M.M.); NIH Grants K08HL136928 and R01 HL089856 (to B.D.H.); NIH Grants R01HL137927 and R01HL135142 (to M.H.C.); NIH Grants R01 HL137927, R01 HL147148, R01 HL133135, and P01 HL14501 (to E.K.S.); Wellcome Trust Investigator Award WT202849/Z/16/Z (to M.D.T.); and the Intramural Research Program of the NIH, National Institute of Environmental Health Sciences Grant ZO1 ES43012 (to S.J.L.). The research was partially supported by the National Institute for Health Research (NIHR) Leicester Biomedical Research Centre. The views expressed are those of the authors and not necessarily those of the National Health Service (NHS), the NIHR, or the Department of Health. L.V.W. holds a GSK/British Lung Foundation Chair in Respiratory Research (C17-1). I.P.H. holds an NIHR Senior Investigator Award.

DISCLOSURES

E.K.S. received grant support from GlaxoSmithKline and Bayer. M.H.C. has received grant support from GlaxoSmithKline and Bayer, consulting fees from Genentech and AstraZeneca, and speaking fees from Illumina. M.D.T. receives grant support from GlaxoSmithKline and Orion. L.V.W. received grant

support from GlaxoSmithKline and Orion. I.P.H. has received grant support from GlaxoSmithKline and Orion. None of the other authors has any conflicts of interest, financial or otherwise, to disclose.

AUTHOR CONTRIBUTIONS

M.M., A.M., V.E.J., L.V.W., E.K.S., M.H.C., B.D.H., S.J.L., S.A.G., and J.D. conceived and designed research; M.M., H.X., J.P., K.H.K., B.H., V.E.J., J.N.N., N.T., P.S., J.L., C.J.B., B.Y., M.H.C., B.D.H., M.L.G., and T.M.B. analyzed data; M.M., V.E.J., M.D.T., L.V.W., E.K.S., M.H.C., B.D.H., and J.D. interpreted results of experiments; M.M. prepared figures; M.M., M.H.C., and B.D.H. drafted manuscript; M.M., H.X., P.A.C., B.K.P., W.K., J.P., K.H.K., B.H., A.M., V.E.J., J.N.N., S.S.R., L.L., N.T., G.B., P.S., C.J.B., I.P.H., M.D.T., B.Y., L.V.W., E.K.S., M.H.C., B.D.H., M.L.G., S.J.L., S.A.G., T.M.B., C.M.S., and J.D. edited and revised manuscript; M.M., G.T.O., H.X., P.A.C., B.K.P., W.K., J.P., K.H.K., B.H., R.B., A.M., V.E.J., J.N.N., S.S.R., L.L., N.T., G.B., P.S., J.L., C.J.B., I.P.H., M.D.T., B.Y., L.V.W., E.K.S., M.H.C., B.D.H., M.L.G., S.J.L., S.A.G., T.M.B., C.M.S., and J.D. approved final version of manuscript.

REFERENCES

1. Vogelmeier CF, Criner GJ, Martinez FJ, Anzueto A, Barnes PJ, Bourbeau J, Celli BR, Chen R, Decramer M, Fabbri LM, Frith P, Halpin DM, López Varela MV, Nishimura M, Roche N, Rodriguez-Roisin R, Sin DD, Singh D, Stockley R, Vestbo J, Wedzicha JA, Agustí A. Global strategy for the diagnosis, management, and prevention of chronic obstructive lung disease 2017. *Am J Respir Crit Care Med* 195: 557–582, 2017. doi:10.1164/rccm.201701-0218PP.
2. Soriano JB, Lamprecht B, Ramírez AS, Martínez-Cambor P, Kaiser B, Alfageme I, Almagro P, Casanova C, Esteban C, Soler-Catalana JJ, de-Torres JP, Miravittles M, Celli BR, Marin JM, Puhan MA, Sobradillo P, Lange P, Stenberg AL, García-Aymerich J, Turner AM, Han MK, Langhammer A, Leivseth L, Bakke P, Johannessen A, Roche N, Sin DD. Mortality prediction in chronic obstructive pulmonary disease comparing the GOLD 2007 and 2011 staging systems: a pooled analysis of individual patient data. *Lancet Respir Med* 3: 443–450, 2015. doi:10.1016/S2213-2600(15)00157-5.
3. Shrine N, Guyatt AL, Erzurumluoglu AM, Jackson VE, Hobbs BD, Melbourne CA; Understanding Society Scientific Group, et al. New genetic signals for lung function highlight pathways and chronic obstructive pulmonary disease associations across multiple ancestries. *Nat Genet* 51: 481–493, 2019. doi:10.1038/s41588-018-0321-7.
4. Sakornsakolpat P, Prokopenko D, Lamontagne M, Reeve NF, Guyatt AL, Jackson VE, SpiroMeta Consortium, et al. Genetic landscape of chronic obstructive pulmonary disease identifies heterogeneous cell-type and phenotype associations. *Nat Genet* 51: 494–505, 2019. doi:10.1038/s41588-018-0342-2.
5. Wain LV, Shrine N, Miller S, Jackson VE, Ntalla I, Soler Artigas M, et al. Novel insights into the genetics of smoking behaviour, lung function, and chronic obstructive pulmonary disease (UK BiLEVE): a genetic association study in UK Biobank. *Lancet Respir Med* 3: 769–781, 2015. doi:10.1016/S2213-2600(15)00283-0.
6. Wain LV, Shrine N, Artigas MS, Erzurumluoglu AM, Noyvert B, Bossini-Castillo L; Understanding Society Scientific Group, et al. Genome-wide association analyses for lung function and chronic obstructive pulmonary disease identify new loci and potential drug-gable targets. *Nat Genet* 49: 416–425, 2017. doi:10.1038/ng.3787.
7. Hobbs BD, de Jong K, Lamontagne M, Bossé Y, Shrine N, Artigas MS; COPDGene Investigators, et al. Genetic loci associated with chronic obstructive pulmonary disease overlap with loci for lung function and pulmonary fibrosis. *Nat Genet* 49: 426–432, 2017. doi:10.1038/ng.3752.
8. Hindorf LA, Sethupathy P, Junkins HA, Ramos EM, Mehta JP, Collins FS, Monolio TA. Potential etiologic and functional implications of genome-wide association loci for human diseases and traits. *Proc Natl Acad Sci USA* 106: 9362–9367, 2009. doi:10.1073/pnas.0903103106.

9. Eriksson S. Studies in alpha 1-antitrypsin deficiency. *Acta Med Scand Suppl* 432: 1–85, 1965.
10. Hobbs BD, Silverman , EC. Genetics and epidemiology. In: *α 1-Antitrypsin Deficiency (ERS Monograph)*, edited by Strnad P, Brantly M BR. Sheffield: European Respiratory Society, 2019. p. 27–38.
11. Bossé Y, Lamontagne M, Gaudreault N, Racine C, Levesque M-H, Smith BM, Auger D, Clemenceau A, Pare ME, Laviolette L, Tremblay V, Maranda B, Morissette MC, Maltais F. Early-onset emphysema in a large French-Canadian family: a genetic investigation. *Lancet Respir Med* 7: 427–436, 2019. doi:10.1016/S2213-2600(19)30056-6.
12. Stanley SE, Chen JJJ, Podlevsky JD, Alder JK, Hansel NN, Mathias RA, Qi X, Rafaels NM, Wise RA, Silverman EK, Barnes KC, Armanios M. Telomerase mutations in smokers with severe emphysema. *J Clin Invest* 125: 563–570, 2015. doi:10.1172/JCI78554.
13. Abecasis Lab at the University of Michigan Center for Statistical Genetics. Exome chip design [Internet]. [cited 2019 Aug 8]. Available from: [http://genome.sph.umich.edu/wiki/https://genome.sph.umich.edu/wiki/Exome_Chip_Design].
14. Hobbs BD, Parker MM, Chen H, Lao T, Hardin M, Qiao D, et al. Exome array analysis identifies a common Variant in IL27 associated with chronic obstructive pulmonary disease. *Am J Respir Crit Care Med* 194: 48–57, 2016. doi:10.1164/rccm.201510-2053OC.
15. Jackson VE, Latourelle JC, Wain LV, Smith AV, Grove ML, Bartz TM; Understanding Society Scientific Group, et al. Meta-analysis of exome array data identifies six novel genetic loci for lung function. *Wellcome Open Res* 3: 4, 2018. doi:10.12688/wellcomeopenres.12583.3.
16. Jackson VE, Ntala I, Sayers I, Morris R, Whincup P, Casas JP, et al. Exome-wide analysis of rare coding variation identifies novel associations with COPD and airflow limitation in MOCOS3, IFIT3 and SERPINA12. *Thorax* 71: 501–509, 2016. doi:10.1136/thoraxjnl-2015-207876.
17. Foreman MG, Wilson C, DeMeo DL, Hersh CP, Beaty TH, Cho MH, Ziniti J, Curran-Everett D, Criner G, Hokanson JE, Brantly M, Rouhani FN, Sandhaus RA, Crapo JD, Silverman EK; Genetic Epidemiology of COPD (COPDGene) Investigators. Alpha-1 antitrypsin PIMZ genotype is associated with chronic obstructive pulmonary disease in two racial groups. *Ann Am Thorac Soc* 14: 1280–1287, 2017. doi:10.1513/AnnalsATS.201611-838OC.
18. Castaldi PJ, DeMeo DL, Kent DM, Campbell EJ, Barker AF, Brantly ML, Eden E, McElvaney NG, Rennard SI, Stoller JM, Strange C, Turino G, Sandhaus RA, Griffith JL, Silverman EK. Development of predictive models for airflow obstruction in alpha-1-antitrypsin deficiency. *Am J Epidemiol* 170: 1005–1013, 2009. doi:10.1093/aje/kwp216.
19. The atherosclerosis risk in communities (ARIC) study: design and objectives. The ARIC investigators. *Am J Epidemiol* 129: 687–702, 1989. [2646917]
20. Fried LP, Borhani NO, Enright P, Furberg CD, Gardin JM, Kronmal RA, et al. The Cardiovascular Health Study: design and rationale. *Ann Epidemiol* 1: 263–276, 1991. doi:10.1016/1047-2797(91)90005-W.
21. Regan EA, Hokanson JE, Murphy JR, Make B, Lynch DA, Beaty TH, Curran-Everett D, Silverman EK, Crapo JD. Genetic Epidemiology of COPD (COPDGene) Study Design. *COPD* 7: 32–43, 2011. doi:10.3109/15412550903499522.
22. Silverman EK, Weiss ST, Drazen JM, Chapman HA, Carey V, Campbell EJ, Denish P, Silverman RA, Celledon JC, Reilly JJ, Ginns LC, Speizer FE. Gender-related differences in severe, early-onset chronic obstructive pulmonary disease. *Am J Respir Crit Care Med* 162: 2152–2158, 2000. doi:10.1164/ajrccm.162.6.2003112.
23. Patel BD, Coxson HO, Pillai SG, Agustí AGN, Calverley PMA, Donner CF, Make BJ, Müller NL, Rennard SI, Vestbo J, Wouters EFM, Hiorns MP, Nakano Y, Camp PG, Fauerbach PVN, Screaton NJ, Campbell EJ, Anderson WH, Paré PD, Levy RD, Lake SL, Silverman EK, Lomas DA; International COPD Genetics Network. Airway wall thickening and emphysema show independent familial aggregation in chronic obstructive pulmonary disease. *Am J Respir Crit Care Med* 178: 500–505, 2008. doi:10.1164/rccm.200801-059OC.
24. Zhu G, Warren L, Aponte J, Gulsvik A, Bakke P, Anderson WH, Lomas DA, Silverman EK, Pillai SG; The International COPD Genetics Network (ICGN) Investigators. The SERPINE2 gene is associated with chronic obstructive pulmonary disease in two large populations. *Am J Respir Crit Care Med* 176: 167–173, 2007. Jul doi:10.1164/rccm.200611-1723OC.
25. Splansky GL, Corey D, Yang Q, Atwood LD, Cupples LA, Benjamin EJ, Agostino RB, Fox CS, Larson MG, Murabito JM, O'Donnell CJ, Vasan RS, Wolf PA, Levy D. The Third Generation Cohort of the National Heart, Lung, and Blood Institute's Framingham Heart Study: design, recruitment, and initial examination. *Am J Epidemiol* 165: 1328–1335, 2007. doi:10.1093/aje/kwm021.
26. Wilk JB, Chen T-H, Gottlieb DJ, Walter RE, Nagle MW, Brandler BJ, Myers RH, Borecki IB, Silverman EK, Weiss ST, O'Connor GT. A genome-wide association study of pulmonary function measures in the Framingham Heart Study. *PLoS Genet* 5: e1000429, 2009. doi:10.1371/journal.pgen.1000429.
27. Kannel WB, Feinleib M, McNamara PM, Garrison RJ, Castelli WP. An investigation of coronary heart disease in families. The Framingham offspring study. *Am J Epidemiol* 110: 281–290, 1979. doi:10.1093/oxfordjournals.aje.a112813.
28. Simonsick EM, Newman AB, Nevitt MC, Kritchevsky SB, Ferrucci L, Guralnik JM, Haris T; Health ABC Study Group. Measuring higher level physical function in well-functioning older adults: expanding familiar approaches in the Health ABC study. *J Gerontol A Biol Sci Med Sci* 56: M644–9, 2001. doi:10.1093/gerona/56.10.M644.
29. Hong CB, Kim YJ, Moon S, Shin Y-A, Cho YS, Lee J-Y. KAREBrowser: SNP database of Korea Association Resource Project. *BMB Rep* 45: 47–50, 2012. doi:10.5483/BMBRep.2012.45.1.47.
30. Hankinson JL, Kawut SM, Shahar E, Smith LJ, Stukovsky KH, Barr RG. Performance of American Thoracic Society-recommended spirometry reference values in a multiethnic sample of adults: the multiethnic study of atherosclerosis (MESA) lung study. *Chest* 137: 138–145, 2010. doi:10.1378/chest.09-0919.
31. Bild DE, Bluemke DA, Burke GL, Detrano R, Diez RAV, Folsom AR, Greenland P, Jacob DR Jr, Kronmal R, Liu K, Nelson JC, O'Leary D, Saad MF, Shea S, Szklo M, Tracy RP. Multi-Ethnic Study of Atherosclerosis: objectives and design. *Am J Epidemiol* 156: 871–881, 2002. doi:10.1093/aje/kwf113.
32. Hofman A, Darwish Murad S, van Duijn CM, Franco OH, Goedegebuure A, Ikram MA, Klaver CC, Nijsten TE, Peeters RP, Sticker BH, Uitterlinden AG, Vernooij MW. The Rotterdam Study: 2014 objectives and design update. *Eur J Epidemiol* 28: 889–926, 2013. doi:10.1007/s10654-013-9866-z.
33. Ikram MA, van der Lugt A, Niessen WJ, Koudstaal PJ, Krestin GP, Hofman A, Boss D, Vernooij MW. The Rotterdam Scan Study: design update 2016 and main findings. *Eur J Epidemiol* 30: 1299–1315, 2015. doi:10.1007/s10654-015-0105-7.
34. Zhou X, Baron RM, Hardin M, Cho MH, Zielinski J, Hawrylkiewicz I, Sliwinski P, Hersh Lugt CP, Mancini JD, Lu KE, Thibault D, Donahue AL, Klanderma BJ, Rosner B, Raby BA, Lu Q, Geldart AM, Layne MD, Perrella MA, Weiss ST, Choi AMK, Silverman EK. Identification of a chronic obstructive pulmonary disease genetic determinant that regulates HHIP. *Hum Mol Genet [Internet]* 21: 1325–1335, 2012. doi:10.1093/hmg/ddr569.
35. Sudlow C, Gallacher J, Allen N, Beral V, Burton P, Danesh J, Downey P, Elliott P, Green J, Landray M, Liu B, Matthews P, Ong G, Pell J, Silman A, Young A, Sprosen T, Peakman T, Collins R. UK biobank: an open access resource for identifying the causes of a wide range of complex diseases of middle and old age. *PLoS Med* 12: e1001779, 2015. doi:10.1371/journal.pmed.1001779.
36. Winkler TW, Day FR, Croteau-Chonka DC, Wood AR, Locke AE, Mägi R, Ferreira T, Fall T, Graff M, Justice AE, Luan J, Gustafsson S, Randall JC, Vedantam S, Workalemahu T, Kilpeläinen TO, Scherag A, Esko T, Kutalik Z, Heid IM, Loos RJF; The Genetic Investigation of Anthropometric Traits (GIANT) Consortium. Quality control and conduct of genome-wide association meta-analyses. *Nat Protoc* 9: 1192–1212, 2014. doi:10.1038/nprot.2014.071.
37. Skol AD, Scott LJ, Abecasis GR, Boehnke M. Joint analysis is more efficient than replication-based analysis for two-stage genome-wide association studies. *Nat Genet* 38: 209–213, 2006. doi:10.1038/ng1706.
38. Buist AS, McBurnie MA, Vollmer WM, Gillespie S, Burney P, Mannino DM, Menezes AMB, Sullivan SD, Lee TA, Weiss KB, Jensen RL, Marks GB, Gulsvik A, Nizankowska-Mogilnicka E; BOLD Collaborative Research Group. International variation in the

- prevalence of COPD (the BOLD Study): a population-based prevalence study. *Lancet* 370: 741–750, 2007. doi:10.1016/s0140-6736(07)61377-4.
39. Pauwels RA, Rabe KF. Burden and clinical features of chronic obstructive pulmonary disease (COPD). *Lancet* 364: 613–620, 2004. doi:10.1016/s0140-6736(04)16855-4.
 40. van Belle G. *Statistical Rules of Thumb (2nd Ed.)*. New York: John Wiley and Sons, 2008, p. 45–46.
 41. Willer CJ, Li Y, Abecasis GR. METAL: fast and efficient meta-analysis of genomewide association scans. *Bioinformatics* 26: 2190–2191, 2010. doi:10.1093/bioinformatics/btq340.
 42. Chang X, Wang K. WANNVAR: annotating genetic variants for personal genomes via the web. *J Med Genet* 49: 433–436, 2012. doi:10.1136/jmedgenet-2012-100918.
 43. Chang CC, Chow CC, Tellier LC, Vattikuti S, Purcell SM, Lee JJ. Second-generation PLINK: rising to the challenge of larger and richer datasets. *GigaSci* 4: 7, 2015. doi:10.1186/s13742-015-0047-8.
 44. Yang J, Ferreira T, Morris AP, Medland SE, Madden PAF, Heath AC, Martin NG, Montgomery GW, Weedon MN, Loos RJ, Frayling TM, McCarthy MI, Hirschhorn JN, Goddard ME, Visscher PM; Genetic Investigation of Anthropometric Traits (GIANT) Consortium; DIAbetes Genetics Replication And Meta-analysis (DIAGRAM) Consortium. Conditional and joint multiple-SNP analysis of GWAS summary statistics identifies additional variants influencing complex traits. *Nat Genet* 44: 369–375, 2012. doi:10.1038/ng.2213.
 45. Wakefield J. Bayes factors for genome-wide association studies: comparison with P-values. *Genet Epidemiol* 33: 79–86, 2009. doi:10.1002/gepi.20359.
 46. Kircher M, Witten DM, Jain P, O’Roak BJ, Cooper GM, Shendure J. A general framework for estimating the relative pathogenicity of human genetic variants. *Nat Genet* 46: 310–315, 2014. doi:10.1038/ng.2892.
 47. Rentzsch P, Witten D, Cooper GM, Shendure J, Kircher M. CADD: predicting the deleteriousness of variants throughout the human genome. *Nucleic Acids Res* 47: D886–D894, 2019. doi:10.1093/nar/gky1016.
 48. Wu G, Haw R. Functional interaction network construction and analysis for disease discovery. *Methods Mol Biol* 1558: 235–253, 2017. doi:10.1007/978-1-4939-6783-4_11.
 49. Fabregat A, Sidiropoulos K, Viteri G, Forner O, Marin-Garcia P, Arnau V, D’Eustachio P, Stein L, Hermjakob H. Reactome pathway analysis: a high-performance in-memory approach. *BMC Bioinformatics* 18: 142, 2017. doi:10.1186/s12859-017-1559-2.
 50. GTEx Consortium. The Genotype-Tissue Expression (GTEx) project. *Nat Genet* 45: 580–585, 2013.
 51. GTEx Consortium. Human genomics. The Genotype-Tissue Expression (GTEx) pilot analysis: multitissue gene regulation in humans. *Science* 348: 648–660, 2015. doi:10.1126/science.1262110.
 52. Westra H-J, Peters MJ, Esko T, Yaghootkar H, Schurmann C, Kettunen J, et al. Systematic identification of trans eQTLs as putative drivers of known disease associations. *Nat Genet* 45: 1238–1243, 2013. doi:10.1038/ng.2756.
 53. Hao K, Bossé Y, Nickle DC, Paré PD, Postma DS, Laviolette M, Sandford A, Hackett TL, Daley D, Hogg JC, Elliott WM, Couture C, Lamontagne M, Brandsma C-A, van den Berge M, Koppelman G, Reicin AS, Nicholson DW, Malkov V, Derry JM, Suver C, Tsou JA, Kulkarni A, Zhang C, Vessey R, Opitck GJ, Curtis SP, Timens W, Sin DD. Lung eQTLs to help reveal the molecular underpinnings of asthma. *PLoS Genet* 8: e1003029, 2012. doi:10.1371/journal.pgen.1003029.
 54. Vösa U, Claringbould A, Westra H-J, Bonder MJ, Deelen P, Zeng B, Kirsten H, Saha A, Kreuzhuber R, Kasela S, Pervjakova N, Alvaes I, Fave M-J, Agbessi M, Christiansen M, Jansen R, Seppälä I, Tong L, Teumer A, Schramm K, Hemani G, Verlouw J, Yaghootkar H, Sönmez R, Andrew AA, Kukushkina V, Kalnapenkis A, Rüeger S, Porcu E, Kronberg-Guzman J, Kettunen J, Powell J, Lee B, Zhang F, Arindrarto W, Beutner F, Brugge H, Dmitrieva J, Elansary M, Fairfax BP, Georges M, Heijmans BT, Kähönen M, Kim Y, Knight JC, Kovacs P, Krohn K, Li S, Loeffler M, Marigorta UM, Mei H, Momozawa Y, Müller-Nurasyid M, Nauck M, Nivard M, Penninx B, Pritchard J, Raitakari O, Rotzschke O, Slagboom EP, Stehouwer CDA, Stumvoll M, Sullivan P, t Hoen PAC, Thiery J, Tönjes A, van Dongen J, van Ijckerson M, Veldink J, Völker U, Wijmenga C, Swertz M, Andiappan A, Montgomery GW, Ripatti S, Perola M, Kutalik Z, Dermizakis E, Bergmann S, Frayling T, van Meurs J, Prokisch H, Ahsan H, Pierce B, Lehtimäki T, Boomsma D, Psaty BM, Gharib SA, Awadalla P, Milani L, Ouwehand WH, Downes K, Stegle O, Battle A, Yang J, Visscher PM, Scholz M, Gibson G, Esko T, Franke L. Unraveling the polygenic architecture of complex traits using blood eQTL metaanalysis (Preprint). *bioRxiv* 2018. doi:10.1101/447367.
 56. Sun BB, Maranville JC, Peters JE, Stacey D, Staley JR, Blackshaw J, Burgess S, Jiang T, Paige E, Surendran P, Oliver-Williams C, Kamat MA, Prins BP, Wilcox SK, Zimmerman ES, Chi A, Bansal N, Spain SL, Wood AM, Morrell NW, Bradley JR, Janjic N, Roberts DJ, Ouwehand WH, Todd JA, Soranzo N, Suhre K, Paul DS, Fox CS, Plenge RM, Danesh J, Runz H, Butterworth AS. Genomic atlas of the human plasma proteome. *Nature* 558: 73–79, 2018.
 57. Schwarzer G. meta: An R package for meta-analysis. *R News* 7: 40–45, 2007.
 58. Busch R, Hobbs BD, Zhou J, Castaldi PJ, McGeachie MJ, Hardin ME, et al. Genetic association and risk scores in a chronic obstructive pulmonary disease meta-analysis of 16,707 subjects. *Am J Respir Cell Mol Biol* 57: 35–46, 2017. doi:10.1165/rcmb.2016-0331oc.
 59. Zhang L, Zhao J, Edenberg HJ. A human Raf-responsive zinc-finger protein that binds to divergent sequences. *Nucleic Acids Res* 27: 2947–2956, 1999. doi:10.1093/nar/27.14.2947.
 60. Mukhopadhyay NK, Cinar B, Mukhopadhyay L, Lutchman M, Ferdinand AS, Kim J, Chung LWK, Adam RM, Ray SK, Leiter AB, Richie JP, Liu Brain C-S, Freeman MR. The zinc finger protein ras-responsive element binding protein-1 is a coregulator of the androgen receptor: implications for the role of the Ras pathway in enhancing androgenic signaling in prostate cancer. *Mol Endocrinol* 21: 2056–2070, 2007. doi:10.1210/me.2006-0503.
 61. Thiagalingam A, De Bustros A, Borges M, Jasti R, Compton D, Diamond L, Mabry M, Ball DW, Baylin SB, Nelkin BD. RREB-1, a novel zinc finger protein, is involved in the differentiation response to Ras in human medullary thyroid carcinomas. *Mol Cell Biol* 16: 5335–5345, 1996. doi:10.1128/MCB.16.10.5335.
 62. Hartz SM, Short SE, Saccone NL, Culverhouse R, Chen L, Schwantes-An T-H, et al. Increased genetic vulnerability to smoking at CHRNA5 in early-onset smokers. *Arch Gen Psychiatry* 69: 854–860, 2012. doi:10.1001/archgenpsychiatry.2012.124.
 63. Glubb DM, Maranian MJ, Michailidou K, Pooley KA, Meyer KB, Kar S, et al. Fine-scale mapping of the 5q11.2 breast cancer locus reveals at least three independent risk variants regulating MAP3K1. *Am J Hum Genet* 96: 5–20, 2015. doi:10.1016/j.ajhg.2014.11.009.
 64. Gallagher MD, Chen-Plotkin AS. The Post-GWAS Era: from association to function. *Am J Hum Genet* 102: 717–730, 2018. doi:10.1016/j.ajhg.2018.04.002.
 65. Wei P, Zhao YG, Zhuang L, Ruben S, Sang QX. Expression and enzymatic activity of human disintegrin and metalloproteinase ADAM19/meltrin beta. *Biochem Biophys Res Commun* 280: 744–755, 2001. doi:10.1006/bbrc.2000.4200.
 66. Pérez-Rubio G, Silva-Zolezzi I, Fernández-López JC, Camarena Á, Velázquez-Uncal M, Morales-Mandujano F, Hernandez-Zenteno RDJ, Flores-Trujillo F, Sanchez-Romero C, Velazquez-Montero A, de Los Monteros CE, Sansores RH, Ramirez-Venegas A, Falfan-Valencia R. Genetic variants in IL6R and ADAM19 are associated with COPD severity in a Mexican Mestizo population. *COPD* 13: 610–615, 2016. doi:10.3109/15412555.2016.1161017.
 67. Buscarlet M, Provost S, Zada YF, Barhdadi A, Bourgoin V, Lépine G, Mollica L, Szuber N, Dube MP, Busque L. DNMT3A and TET2 dominate clonal hematopoiesis and demonstrate benign phenotypes and different genetic predispositions. *Blood* 130: 753–762, 2017. doi:10.1182/blood-2017-04-777029.
 68. Kayagaki N, Stowe IB, Lee BL, O’Rourke K, Anderson K, Warming S, Cuellar T, Haley B, Roose-Girma M, Phung QT, Liu PS, Lill JR, Li H, Wu J, Kummerfeld S, Zhang J, Lee WP, Snipas SJ, Salvesen GS, Morris LX, Fitzgerald L, Zhang Y, Bertram EM, Goodnow CC, Dixit VM. Caspase-11 cleaves gasdermin D for non-canonical inflammatory signalling. *Nature* 526: 666–671, 2015. doi:10.1038/nature15541.
 69. Ding J, Wang K, Liu W, She Y, Sun Q, Shi J, Sun H, Wang DC, Shao F. Pore-forming activity and structural autoinhibition of the gasdermin family. *Nature* 535: 111–116, 2016. doi:10.1038/nature18590.

70. Shi J, Zhao Y, Wang K, Shi X, Wang Y, Huang H, Zhuang Y, Cai T, Wang F, Shao F. Cleavage of GSDMD by inflammatory caspases determines pyroptotic cell death. *Nature* 526: 660–665, 2015. doi:10.1038/nature15514.
71. Panganiban RA, Sun M, Dahlin A, Park H-R, Kan M, Himes BE, Mitchel JA, Iribarren C, Jorgenson E, Randell SH, Israel E, Tantisira E, Shore S, Park JA, Weiss ST, Wu AC, Lu Q. A functional splice variant associated with decreased asthma risk abolishes the ability of gasdermin B to induce epithelial cell pyroptosis. *J Allergy Clin Immunol* 142: 1469–1478.e2, 2018. doi:10.1016/j.jaci.2017.11.040.
72. Hayden LP, Cho MH, Raby BA, Beaty TH, Silverman EK, Hersh CP; COPDGene Investigators. Childhood asthma is associated with COPD and known asthma variants in COPDGene: a genome-wide association study. *Respir Res* 19: 209, 2018. doi:10.1186/s12931-018-0890-0.
73. McGeachie MJ, Yates KP, Zhou X, Guo F, Sternberg AL, Van Natta ML, et al. Patterns of Growth and decline in lung function in persistent childhood asthma. *N Engl J Med* 374: 1842–1852, 2016. doi:10.1056/NEJMoa1513737.
74. Busch R, Hobbs BD, Zhou J, Castaldi PJ, McGeachie MJ, Hardin ME, Hawrylkiewicz I, Sliwinski P, Yim JJ, Kim WJ, Kim DK, Agusti A, Make BJ, Crapo D, Calverley PM, Donner CF, Lomas DA, Wouters EF, Vestbo J, Tal-Singer R, Bakke P, Gulsvik A, Litonjua AA, Sparrow D, Paré PD, Levy RD, Rennard SI, Beaty TH, Hokanson J, Silverman EK, Cho MH; National Emphysema Treatment Trial Genetics; Evaluation of COPD Longitudinally to Identify Predictive Surrogate End-Points; International COPD Genetics Network; COPDGene Investigators. Genetic association and risk scores in a chronic obstructive pulmonary disease meta-analysis of 16,707 subjects. *Am J Respir Cell Mol Biol* 57: 35–46, 2017. doi:10.1165/rmb.2016-0331OC.
75. Li X, Ortega VE, Ampleford EJ, Graham Barr R, Christenson SA, Cooper CB, Dransfield MT, Han MLK, Hanse NN, Hoffman EA, Kanner RE, Kleerup EC, Martinez FJ, Paine R, Woodruff PG, Hawkins GA, Bleecker ER, Meyers DA; for the SPIROMICS Research Group. Genome-wide association study of lung function and clinical implication in heavy smokers. *BMC Med Genet* 19: 134, 2018. doi:10.1186/s12881-018-0656-z.
76. Silverman EK, Province MA, Campbell EJ, Pierce JA, Rao DC, Boerwinkle E. Family study of alpha 1-antitrypsin deficiency: effects of cigarette smoking, measured genotype, and their interaction on pulmonary function and biochemical traits. *Genet Epidemiol* 9: 317–331, 1992. doi:10.1002/gepi.1370090504.
77. Miosge LA, Field MA, Sontani Y, Cho V, Johnson S, Palkova A, Balakishnan B, Liang R, Zhang Y, Lyon S, Beutler B, Whittle B, Bertram EM, Enders A, Goodnow CC, Andrews TD. Comparison of predicted and actual consequences of missense mutations. *Proc Natl Acad Sci USA* 112: E5189–E5198, 2015. doi:10.1073/pnas.1511585112.