



Article

# Genome-Wide Association Study of Fluorescent Oxidation Products Accounting for Tobacco Smoking Status in Adults from the French EGEA Study

Laurent Orsi <sup>1,\*</sup>, Patricia Margaritte-Jeannin <sup>2,†</sup>, Miora Andrianjafimasy <sup>1,†</sup>, Orianne Dumas <sup>1</sup>, Hamida Mohamdi <sup>2</sup>, Emmanuelle Bouzigon <sup>2</sup>, Florence Demenais <sup>2</sup>, Régis Matran <sup>3,4,5</sup>, Farid Zerimech <sup>3,4,5</sup>, Rachel Nadif <sup>1,‡</sup> and Marie-Hélène Dizier <sup>2,‡</sup>

- Université Paris-Saclay, UVSQ, Univ. Paris-Sud, INSERM, Équipe d'Epidémiologie Respiratoire Intégrative, CESP, 94807 Villejuif, France; mioraandria3@gmail.com (M.A.); orianne.dumas@inserm.fr (O.D.); rachel.nadif@inserm.fr (R.N.)
- Université Paris Cité, INSERM, UMR 1124, Group of Genomic Epidemiology and Multifactorial Diseases, 75006 Paris, France; patricia.jeannin@inserm.fr (P.M.-J.); hamida.mohamdi@inserm.fr (H.M.); emmanuelle.bouzigon@inserm.fr (E.B.); florence.demenais@inserm.fr (F.D.); marie-helene.dizier@inserm.fr (M.-H.D.)
- Univ. Lille, ULR 4483—IMPECS, 59000 Lille, France; regis.matran@univ-lille.fr (R.M.); farid.zerimech@chu-lille.fr (F.Z.)
- 4 CHU Lille, 59000 Lille, France
- <sup>5</sup> Institut Pasteur de Lille, 59000 Lille, France
- \* Correspondence: laurent.orsi@inserm.fr
- † These authors contributed equally to the work.
- ‡ These authors contributed equally to the work.

**Abstract:** Oxidative stress (OS) is the main pathophysiological mechanism involved in several chronic diseases, including asthma. Fluorescent oxidation products (FlOPs), a global biomarker of damage due to OS, is of growing interest in epidemiological studies. We conducted a genome-wide association study (GWAS) of the FlOPs level in 1216 adults from the case-control and family-based EGEA study (mean age 43 years old, 51% women, and 23% current smokers) to identify genetic variants associated with FlOPs. The GWAS was first conducted in the whole sample and then stratified according to smoking status, the main exogenous source of reactive oxygen species. Among the top genetic variants identified by the three GWAS, those located in BMP6 ( $p = 3 \times 10^{-6}$ ), near BMPER ( $p = 9 \times 10^{-6}$ ), in GABRG3 ( $p = 4 \times 10^{-7}$ ), and near ATG5 ( $p = 2 \times 10^{-9}$ ) are the most relevant because of both their link to biological pathways related to OS and their association with several chronic diseases for which the role of OS in their pathophysiology has been pointed out. BMP6 and BMPER are of particular interest due to their involvement in the same biological pathways related to OS and their functional interaction. To conclude, this study, which is the first GWAS of FlOPs, provides new insights into the pathophysiology of chronic OS-related diseases.

**Keywords:** fluorescent oxidation products; oxidative stress; genome-wide association study; chronic diseases; asthma; smoking



Citation: Orsi, L.; Margaritte-Jeannin, P.; Andrianjafimasy, M.; Dumas, O.; Mohamdi, H.; Bouzigon, E.; Demenais, F.; Matran, R.; Zerimech, F.; Nadif, R.; et al. Genome-Wide Association Study of Fluorescent Oxidation Products Accounting for Tobacco Smoking Status in Adults from the French EGEA Study.

Antioxidants 2022, 11, 802. https://doi.org/10.3390/antiox11050802

Academic Editor: Stephen M. Black

Received: 17 February 2022 Accepted: 18 April 2022 Published: 20 April 2022

**Publisher's Note:** MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

### 1. Introduction

Oxidative stress (OS) was defined in 1985 as "a disturbance in the pro-oxidant/ antioxidant balance in favour of the former" [1]. Beyond its essential role in life processes, OS is involved in the pathophysiology of several chronic diseases, including cardiovascular diseases, chronic kidney diseases, and asthma [2]. Sources of reactive oxygen species include the diseases themselves, through their intracellular metabolisms, and some exogenous sources, among which the most important is cigarette smoke [3].

Among the numerous biomarkers related to OS [1,4], Fluorescent Oxidation Products (FIOPs), which reflect a global measurement of oxidation of lipids, proteins, carbohydrates,

Antioxidants 2022, 11, 802 2 of 17

and DNA [5], is of growing interest for epidemiological studies [6], as an easily quantifiable and stable biomarker of damage due to OS. The FIOPs level was found to be associated with chronic diseases such as coronary heart disease (CHD) (e.g., incidence of CHD among men without previous cardiovascular events, and risk of future CHD in healthy women) [7,8], and chronic kidney diseases [9]. Recently, we reported that high FIOPs level was associated with asthma attacks, the use of any asthma treatment, and poor control of asthma and was a predictor of asthma evolution in adults from the French Epidemiological study on the Genetics and Environment of Asthma (EGEA) [10,11]. We also found that smoking increased the FIOPs level [11].

Understanding the aetiology of multifactorial and heterogeneous chronic diseases is challenging. We hypothesised that genome-wide association studies (GWAS) of FIOPs may provide new insights into the pathophysiology of complex chronic diseases related to the OS pathway, including asthma. Indeed, previous GWAS of levels of circulating protein biomarkers related to chronic obstructive pulmonary disease, another chronic lung disease, was useful to identify new genes linked to this disease [12]. Such an approach was also useful to identify new genes through the study of biomarkers of other chronic diseases such as kidney or cardiovascular diseases [13,14]. To our knowledge, no GWAS of biomarkers related to the OS pathway, and in particular FIOPs, has been published to date.

Taking advantage of the extensive biological, genotypic, and phenotypic characterisation of >1000 adults from the EGEA study, we aimed to identify genetic loci associated with the FIOPs level through a GWAS. As smoking is the main environmental source of OS and is associated with the FIOPs level, we performed two supplementary GWAS analyses separately in contrasted groups according to tobacco smoking status that could help us to identify genetic loci that could have been missed in the whole sample.

### 2. Materials and Methods

### 2.1. Study Population (EGEA Study)

EGEA is a French cohort study based on an initial group of asthma cases recruited in five chest clinics from Grenoble, Lyon, Marseille, Montpellier, and Paris, along with their first-degree relatives, and population-based controls (EGEA1, 1991–1995). The protocol of the study has been described previously [15,16]. Briefly, the asthma cases and their first-degree relatives were recruited from respiratory or allergic clinics. The adult cases were recruited in the five cities, and the child cases were recruited in Paris, Grenoble, and Marseille. Control adults were recruited from electoral rolls in Paris, Lyon, Montpellier, and Grenoble, a check-up centre in Marseille, and surgery clinic from the same hospital in Paris and Grenoble. Control children were always recruited from surgery clinics. Overall matching by month of exam, age decade, sex, and centre was done. A first follow-up of the initial cohort was conducted between 2003 and 2007 (EGEA2) including 1602 participants (98% adults) with complete examination. At each survey, all participants answered standardised and validated questionnaires to identify asthma and to determine respiratory and allergic symptoms, treatments, environmental exposures, and lifestyle characteristics, including tobacco smoking status. More details are given in Supplementary Materials. The data used for the present analyses were elicited at EGEA2.

The EGEA collection was certified ISO 9001 from 2006 to 2018 [17]. All participants signed a written informed consent, and ethical approval was obtained from the relevant institutional review board committees (Cochin Port-Royal Hospital and Necker-Enfants Malades Hospital, Paris, France).

# 2.2. FlOPs Level

Plasma samples were collected in EGEA2 between 2003 and 2006 and stored immediately at  $-80\,^{\circ}\text{C}$  during 5.0 to 8.0 years until FlOPs measurements. The plasma FlOPs level was measured as previously described [7]. Briefly, plasma was extracted into a mixture of ethanol/ether (3/1 v/v) and measured using a spectrofluorometer (360 nm excitation wavelength, 430 nm emission wavelength). Fluorescence was expressed as a unit of relative

Antioxidants 2022, 11, 802 3 of 17

fluorescence intensity (RFU)· $mL^{-1}$  of plasma. Each sample was replicated. The intra-assay coefficient of variation (CV) for FlOPs was less than 20%. The dosages for which the CV were  $\geq$ 20 % or those that were haemolysed were removed of analysis (n = 11 and n = 8, respectively, see Figure S1 in Supplementary Materials).

### 2.3. Genotyping

The EGEA participants were genotyped using Illumina 610 Quad array at the Centre National de Génotypage (CNG, Evry, France) as part of the European Gabriel consortium asthma GWAS [18]. As part of this consortium, principal-components analysis was conducted for all participants to control population admixture and was carried out using the EIGENSTRAT2.0 software. Putative non-European samples were flagged as outliers and eliminated from subsequent analyses [18]. Stringent quality control (QC) criteria were used to select both individuals and genotyped Single Nucleotide Polymorphisms (SNPs) for analysis [19]. Among participants with genotyped data (n = 1481), 44 with invalid genotyped data were excluded (see Supplementary Materials: Figure S1, flow chart, for details). The following SNPs quality controls were applied: genotyping call rates  $\geq 97\%$ and departure from the Hardy–Weinberg equilibrium in the controls (p-value  $\geq 1.0 \times 10^{-4}$ ) and minor allele frequencies (MAF)  $\geq$  5%. After this SNPs QC control, 66,422 SNPs were excluded, and a total of 501 167 SNPs were available for the analysis. To investigate regions of interest, including the top three SNPs, imputed SNPs from the reference panel 1000 Genome Phase I were used [20]. The software IMPUTE2 was used for imputation [21]. Imputed SNPs were kept for analysis if their imputation information score was greater than or equal to 0.70 and if their minor allele frequency (MAF) was greater than or equal to 0.05.

### 2.4. Definitions of Population's Characteristics

## 2.4.1. Asthma

Ever-asthma status was generated as a dichotomous variable (never-asthmatic/ever-asthmatic). Ever-asthmatics were participants who answered positively to at least one of the two following questions: "Have you ever had attacks of breathlessness at rest with wheezing?" or "Have you ever had asthma attacks?", or those who were recruited as asthmatic cases at EGEA1. Never-asthmatics were those who answered negatively to the two questions above; they were not recruited as asthmatic cases at EGEA1.

### 2.4.2. Chronic Bronchitis

Chronic bronchitis was generated as a dichotomous variable (yes/no). Participants with chronic bronchitis were those who answered positively to at least one of the two following questions: "Do you usually cough during the day or at night in winter almost every day for three months of continued every year?" or "Do you usually spit during the day or at night in winter, almost every day for three months of continued every year?".

### 2.4.3. Lung Function

A lung function test with spirometry and methacholine challenge was performed using standardised protocol with similar equipment across centres and according to the American Thoracic Society/European Respiratory Society guidelines [22]. The forced expiratory volume in one second (FEV<sub>1</sub>) percent predicted value was based on Quanjer et al. reference equations [23]. For participants with a FEV<sub>1</sub>  $\geq$  80% of the predicted value, a methacholine bronchial challenge test was performed (maximum dose 4 mg) using a Biomedin spirometer (Biomedin Srl, Padua, Italy) in all centres, except in Lyon, where a Pneumotach Jaeger spirometer (Jaeger) was used. The following measures of lung function were used as continuous variables and expressed as %: FEV<sub>1</sub> and Forced Vital Capacity (FVC). FEV<sub>1</sub> was also generated as a dichotomous variable (FEV<sub>1</sub> < 80%, FEV<sub>1</sub>  $\geq$  80%).

Antioxidants 2022, 11, 802 4 of 17

### 2.4.4. Smoking Status

Tobacco consumption was defined by the answer to the question "Do you smoke or have you smoked previously one cigarette per day or more, for at least a year?". If so, participants were asked their age at the start of smoking and the age of quitting, if applicable. Participants were also asked to quantify the average daily consumption of cigarettes and the average weekly consumption of cigars, if applicable. Current smoking status was generated as a 3-class categorical variable: never-smoker, ex-smoker, or current smoker. Lifelong cumulative quantity of tobacco was generated as a continuous variable and also categorised using a 4-class variable, with cut-offs defined a priori: never-smokers; <10 pack-year; 10–20 pack-year; and >20 pack-year.

### 2.4.5. Body Mass Index (BMI)

BMI was generated as a continuous variable and was also expressed as a dichotomous variable ( $<30 \text{ kg/m}^2$ ;  $\ge 30 \text{ kg/m}^2$ ).

### 2.4.6. Biological Parameters

Total serum Immunoglobulin E (IgE) determination was assessed by the UniCAP system (Pharmacia<sup>®</sup>) from blood samples in a centralised laboratory and expressed in international units (IU) per millilitre. For the analysis, total IgE level was examined as a continuous variable.

Blood neutrophil and eosinophil counts were expressed in cells/mm<sup>3</sup> and coded as continuous variables [24,25].

# 2.5. Statistical Methods and Strategy of Analysis

# 2.5.1. Characteristics of the Studied Population and Association with the FIOPs Level

First, characteristics of the studied population were described and summarised as n (%) or mean (m)  $\pm$  standard deviation (sd), according to the type of variable, either quantitative or qualitative. Due to their skewed distribution, the FlOPs level was log-transformed and expressed as geometric mean (GM) and values of first quartile (Q1) and third quartile (Q3).

In order to select potential confounding factors prior to GWAS, we estimated associations between log-FIOPs and several characteristics of the whole sample using Gaussian linear models, taking into account EGEA family structure, by Generalised Estimated Equation (GEE, SAS v9.4 (SAS Institute, Cary, NC, USA), proc genmod, option repeated). We previously identified the following characteristics as factors associated with FIOPs: age, sex, current smoking status, lifelong cumulative quantity of tobacco, blood neutrophil count, and FEV1. Age was entered either as a continuous variable or a categorical one, with cut-points defined a priori (<25 years; 25–34 years; 35–44 years; 45–54 years; and  $\geq$ 55 years). Regarding tobacco smoking, models included either smoking status as a categorical variable (never smokers; ex-smokers; and current smokers), or lifelong cumulative quantity of tobacco as a continuous variable or a 4-class categorical variable. The best model was selected based on the QIC, an Akaike's Information Criterion in the framework of GEE models [26]. Among all models tested, the best model included age (continuous), sex, and lifelong cumulative quantity of tobacco (never-smokers; <10 pack-year; 10–20 pack-year; and >20 pack-year).

Adjusted log-FIOPs were obtained as residuals of the best linear model identified in the previous step. Z-scores were then obtained by standardizing residuals, and adequacy to Gaussian distribution was assessed using the Kolmogorov test. In order to exclude participants whose log-FIOPs were poorly predicted by the linear model, participants with the highest Z-score (i.e., |Z-score |>3, corresponding to the 0.1th and 99.9th percentiles of a standard Gaussian distribution) were excluded. The process was repeated until no significant deviation from Gaussian distribution was evidenced. This process excluded 20 participants (see Figure S1 in Supplementary Materials).

Antioxidants 2022, 11, 802 5 of 17

Adjusted log-FIOPs used for GWAS stratified on smoking status (see below) were generated by applying the same procedure as described above, except that lifelong cumulative quantity of tobacco was not entered in the model.

### 2.5.2. GWAS of the FlOPs Level

We first conducted a GWAS of the FIOPs level in the whole sample with genotyped data. Then, we conducted two supplementary GWAS separately in contrasted groups according to smoking status at the time of measurement: never-smokers and current smokers. Ex-smokers were excluded from this analysis.

An association analysis between adjusted log-FIOPs (standardised residual) and each SNP was performed by the Gaussian linear model, adjusted for principal components (PCs) to account for within European diversity. The EGEA family structure was taken into account using a robust variance estimator for clustered data (STATA command: regress, option vce(cluster), within family). SNPs were coded under an additive genetic model.

For the top three SNPs obtained by each of the three GWAS (in the whole sample, in never-smokers and in current smokers), further analyses were conducted. First, we split the sample into two actual independent sub-samples regarding the ascertainment mode (controls vs. cases/relatives) to check the consistency of the results by using a homogeneity test between the sub-samples. Second, due to the mode of ascertainment of EGEA families, i.e., through asthmatic participants, the independence of the results regarding the asthma status was verified by homogeneity test according to ever-asthma status (never-asthmatics vs. ever-asthmatics). A test for homogeneity was performed by fitting the interaction term between the SNP and dummy variables (cases/related vs. controls, and ever-asthmatics vs. never-asthmatics, respectively) in models. The top three SNPs of the three GWAS (in the whole sample, the never-smokers and the current smokers) was also focused on: we used imputed data from the reference panel 1000 Genome project Phase 1 [20] CEU population, spanning 500 kb on each side of each top SNP. For each region of interest, association results were graphically represented using LocusZoom [27].

All analyses were performed using SAS v9.4 (SAS Institute, Cary, NC, USA) or STATA v14.1 (StataCorp. 2015. Stata Statistical Software: Release 14. College Station, TX, USA: StataCorp LP). All tests were two-sided. To account for multiple testing, the Bonferroni-corrected significance p-value threshold applied to the Meff (effective number of independent tests after discarding dependence due to linkage disequilibrium (LD) between the SNPs) was calculated. For a chip of 610K SNPs, the significance p-value threshold was estimated to be  $1.3 \times 10^{-7}$  [28].

# 2.5.3. eQTLs, meQTLs, and Functional Annotations

We investigated whether the top three SNPs (or their proxies,  $r^2 \ge 0.8$ ) in the whole sample, in never-smokers, and in current smokers were cis-expression Quantitative Trait Loci (cis-eQTLs) or methylation Quantitative Trait Loci (meQTLs). For eQTLs and meQTLs, we used the browser Phenoscanner v2 (http://www.phenoscanner.medschl.cam.ac.uk/, accessed on 18 October 2021), which combines several databases, e.g., the Genotype-Tissue Expression project (GTEx, https://www.gtexportal.org/home/, accessed on 18 October 2021) for eQTLs, and BioSQTL and Gaunt's databases for meQTLs) and that includes e-QTL data from many tissues [29-32]. Furthermore, functional annotations of these SNPs (or proxies) were done using the HaploReg v4.1 tool (https://pubs.broadinstitute.org/mammals/ haploreg/haploreg.php, accessed on 18 October 2021). HaploReg annotates SNPs in terms of colocalisation with regulatory elements, such as promoter and enhancer marks, DNase I hypersensitivity sites, and transcription factor (TF) and protein-binding sites, based on Roadmap Epigenomics data and Encyclopedia of DNA Elements data [33]. We checked the potential deleteriousness of SNPs using the combined annotation-dependent depletion tool (CADD v1.4, https://cadd.gs.washington.edu/, accessed on 1 April 2022). The CADD tool scores the predicted deleteriousness of single nucleotide variants and insertion/deletions

Antioxidants 2022, 11, 802 6 of 17

variants in the human genome by integrating multiple annotations [34]. Note that a CADD score  $\geq$  15 indicates a deleterious effect of an SNP.

#### 3. Results

The present analysis was carried out among adult participants ( $\geq$ 16 years old) at EGEA2 with available data on the FIOPs level, valid genotyped data, and asthma and tobacco smoking status. A total of 1216 adult participants were included in the analyses (see Figure S1 in Supplementary Materials).

Compared to the 355 adult participants not included in the analyses, the 1216 participants did not differ in terms of age, sex, and asthma status (data not shown).

### 3.1. Characteristics of the Studied Population

The characteristics of the 1216 participants are presented in Table 1. The results are presented for the whole sample and according to asthma status (ever-asthmatics and never-asthmatics), to the current tobacco smoking status (never-smokers and current smokers), and to the study design (controls and cases/relatives). In the whole sample (mean age 43.3 years, 51% women), 44% had ever-asthma and 23% were current smokers. The geometric mean (GM) (Q1, Q3) of the FIOPs level was 92.3 (80, 105) RFU/mL.

Associations between the FIOPs level and the characteristics of the whole sample are presented in Table S1 (see Supplementary Materials). the FIOPs level was independently associated with age, sex, and smoking (all p-values  $< 5.0 \times 10^{-3}$ ): it increased significantly with age, was significantly higher in women than in men, in ex-/current smokers (GM = 97.2 and 93.8 RFU/mL, respectively) as compared to never-smokers (GM = 89.1 RFU/mL), and increased significantly with lifelong cumulated quantity of cigarettes smoked. The geometric mean (GM) (Q1, Q3) of the FIOPs level was 93.4 (81, 107), 98.7 (88, 108), and 100.3 (88, 114) RFU/mL in participants with lifelong quantity of cigarettes smoked of <10, 10–20, and >20 pack-year, respectively ( $p < 1.0 \times 10^{-4}$ ).

Table 1. The	characteristics	of the studied	population.
--------------	-----------------	----------------	-------------

	Whole Sample (n = 1216)	Never- Asthmatics (n = 684)	Ever- Asthmatics (n = 532)	Never- Smokers (n = 604)	Current Smokers (n = 275)	Controls (n = 243)	Cases/Relatives (n = 973)
	(11 = 1210)	(11 = 004)	(11 = 552)	(11 = 004)	(11 = 273)	(11 = 243)	(11 = 973)
Age, m $\pm$ sd	$43.3 \pm 16.4$	$46.3 \pm 15.9$	$39.4 \pm 16.4$	$42.7 \pm 16.9$	$35.5 \pm 14.1$	$47.2 \pm 17.2$	$42.3 \pm 16.1$
Sex, women, n (%)	621 (51.1)	374 (54.7)	247 (46.4)	338 (56.0)	131 (47.6)	125 (51.4)	496 (51.0)
Current smoking status, n (%)							
Never-smokers	604 (49.7)	342 (50.0)	262 (49.2)	604 (100)	-	114 (46.9)	490 (50.4)
Ex-smokers	337 (27.7)	202 (29.5)	135 (25.4)	-	-	70 (28.8)	267 (27.4)
Current smokers	275 (22.6)	140 (20.5)	135 (25.4)	-	275 (100)	59 (24.3)	216 (22.2)
Smoking, pack-year, n (%)	, ,	, ,	, ,		, ,	, ,	` ,
Never-smokers	604 (49.7)	342 (50.0)	262 (49.3)	604 (100)	-	114 (46.9)	490 (50.4)
<10	384 (31.6)	197 (28.8)	187 (35.1)	-	186 (67.6)	75 (30.9)	309 (31.8)
10–20	111 (9.1)	68 (9.9)	43 (8.1)	-	44 (16.0)	23 (9.5)	88 (9.0)
>20	117 (9.6)	77 (11.3)	40 (7.5)	-	45 (16.4)	31 (12.7)	86 (8.8)
BMI, kg·m <sup>-2</sup> , n (%)	n = 1201	n = 676	n = 525	n = 597	n = 272	n = 240	n = 961
≥30	118 (9.8)	66 (9.8)	52 (9.9)	56 (9.4)	16 (5.9)	20 (8.3)	98 (10.2)
IgE	n = 1214	n = 682	n = 532	n = 603	n = 274	n = 242	n = 972
IgE, IU/mL, m $\pm$ sd	$222\pm453$	$134 \pm 352$	$333 \pm 537$	$198 \pm 431$	$304 \pm 528$	$116 \pm 258$	$248 \pm 487$
White blood count	n = 1206	n = 677	n = 529	n = 601	n = 273	n = 242	n = 964
Neutrophils, cells/mm <sup>3</sup> , m $\pm$ sd	$3986\pm1391$	$3959\pm1317$	$4020\pm1481$	$3879\pm1278$	$4314\pm1535$	$3985\pm1317$	$3986\pm1410$
Eosinophils, cells/mm <sup>3</sup> , m $\pm$ sd	$202\pm155$	$168\pm125$	$244\pm179$	$203\pm166$	$220\pm162$	$160\pm116$	$212\pm162$
Lung Function	n = 1197	n = 673	n = 524	n = 594	n = 272	n = 238	n = 959
$FEV_1$ , % predicted, m $\pm$ sd	$103\pm17.8$	$107\pm16.3$	$97\pm18.2$	$104\pm17.5$	$100\pm15.6$	$105\pm15.4$	$102\pm18.3$
FVC, % predicted, m $\pm$ sd	$110\pm17.1$	$112\pm17.5$	$108 \pm 16.3$	$112\pm17.1$	$107\pm15.0$	$109\pm15.3$	$111\pm17.5$

Antioxidants 2022, 11, 802 7 of 17

		Cont	

	Whole Sample (n = 1216)	Never- Asthmatics (n = 684)	Ever- Asthmatics (n = 532)	Never- Smokers (n = 604)	Current Smokers (n = 275)	Controls (n = 243)	Cases/Relatives (n = 973)
FEV <sub>1</sub> > 80%, n (%)	1097 (91.7)	644 (95.7)	453 (86.5)	556 (93.6)	253 (93.0)	228 (95.8)	869 (90.6)
Chronic bronchitis, n (%)	n = 1205	n = 679'	n = 526	n = 597	n = 274	n = 241	n = 964
Yes	114 (9.5)	39 (5.7)	75 (14.3)	47 (7.9)	40 (14.6)	19 (7.9)	95 (9.9)
FIOPs, RFU/mL, GM (O1, O3)	92.3 (80, 105)	93.9 (82, 108)	90.4 (78, 102)	89.1 (77, 101)	93.8 (82, 107)	92.6 (81, 107)	92.3 (79, 105)

m, mean; sd, standard deviation; FEV<sub>1</sub>, forced expiratory volume in one second; FVC, force vital capacity; GM, geometric mean; Q1, first quartile; and Q3, third quartile.

### 3.2. GWAS of the FlOPs Level

### 3.2.1. Whole Sample

Table 2 reports the results of the associations in the whole sample for the 10 SNPs showing the strongest signals. The Manhattan plot is available in Supplementary Materials, Figure S2A, and the Q-Q plot in Figure S3A shows that there was no inflation in the statistical test, with the genomic inflation factor estimated to 1.002. The top three SNPs were rs270404, located in the *BMP6* gene on chromosome 6p24.3 ( $p = 3.0 \times 10^{-6}$ ); rs13223298, located upstream (from 2 kb apart) of the *BMPER* gene on chromosome 7p14.3 (p-value = 8.7 × 10<sup>-6</sup>); and rs491274, located in the intergenic region nearest *SEMA6D* (from 607 kb apart) genes on chromosome 15q21.1 ( $p = 8.9 \times 10^{-6}$ ). The association analysis for these top three SNPs in the two independent sub-samples (controls vs. cases/relatives) showed no indication of heterogeneity (all p-values > 0.6, see Table S2 in Supplementary Materials).

The associations stratified by asthma status (never-asthmatics, ever-asthmatics) for the top three SNPs associated with the FIOPs level in the whole sample are reported in Table 3. No indication of heterogeneity was observed (all p-values  $\geq 0.25$ ).

An analysis using imputed SNPs spanning 500 kb on each side of each top SNP in the regions of the top three SNPs located in BMP6, near BMPER and near SEMA6D, confirmed the initial results (see Supplementary Materials: Figure S4A–C). Analyses of imputed SNPs in these regions found signals with similar or slightly improved significance levels at genotyped SNPs, and for at least two other imputed SNPs, which were close to and in strong linkage disequilibrium (LD,  $r^2 > 0.8$ ) with the genotyped top SNP (Figure S4A–C).

Table 2. The top 10 SNPs associated with the FIOPs level in 1216 adults from the EGEA study.

Chr	Gene	Nearest Gene	Genomic Location	Marker	Position bp (hg38)	Band	A1/A2	EAF	Beta $\pm$ se	p
6	BMP6	TXNDC5	Intronic	rs270404	7,757,141	p24.3	A/G	0.41	$-0.20\pm0.04$	$3.0 \times 10^{-6}$
7		BMPER	3'-UTR	rs13223298	34,158,658	p14.3	G/T	0.08	$-0.34 \pm 0.08$	$8.7 \times 10^{-6}$
15		SEMA6D	Intergenic	rs491274	46,577,328	q21.1	A/G	0.09	$-0.31 \pm 0.07$	$8.9 \times 10^{-6}$
1	RGL1	APOBEC4	Intronic	rs6664058	183,687,143	q25.3	C/T	0.36	$0.21\pm0.05$	$1.2 \times 10^{-5}$
7	PKD1L1	TNS3	Intronic	rs10276437	47,766,479	p12.3	C/T	0.78	$0.21\pm0.05$	$1.3 \times 10^{-5}$
14		VRK1	Intergenic	rs4905587	97,213,901	q32.2	G/T	0.12	$0.31\pm0.07$	$1.4 \times 10^{-5}$
1	RGL1	APOBEC4	Intronic	rs6424909	183,727,521	q25.3	A/G	0.36	$0.21\pm0.05$	$1.5 \times 10^{-5}$
16		HS3ST6	5'-UTR	rs344363	1,922,547	p13.3	C/T	0.17	$-0.26\pm0.06$	$1.7 \times 10^{-5}$
20	PMEPA1	ZBP1	Intronic	rs6025728	57,697,562	q13.31	C/T	0.63	$0.20\pm0.05$	$2.0 \times 10^{-5}$
12	CACNA1C	FKBP4	Intronic	rs4765961	2,559,306	p13.33	C/T	0.82	$0.23\pm0.05$	$2.2 \times 10^{-5}$

Chr, chromosome; A1/A2, baseline/effect allele; and EAF, effect allele frequency estimated from the reference panel 1000 G (European population). Beta and standard error (se) were estimated using the Gaussian linear model, taking into account the EGEA family structure and adjusted for principal components.

Antioxidants 2022, 11, 802 8 of 17

<b>Table 3.</b> A stratified anal	vsis according to asthma	status for the top	three SNPs in the whole sample.

Chr	Gene	Nearest Gene	Genomic Location	Marker	A1/A2	EAF	Never-Asthmatics (n = 684)		Ever-Asthmat	Homogeneity Test		
							Beta $\pm$ se $p$		Beta $\pm$ se	p	Khi <sup>2</sup>	p
6	ВМР6	TXNDC5	Intronic	rs270404	A/G	0.41	$-0.20 \pm 0.06$	$5.1 \times 10^{-4}$	$-0.20 \pm 0.06$	$5.4 \times 10^{-4}$	0.01	0.91
7		BMPER	3'-UTR	rs13223298	G/T	0.08	$-0.42\pm0.10$	$4.5 \times 10^{-5}$	$-0.23 \pm 0.12$	$5.5 \times 10^{-2}$	1.32	0.25
15		<i>SEMA6D</i>	Intergenic	rs491274	A/G	0.09	$-0.36 \pm 0.08$	$2.7 \times 10^{-5}$	$-0.23 \pm 0.11$	$4.1 \times 10^{-2}$	0.75	0.39

Chr, chromosome; A1/A2, baseline/effect allele; and EAF, effect allele frequency estimated from the reference panel 1000 G (European population). Beta and standard error (se) were estimated using Gaussian linear model, taking into account EGEA family structure and adjusted for principal components.

### 3.2.2. In Never-Smokers and in Current Smokers

Table 4 presents the associations with FIOPs for the top 10 SNPs in never-smokers and in current smokers. Manhattan plots are available for the two GWAS in Supplementary Materials; Figure S2B,C; and the Q-Q plots in Figure S3B,C and show that there was no inflation in the statistical test for the two GWAS, with genomic inflation factors estimated to 1.006 and 1.03, respectively.

**Table 4.** The GWAS of FIOPs: the top 10 SNPs in never-smokers and in current smokers.

Chr	Gene	Nearest Gene	Genomic Location	Marker	Position bp (hg38)	Band	A1/A2	EAF	Beta $\pm$ se	p
	r-smokers									
(n	= 604)									_
6	COL21A1	DST	Intronic	rs17823624	56,348,021	p12.1	A/G	0.92	$0.44 \pm 0.08$	$2.3 \times 10^{-7}$
15	<i>GABRG3</i>	GABRA5	Intronic	rs6606856	27,022,887	q12	C/T	0.70	$-0.28 \pm 0.05$	$4.1 \times 10^{-7}$
5		NUDT12	Intergenic	rs2962642	104,131,010	q21.2	A/G	0.24	$0.30 \pm 0.06$	$4.4 \times 10^{-7}$
10	PAOX	MTG1	Intronic	rs6537600	133,391,295	q26.3	C/T	0.88	$0.40\pm0.08$	$6.5 \times 10^{-7}$
5		NUDT12	Intergenic	rs7725285	104,111,482	q21.2	G/T	0.75	$-0.29 \pm 0.06$	$1.5 \times 10^{-6}$
10	PAOX	MTG1	Intronic	rs10776679	133,389,090	q26.3	C/T	0.05	$-0.49 \pm 0.10$	$1.6 \times 10^{-6}$
8	DEFB135	DEFB136	Intronic	rs6985349	11,982,562	p23.1	C/T	0.06	$-0.43 \pm 0.09$	$2.0 \times 10^{-6}$
8	DEFB135	DEFB136	Intronic	rs7004833	11,982,502	p23.1	A/G	0.06	$-0.43 \pm 0.09$	$2.0 \times 10^{-6}$
3		ZNF385D	Intronic	rs1391857	20,857,452	p24.3	A/G	0.61	$-0.27\pm0.06$	$2.5 \times 10^{-6}$
10	ECHS1	PAOX	Missense	rs1049951	133,370,622	q26.3	A/G	0.06	$-0.41\pm0.09$	$3.6 \times 10^{-6}$
Curre	nt smokers					_				
(n	= 275)									
6	CRYBG1	ATG5	Intronic	rs3851212	106,375,664	q21	A/G	0.94	$-0.81\pm0.13$	$2.4 \times 10^{-9}$
12	COL2A1	TMEM106	C Intronic	rs1793958	47,998,650	q13.11	A/G	0.61	$-0.40\pm0.08$	$4.7 \times 10^{-7}$
12		PTPRO	Intergenic	rs17174795	15,603,555	p12.3	G/T	0.87	$-0.62\pm0.12$	$9.2 \times 10^{-7}$
15	ISG20	AEN	Intronic	rs8041687	88,655,329	q26.1	A/G	0.07	$0.56\pm0.11$	$1.1 \times 10^{-6}$
3	CMC1	AZI2	Intronic	rs7641491	28,301,843	p24.1	A/G	0.53	$0.39 \pm 0.08$	$2.8 \times 10^{-6}$
3	CMC1	AZI2	Intronic	rs13085075	28,309,712	p24.1	C/T	0.48	$-0.39 \pm 0.08$	$3.1 \times 10^{-6}$
7		CREB5	Intergenic	rs10228137	28,848,469	p14.3	A/C	0.81	$-0.43 \pm 0.09$	$4.3 \times 10^{-6}$
2		LRP1B	Intergenic	rs961109	142,396,452	q22.2	C/T	0.91	$0.66\pm0.14$	$4.6 \times 10^{-6}$
4	TENM3	DCTD	Intronic	rs4557308	182,734,597	q35.1	A/G	0.26	$0.41\pm0.09$	$5.0 \times 10^{-6}$
13		ATP7B	5′-UTR	rs4943040	51,919,816	q14.3	C/T	0.55	$0.38\pm0.08$	$5.2 \times 10^{-6}$

Chr, chromosome; A1/A2, baseline/effect allele; and EAF, effect allele frequency estimated from the reference panel 1000 G (European population). Beta and standard error (se) were estimated using Gaussian linear model, taking into account EGEA family structure and adjusted for principal components.

In never-smokers, the top three SNPs (all p-values  $< 5.0 \times 10^{-7}$ ) were rs17823624 located in the COL21A1 gene on the chromosome 6p12.1 ( $p = 2.3 \times 10^{-7}$ ), rs6606856 located in GABRG3 gene on chromosome 15q12 ( $p = 4.1 \times 10^{-7}$ ), and rs2962642 located in an intergenic region near NUDT12 (from 568 kb apart) on chromosome 5q21.2 ( $p = 4.4 \times 10^{-7}$ ). For these top three SNPs, association analysis in the two independent sub-samples (controls vs. cases/relatives) showed no indication of heterogeneity (all p-values > 0.6, see Table S3 in Supplementary Materials). Besides that, association analysis for these top SNPs yielded

Antioxidants 2022, 11, 802 9 of 17

similar results in never-asthmatics and in ever-asthmatics, with no indication of heterogeneity ( $p \ge 0.10$ , Table 5). Note that none of the top three SNPs found in never-smokers showed indication of association in current smokers (all p-values > 0.10).

In current smokers, the top three SNPs were rs3851212 located in *CRYBG1* on chromosome 6q21 ( $p = 2.4 \times 10^{-9}$ , exceeding the significance level of  $1.3 \times 10^{-7}$ ), rs1793958 located in *COL2A1* on chromosome 12q13.11 ( $p = 4.7 \times 10^{-7}$ ), and rs17174795 located upstream *PTPRO* (from 1.4 kb apart) on chromosome 12 p12.3 ( $p = 9.2 \times 10^{-7}$ ). For these top three SNPs, association analysis in the two independent sub-samples (controls vs. cases/relatives) showed no indication of heterogeneity (all p-values  $\geq 0.4$ , see Table S3 in Supplementary Materials). No heterogeneity of association signals was detected according to asthma status (all p-values  $\geq 0.7$ , except for rs17174795 with p-value = 0.05, but not significant after correction for multiple testing; see Table 5). The top three SNPs found in current smokers showed no indication of association in never-smokers (p > 0.20) or only a weak signal (p = 0.05).

**Table 5.** The stratified analysis according to asthma status for the top three SNPs, in never-smokers and in current smokers.

								Never-Asthmatics		Ever-Asthmatics		Homogeneity Test	
Chr	Gene	Nearest Gene	Genomic Location	Marker	Position bp (hg38)	A1/A2	EAF	Beta $\pm$ se	p	Beta $\pm$ se	p	khi <sup>2</sup>	p
	Never- smokers (n = 604)							n = 342		n = 262			
6	COL21A1	DST	Intronic	rs17823624	56 348 021	A/G	0.92	$0.46 \pm 0.11$	$2.9 \times 10^{-5}$	$0.43 \pm 0.13$	$1.1 \times 10^{-3}$	0.07	0.79
15	GABRG3	GABRA5	Intronic	rs6606856	27 022 887	C/T	0.70	$-0.29 \pm 0.08$	$2.4 \times 10^{-4}$	$-0.30 \pm 0.08$	$1.7 \times 10^{-4}$	0.00	0.97
5		NUDT12	Intergenic	rs2962642	104 131 010	A/G	0.24	$0.36 \pm 0.07$	$2.0 \times 10^{-6}$	$0.22 \pm 0.09$	$1.5 \times 10^{-2}$	1.89	0.17
	Current smokers (n = 275)		Ü					n = 140		n = 135			
6	CRYBG1	ATG5	Intronic	rs3851212	106 375 664	A/G	0.94	$-0.79 \pm 0.22$	$5.5 \times 10^{-4}$	$-0.85 \pm 0.16$	$3.2 \times 10^{-7}$	0.08	0.78
12	COL2A1	TMEM106C	Intronic	rs1793958	47 998 650	A/G	0.61	$-0.38 \pm 0.12$	$1.7 \times 10^{-3}$	$-0.42\pm0.10$	$4.9 \times 10^{-5}$	0.09	0.77
12		PTPRO	Intergenic	rs17174795	15 603 555	G/T	0.87	$-0.85\pm0.18$	$5.1 \times 10^{-6}$	$-0.36 \pm 0.16$	$2.7 \times 10^{-2}$	3.86	0.05

Chr, chromosome; A1/A2, baseline/effect allele; and EAF, effect allele frequency estimated from the reference panel 1000 G (European population). Beta and standard error (se) were estimated using Gaussian linear model, taking into account EGEA family structure and adjusted for principal components.

Analysis using imputed SNPs spanning 500 kb on each side of each top SNP in the regions of the top three SNPs in both never-smokers and current smokers confirmed the initial results, with a similar significance level as those observed with genotyped SNPs (Figures S5A–C and S6A–C in Supplementary Materials). Analyses of imputed data in the region around two of the top six SNPs found additional signals at imputed SNPs close to and in strong linkage disequilibrium (LD,  $r^2 > 0.8$ ), with the genotyped top SNPs, 12 for rs2962642 located near *NUDT12* with similar significance level (Figure S5C) and two for rs17174795 located near *PTPRO* with improved significance level (Figure S6C). These results also supported the initial findings for these top two SNPs.

### 3.3. eQTLs, meQTLs, and Functional Annotations

Using the browser Phenoscanner v2 (http://www.phenoscanner.medschl.cam.ac.uk/, accessed on 18 October 2021), we found that top two SNPs, one in never-smokers (rs17823624 in COL21A1) and one in current smokers (rs1793958 in COL2A1), were associated with gene expression in a whole blood sample from subject of European ancestry (Table S4 in Supplementary Materials). The SNP rs1783624 was associated with gene expression of DST (p-value =  $2.0 \times 10^{-15}$ ), while the SNP rs1793958 was associated with the expression of five genes belonging to the 12q13.11 region: OR10AD1, PFKM, SENP1, TMEM106C, and VDR (all p-values <  $2.5 \times 10^{-8}$ ). No eQTL was found for the other top SNPs. Furthermore, we found from 1 to 26 CpG sites considering all top three SNPs of GWAS in the whole sample, in never-smokers and in current smokers (See Table S5 in Supplementary Materials). Most CpG sites were located near or in the same gene as the associated SNP. The SNP rs13223298 in BMPER was found to be more associated with the

Antioxidants 2022, 11, 802 10 of 17

methylation level of one CpG site located on another chromosome than *BMPER*, in the *PTPN22* gene on chromosome 1p13.2 (p-value =  $9.3 \times 10^{-8}$ , not significant after correction for multiple testing).

Note that a proxy of rs3851212 (the top SNP in current smokers located in *CRYBG1*) rs79231630 had a CADD score equal to 14.5. Detailed results for CADD scores are presented in Table S6.

Using the functional annotation tool HaploReg-v4.1, we found that all top three SNPs (or their proxies) evidenced respectively in the whole sample, in never-smokers and in current smokers, mapped to marks of active regulatory elements, including cells from heart, lung, kidney, breast, and brain. Detailed results for functional annotations are presented in Table S6 (see Supplementary Materials).

#### 4. Discussion

This first genetic study on the FIOPs level identified several variants, among which those located in *BMP6*, near *BMPER* and between *SQOR* and *SEMA6D* were the most strongly associated with this biomarker in the whole sample. Stratified analyses on tobacco smoking status identified other genetic variants: among them, the top three SNPS in neversmokers located in *COL21A1*, in *GABRG3*, and near *NUDT12*, and the top three SNPS in current smokers located in *CRYBG1*, in *COL2A1*, and near *PTPRO*.

Our study is based on the hypothesis that GWAS of FIOPs may provide new insights nito the pathophysiology of chronic diseases related to the OS pathway. The GWAS analyses we performed were based on the EGEA study, whose participants had extensive clinical, genetic, biological, and environmental characterisation. To our knowledge, there was no other epidemiological study with such data for a replication sample. Interestingly, all our association results were supported by consistent results observed in controls and cases/relative sub-samples. Furthermore, analyses of imputed data in the region around each top SNP confirmed our initial association results obtained with genotyped data. However, all our findings should be validated/replicated in other independent cohorts.

Due to the ascertainment mode of families in the EGEA study, i.e., through asthmatic participants, and the involvement of the OS pathway in the pathophysiology of asthma, we repeated our analyses in ever- and never-asthmatics in order to evaluate the associations independently of the disease. The results were consistent between never- and ever-asthmatics, which showed the independence of our results from the disease. Furthermore, we verified that any of our top SNPs were associated with lung function or adult-onset asthma in EGEA sample [19]. All these results suggest that our main results are not driven by asthma.

In the whole population, the strongest association signals were observed for rs270404 located in BMP6 and rs13223298 located near BMPER (i.e., 2.2 kb from that gene). BMP6 and BMPER were reported to interact physically in a functional study [35]. In line with this result, we tested the effect of the statistical interaction between these SNPs on FIOPs and found a borderline significant interaction (p-value = 0.07). BMP6 (Bone Morphogenetic Protein 6) encodes a secreted ligand of the transforming growth factor-beta (TGF-beta) superfamily of proteins, and BMPER (BMP Binding Endothelial Regulator) encodes a secreted protein that interacts with and inhibits the bone morphogenetic protein (BMP) function. It is noteworthy that these two genes belong to the biological process "regulation of pathway restricted SMAD protein phosphorylation" pathway (GO:006093) that is involved in the TGF-beta receptor signalling pathways [36]. The role of TGF-beta has been discussed in chronic asthma, as a potent fibrogenic growth factor overexpressed in the asthmatic lung [37]. Moreover, BMPER belongs to the biological process "immune response" pathway (GO:0006954) [38]. From the GWAS Catalog [39], we found that BMP6 was associated with FVC [40–42];  $FEV_1$  [42]; and, to a lesser extent, chronic obstructive pulmonary disease [43] and small cell lung carcinoma [44]. In previous GWAS, associations were reported between BMPER and FVC [40], FEV<sub>1</sub> [45], and other chronic diseases such as Alzheimer's disease [46] and metastatic colorectal cancer [47]. Moreover, the top two SNPs in BMP6 and near the BMPER map to marks of active regulatory elements in heart, lung, brain, breast, Antioxidants 2022, 11, 802 11 of 17

and kidney tissues and the top SNP near *BMPER* was associated with the methylation level of one CpG site located in *PTPN22* (Protein Tyrosine Phosphatase Non-Receptor Type 22), a gene involved in "NF-Kappa B signalling" and "immune response" pathways.

The third strongest association signal was observed for rs491274 located nearest *SEMA6D* (i.e., 607 kb appart). *SEMA6D* (Semaphorin 6D) was found to be associated with parental longevity [48,49] and lung carcinoma [44] in previous GWAS.

As cigarette smoke is the most important exogenous source of ROS, we performed GWAS separately in two contrasted sub-groups according to smoking status and identified specific association signals in each sub-group. In never-smokers, the top SNP was rs1782324 located in COL21A1 (Collagen Type XXI Alpha 1 Chain). In previous GWAS, COL21A1 showed associations with lung function [40] and to a lesser extend with allergic sensitisation [50] and small cell lung carcinoma [44]. We also found that rs17823624 was eQTL of DST (Dystonine), a gene close to COL21A1, for which variants were found to be associated with lung function [40,42] and Alzheimer's disease [51]. The next top SNP rs6606856 was located in GABRG3 (Gamma-Aminobutyric Acid Type A Receptor Subunit Gamma3), a gene involved in the "response to drug" biological pathway (GO:0042493). This gene was shown to be associated with gene methylation in the lung tissue of smokers, as reported in a previous GWAS [52]. An association between GABRG3 and several chronic diseases, including Alzheimer's disease [53], ovarian carcinoma [54,55], and non-melanoma carcinoma [56], was also reported in other previous GWAS. Finally, the third highest SNP rs2962642 was located near (i.e., 568 kbp apart) to NUDT12 (Nudix Hydrolase 12). This gene was involved in the "NADH metabolic process" biological pathway (GO:0006734), and was shown to be associated with longevity [57] and smoking behaviour [58] in previous GWAS. Furthermore, proxies of rs2962642 map onto the regulatory motifs altered for histone deacetylase 2 (HDAC2), whose activity is regulated by oxidative stress.

In current smokers, the top SNP, rs3851212, was located in CRYBG1, which exceeded the genome-wide significance threshold level of  $4.3 \times 10^{-8}$  when accounting for the three GWAS. The role of CRYBG1 (crystallin beta-gamma domain containing 1), also called AIM1 (absent in melanoma 1 protein) in malignant melanoma, is well-known [59]. To note, rs3851212 is located 50 kb from ATG5 (autophagy-related 5), which belongs to the biological pathway "immune system process" (GO:0002376) and is involved in mitochondrial quality control after oxidative damage, and in subsequent cellular longevity. In previous GWAS, ATG5 was found to be associated with allergic diseases [60], including asthma [61–64], and with several other chronic diseases such as systemic lupus erythematous [65–68], rheumatoid arthritis [69,70], and multiple myeloma [71]. Furthermore, note that a proxy of rs3851212—rs79231630—has a CADD score close to 15, indicating deleterious effect of the SNP. The next top SNP is rs1793958, located in COL2A1 (collagen type II alpha 1 chain), a gene involved in "regulation of immune response" biological process (GO:0050776). COL2A1 was found to be associated with rheumatoid arthritis [72] and with prostate carcinoma [73–75] in previous GWAS. On the other hand, the third highest SNP rs17174795 is located 1.4 kb apart from PTPRO (Protein Tyrosine Phosphatase Receptor type O), which has been suggested as a candidate tumour suppressor via the NF-Kappa B signalling pathway [76,77], and the transcription factor NF-Kappa B plays a central role in inflammatory airway diseases such as asthma [78].

None of the top signals found in one sub-group of smoking status were found in the other sub-group, nor in the whole sample, showing that, as we hypothesised, accounting for smoking status may help one to identify loci not found in the whole sample. These results are likely explained by the existing interactions between the environment (here smoking) and genes that lead to "up" or "down" regulation of the pathways that influence the level of FIOPs.

None of the top signals found in the whole sample were found in the two contrasted sub-groups according to smoking status, which is an interesting result. Indeed, these analyses were carried out with the objective to identify genetic loci that could have been missed in the whole sample as smoking is the main environmental source of OS and is

Antioxidants 2022, 11, 802 12 of 17

associated with FlOPs. The two GWAS in groups contrasted by smoking revealed additional genetic loci to those found in the whole sample.

Overall, many of the top SNPs identified by the three GWAS are located in regions comprising promising candidate genes. Among them, *BMP6*, *BMPER*, *GABRG3*, and *ATG5* are the most relevant because of both their link to biological pathways related to OS and their association with several chronic diseases, for which the role of OS in their pathophysiology has been pointed out. *BMP6* and *BMPER* are of particular interest due to their involvement in the same biological pathways related to OS and their functional interaction.

#### 5. Conclusions

In conclusion, the present study identified, for the first time, new and promising candidate genes associated with the FIOPs level potentially involved in the pathophysiology of chronic diseases through their link with the oxidative stress pathway. Although further studies are needed to replicate these findings, this work highlights the interest in performing genome-wide analyses of biomarkers to identify new genes and potential mechanisms related to specific pathways common to chronic diseases.

Supplementary Materials: The following supporting information can be downloaded at: https: //www.mdpi.com/article/10.3390/antiox11050802/s1. References [15,16,79] are cited in the supplementary materials. The description of the EGEA study; Figure S1: a flow chart of the studied population; Figure S2: a Manhattan plot of the GWAS results of the FlOPs levels (A) in the whole sample (n = 1216), (B) in never-smokers (n = 604), and (C) in current smokers (n = 275); Figure S3: a quantile-quantile (QQ) plot of the GWAS results of the FIOPs levels (A) in the whole sample (n = 1216), (B) in never-smokers (n = 604), and (C) in current smokers (n = 275); Figure S4: a regional plot of the association results using imputed genetic data for the top three SNPs in the whole sample (n = 1216), the region around rs270404 (A), the region around rs13223298 (B), and the region around rs491274 (C); Figure S5: a regional plot of the association results using imputed genetic data for the top three SNPs in never-smokers (n = 604), the region around rs17823624 (A), the region around rs6606856 (B), and the region around rs2962642 (C); Figure S6: the regional plot of association results using imputed genetic data for the top three-SNPs in current smokers (n = 275), the region around rs3851212 (A), the region around rs1793958 (B), and the region around rs17174795 (C); Table S1: the association between the FIOPs level and the characteristics of the studied population (n = 1216); Table S2: the top three SNPs in the whole sample: the consistency of the results in two independent sub-samples; Table S3: the top three SNPs in never-smokers and in current smokers: the consistency of the results in two independent sub-samples; Table S4: the results from the eQTL browser Phenoscanner v2; Table S5: the meQTLs for the top three-SNPs identified in GWAS in the whole sample, in never-smokers and in current smokers; Table S6: Regulatory elements for the top three SNPs (and proxies with  $r^2 > 0.80$ ) identified in GWAS in the whole sample, in never-smokers and in current smokers.

**Author Contributions:** Conceptualisation, L.O., R.N. and M.-H.D.; data curation, L.O., P.M.-J. and M.-H.D.; formal analysis, L.O., P.M.-J. and M.A.; methodology, L.O., O.D., R.N. and M.-H.D.; project administration, R.N. and M.-H.D.; resources, L.O., P.M.-J., H.M., E.B., F.D., R.M., F.Z., R.N. and M.-H.D.; software, L.O., P.M.-J. and H.M.; supervision, R.N. and M.-H.D.; validation, L.O., R.N. and M.-H.D.; visualisation, L.O., R.N. and M.-H.D.; writing—original draft preparation, L.O., R.N. and M.-H.D.; and writing—review and editing, all authors. All authors have read and agreed to the published version of the manuscript.

**Funding:** The French National Research Program for Environmental and Occupational Health of Anses (EST/2017/1/158); the National Hospital program of clinical research (PHRC-National 2012, EvAdA); the National Research Agency—Health Environment, Health-Work Program (ANR-CES-2009, BIO2NEA); the Fonds AGIR pour les maladies chroniques; and the Region Hauts de France.

Antioxidants 2022, 11, 802 13 of 17

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki. Approvals were obtained from the relevant Ethics Committees and the Institutional Review Board Committees: INSERM, RBM 'Recherche BioMédicale' (no RBM 91-005, 08/1991; and no RBM 01-11, 02/2002); CNIL 'Commission Nationale de l'Informatique et des Libertés' (no 109 427, 04/1990; and no 900 198, 10/2000); the Institutional Review Board Committees of Cochin Port-Royal Hospital and Necker-Enfants Malades Hospital, Paris, France (no 01-07-07, 09/2001; no 04-05-03, 11/2004; no 04-11-13, 11/2004; and no 04-11-18, 12/2004); and DGS 'Direction Générale de la Santé' (no DGS 910 048, 07/1991; and no DGS 2002/0106, 02/2002).

**Informed Consent Statement:** Written informed consent was obtained from all subjects involved in the study.

**Data Availability Statement:** Due to third-party restrictions, EGEA data are not publicly available. Please see the following URL for more information: <a href="https://egeanet.vjf.inserm.fr/index.php/en/contacts-en">https://egeanet.vjf.inserm.fr/index.php/en/contacts-en</a>, accessed on 17 February 2022. Interested researchers should contact egea.cohorte@inserm.fr with further questions regarding data access.

Acknowledgments: The EGEA cooperative group. Coordination: V Siroux (epidemiology, PI since 2013); F Demenais (genetics); I Pin (clinical aspects); R Nadif (biology); and F Kauffmann (PI 1992-2012). Respiratory epidemiology: Inserm ex-U 700, Paris: M Korobaeff (Egea1) and F Neukirch (Egea1); Inserm ex-U 707, Paris: I Annesi-Maesano (Egea1-2); Inserm U 1018, Villejuif: O Dumas, F Kauffmann, N Le Moual, R Nadif, MP Oryszczyn (Egea1-2), and R Varraso; Inserm U 1209 Grenoble: J Lepeule, and V Siroux. Genetics: Inserm ex-U 393, Paris: J Feingold; Inserm UMR 1124, Paris: E Bouzigon, MH Dizier, and F Demenais; and CNG, Evry: I Gut (now CNAG, Barcelona, Spain), M Lathrop (now Univ McGill, Montreal, Canada). Clinical centres: Grenoble: I Pin and C Pison; Lyon: D Ecochard (Egea1), F Gormand, and Y Pacheco; Marseille: D Charpin (Egea1) and D Vervloet (Egea1-2); Montpellier: J Bousquet; Paris Cochin: A Lockhart (Egea1) and R Matran (now in Lille); Paris Necker: E Paty (Egea1-2) and P Scheinmann (Egea1-2); Paris-Trousseau: A Grimfeld (Egea1-2) and J Just. Data management and quality: Inserm ex-U155, Paris: J Hochez (Egea1); Inserm U 1018, Villejuif: N Le Moual and L Orsi; Inserm ex-U780, Villejuif: C Ravault (Egea1-2); Inserm ex-U794, Evry: N Chateigner (Egea1-2); Inserm UMR 1124, Paris: H Mohamdi; and Inserm U1209, Grenoble: A Boudier and J Quentin (Egea1-2). The authors thank all those who participated in the setting of the study and in the various aspects of the examinations involved: interviewers; technicians for lung function testing and skin prick tests, blood sampling, and IgE determinations; coders; those involved in quality control, data, and sample management; and all those who supervised the study in all centres. The authors are grateful to the three CIC-Inserm of Necker, Grenoble, and Marseille, who supported the study and in which participants were examined. They are also grateful to the biobanks in Lille (CIC Inserm), and at Annemasse (Etablissement Français du sang), where biological samples are stored. They are indebted to all the individuals who participated, without whom the study would not have been possible. We also thank P. Dessen for his helpful suggestions regarding genes bioinformatics applications.

**Conflicts of Interest:** The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

### References

- 1. Sies, H.; Berndt, C.; Jones, D.P. Oxidative Stress. Annu. Rev. Biochem. 2017, 86, 715–748. [CrossRef] [PubMed]
- 2. Sharifi-Rad, M.; Anil Kumar, N.V.; Zucca, P.; Varoni, E.M.; Dini, L.; Panzarini, E.; Rajkovic, J.; Tsouh Fokou, P.V.; Azzini, E.; Peluso, I.; et al. Lifestyle, Oxidative Stress, and Antioxidants: Back and Forth in the Pathophysiology of Chronic Diseases. *Front. Physiol.* **2020**, *11*, 694. [CrossRef] [PubMed]
- 3. Bermúdez, E.; Stone, K.; Carter, K.M.; Pryor, W.A. Environmental Tobacco Smoke Is Just as Damaging to DNA as Mainstream Smoke. *Environ. Health Perspect.* **1994**, *102*, 870–874. [CrossRef] [PubMed]
- Sies, H. Oxidative Stress: Concept and Some Practical Aspects. Antioxidants 2020, 9, 852. [CrossRef]
- 5. Dillard, C.J.; Tappel, A.L. Fluorescent Damage Products of Lipid Peroxidation. Methods Enzymol. 1984, 105, 337–341. [CrossRef]
- 6. Wu, T.; Willett, W.C.; Rifai, N.; Rimm, E.B. Plasma Fluorescent Oxidation Products as Potential Markers of Oxidative Stress for Epidemiologic Studies. *Am. J. Epidemiol.* **2007**, *166*, 552–560. [CrossRef]
- 7. Wu, T.; Rifai, N.; Willett, W.C.; Rimm, E.B. Plasma Fluorescent Oxidation Products: Independent Predictors of Coronary Heart Disease in Men. *Am. J. Epidemiol.* **2007**, *166*, 544–551. [CrossRef]

Antioxidants 2022, 11, 802 14 of 17

8. Jensen, M.K.; Wang, Y.; Rimm, E.B.; Townsend, M.K.; Willett, W.; Wu, T. Fluorescent Oxidation Products and Risk of Coronary Heart Disease: A Prospective Study in Women. *J. Am. Heart Assoc.* **2013**, *2*, e000195. [CrossRef]

- 9. Rebholz, C.M.; Wu, T.; Hamm, L.L.; Arora, R.; Khan, I.E.; Liu, Y.; Chen, C.-S.; Mills, K.T.; Rogers, S.; Kleinpeter, M.A.; et al. The Association of Plasma Fluorescent Oxidation Products and Chronic Kidney Disease: A Case-Control Study. *Am. J. Nephrol.* **2012**, 36, 297–304. [CrossRef]
- 10. Akiki, Z.; Andrianjafimasy, M.; Zerimech, F.; Le Moual, N.; Siroux, V.; Dumas, O.; Matran, R.; Nadif, R. High Level of Fluorescent Oxidation Products and Worsening of Asthma Control over Time. *Respir. Res.* **2019**, *20*, 203. [CrossRef]
- 11. Andrianjafimasy, M.; Zerimech, F.; Akiki, Z.; Huyvaert, H.; Le Moual, N.; Siroux, V.; Matran, R.; Dumas, O.; Nadif, R. Oxidative Stress Biomarkers and Asthma Characteristics in Adults of the EGEA Study. *Eur. Respir. J.* **2017**, *50*, 1701193. [CrossRef] [PubMed]
- 12. Kim, D.K.; Cho, M.H.; Hersh, C.P.; Lomas, D.A.; Miller, B.E.; Kong, X.; Bakke, P.; Gulsvik, A.; Agustí, A.; Wouters, E.; et al. Genome-Wide Association Analysis of Blood Biomarkers in Chronic Obstructive Pulmonary Disease. *Am. J. Respir. Crit. Care Med.* 2012, 186, 1238–1247. [CrossRef] [PubMed]
- 13. Liu, X.; Wang, W.; Bai, Y.; Zhang, H.; Zhang, S.; He, L.; Zhou, W.; Zhang, D.; Xu, J. Identification of a Genome-Wide Serum MicroRNA Expression Profile as Potential Noninvasive Biomarkers for Chronic Kidney Disease Using next-Generation Sequencing. *J. Int. Med. Res.* **2020**, *48*, 300060520969481. [CrossRef] [PubMed]
- 14. Wallace, C.; Newhouse, S.J.; Braund, P.; Zhang, F.; Tobin, M.; Falchi, M.; Ahmadi, K.; Dobson, R.J.; Marçano, A.C.B.; Hajat, C.; et al. Genome-Wide Association Study Identifies Genes for Biomarkers of Cardiovascular Disease: Serum Urate and Dyslipidemia. *Am. J. Hum. Genet.* 2008, 82, 139–149. [CrossRef] [PubMed]
- 15. Kauffmann, F.; Dizier, M.H.; Annesi-Maesano, I.; Bousquet, J.; Charpin, D.; Demenais, F.; Ecochard, D.; Feingold, J.; Gormand, F.; Grimfeld, A.; et al. EGEA (Epidemiological Study on the Genetics and Environment of Asthma, Bronchial Hyperresponsiveness and Atopy)—Descriptive Characteristics. *Clin. Exp. Allergy* 1999, 29 (Suppl. S4), 17–21. [PubMed]
- 16. Kauffmann, F.; Dizier, M.H. EGEA (Epidemiological Study on the Genetics and Environment of Asthma, Bronchial Hyperresponsiveness and Atopy)—Design Issues. EGEA Co-Operative Group. *Clin. Exp. Allergy* **1995**, *25* (Suppl. S2), 19–22. [CrossRef]
- 17. Nadif, R.; Bouzigon, E.; Moual, N.L.; Siroux, V. EGEA Collection: A Biobank Devoted to Asthma and Asthma-Related Phenotypes. Open J. Bioresour. 2017, 4, 5. [CrossRef]
- 18. Moffatt, M.F.; Gut, I.G.; Demenais, F.; Strachan, D.P.; Bouzigon, E.; Heath, S.; von Mutius, E.; Farrall, M.; Lathrop, M.; Cookson, W.O.C.M.; et al. A Large-Scale, Consortium-Based Genomewide Association Study of Asthma. *N. Engl. J. Med.* **2010**, *363*, 1211–1221. [CrossRef]
- 19. Imboden, M.; Bouzigon, E.; Curjuric, I.; Ramasamy, A.; Kumar, A.; Hancock, D.B.; Wilk, J.B.; Vonk, J.M.; Thun, G.A.; Siroux, V.; et al. Genome-Wide Association Study of Lung Function Decline in Adults with and without Asthma. *J. Allergy Clin. Immunol.* **2012**, 129, 1218–1228. [CrossRef]
- 20. McVean, G.A.; Altshuler, D.M.; Durbin, R.M.; Abecasis, G.R.; Bentley, D.R.; Chakravarti, A.; Clark, A.G.; Donnelly, P.; Eichler, E.E.; Flicek, P.; et al. An Integrated Map of Genetic Variation from 1092 Human Genomes. *Nature* **2012**, *491*, 56–65. [CrossRef]
- 21. Howie, B.N.; Donnelly, P.; Marchini, J. A Flexible and Accurate Genotype Imputation Method for the Next Generation of Genome-Wide Association Studies. *PLoS Genet.* **2009**, *5*, e1000529. [CrossRef] [PubMed]
- 22. Miller, M.R.; Hankinson, J.; Brusasco, V.; Burgos, F.; Casaburi, R.; Coates, A.; Crapo, R.; Enright, P.; van der Grinten, C.P.M.; Gustafsson, P.; et al. Standardisation of Spirometry. *Eur. Respir. J.* **2005**, *26*, 319–338. [CrossRef]
- 23. Quanjer, P.H.; Tammeling, G.J.; Cotes, J.E.; Pedersen, O.F.; Peslin, R.; Yernault, J.-C. Lung Volumes and Forced Ventilatory Flows. *Eur. Respir. J.* 1993, 6, 5–40. [CrossRef] [PubMed]
- 24. Nadif, R.; Siroux, V.; Oryszczyn, M.-P.; Ravault, C.; Pison, C.; Pin, I.; Kauffmann, F. Epidemiological study on the Genetics and Environment of Asthma (EGEA) Heterogeneity of Asthma According to Blood Inflammatory Patterns. *Thorax* 2009, 64, 374–380. [CrossRef] [PubMed]
- 25. Nadif, R.; Siroux, V.; Boudier, A.; le Moual, N.; Just, J.; Gormand, F.; Pison, C.; Matran, R.; Pin, I. Blood Granulocyte Patterns as Predictors of Asthma Phenotypes in Adults from the EGEA Study. *Eur. Respir. J.* **2016**, *48*, 1040–1051. [CrossRef] [PubMed]
- 26. Pan, W. Akaike's Information Criterion in Generalized Estimating Equations. Biometrics 2001, 57, 120–125. [CrossRef]
- 27. Pruim, R.J.; Welch, R.P.; Sanna, S.; Teslovich, T.M.; Chines, P.S.; Gliedt, T.P.; Boehnke, M.; Abecasis, G.R.; Willer, C.J. LocusZoom: Regional Visualization of Genome-Wide Association Scan Results. *Bioinformatics* **2010**, *26*, 2336–2337. [CrossRef]
- 28. Li, M.-X.; Yeung, J.M.Y.; Cherny, S.S.; Sham, P.C. Evaluating the Effective Numbers of Independent Tests and Significant P-Value Thresholds in Commercial Genotyping Arrays and Public Imputation Reference Datasets. *Hum. Genet.* **2012**, *131*, 747–756. [CrossRef]
- 29. Kamat, M.A.; Blackshaw, J.A.; Young, R.; Surendran, P.; Burgess, S.; Danesh, J.; Butterworth, A.S.; Staley, J.R. PhenoScanner V2: An Expanded Tool for Searching Human Genotype-Phenotype Associations. *Bioinformatics* **2019**, *35*, 4851–4853. [CrossRef]
- 30. Staley, J.R.; Blackshaw, J.; Kamat, M.A.; Ellis, S.; Surendran, P.; Sun, B.B.; Paul, D.S.; Freitag, D.; Burgess, S.; Danesh, J.; et al. PhenoScanner: A Database of Human Genotype-Phenotype Associations. *Bioinformatics* **2016**, 32, 3207–3209. [CrossRef]
- 31. Zhernakova, D.V.; Deelen, P.; Vermaat, M.; van Iterson, M.; van Galen, M.; Arindrarto, W.; van 't Hof, P.; Mei, H.; van Dijk, F.; Westra, H.-J.; et al. Identification of Context-Dependent Expression Quantitative Trait Loci in Whole Blood. *Nat. Genet.* **2017**, 49, 139–145. [CrossRef] [PubMed]

Antioxidants 2022, 11, 802 15 of 17

32. Gaunt, T.R.; Shihab, H.A.; Hemani, G.; Min, J.L.; Woodward, G.; Lyttleton, O.; Zheng, J.; Duggirala, A.; McArdle, W.L.; Ho, K.; et al. Systematic Identification of Genetic Influences on Methylation across the Human Life Course. *Genome Biol.* 2016, 17, 61. [CrossRef] [PubMed]

- Ward, L.D.; Kellis, M. HaploReg: A Resource for Exploring Chromatin States, Conservation, and Regulatory Motif Alterations within Sets of Genetically Linked Variants. Nucleic Acids Res. 2012, 40, D930–D934. [CrossRef] [PubMed]
- 34. Kircher, M.; Witten, D.M.; Jain, P.; O'Roak, B.J.; Cooper, G.M.; Shendure, J. A General Framework for Estimating the Relative Pathogenicity of Human Genetic Variants. *Nat. Genet.* **2014**, *46*, 310–315. [CrossRef]
- 35. Moser, M.; Binder, O.; Wu, Y.; Aitsebaomo, J.; Ren, R.; Bode, C.; Bautch, V.L.; Conlon, F.L.; Patterson, C. BMPER, a Novel Endothelial Cell Precursor-Derived Protein, Antagonizes Bone Morphogenetic Protein Signaling and Endothelial Cell Differentiation. *Mol. Cell. Biol.* 2003, 23, 5664–5679. [CrossRef]
- 36. Shi, Y.; Massagué, J. Mechanisms of TGF-β Signaling from Cell Membrane to the Nucleus. Cell 2003, 113, 685–700. [CrossRef]
- 37. Boxall, C.; Holgate, S.T.; Davies, D.E. The Contribution of Transforming Growth Factor-Beta and Epidermal Growth Factor Signalling to Airway Remodelling in Chronic Asthma. *Eur. Respir. J.* **2006**, 27, 208–229. [CrossRef]
- 38. Adewoye, A.H.; Nolan, V.G.; Ma, Q.; Baldwin, C.; Wyszynski, D.F.; Farrell, J.J.; Farrer, L.A.; Steinberg, M.H. Association of Polymorphisms of IGF1R and Genes in the Transforming Growth Factor–β/Bone Morphogenetic Protein Pathway with Bacteremia in Sickle Cell Anemia. *Clin. Infect. Dis.* **2006**, *43*, 593–598. [CrossRef]
- 39. Buniello, A.; MacArthur, J.A.L.; Cerezo, M.; Harris, L.W.; Hayhurst, J.; Malangone, C.; McMahon, A.; Morales, J.; Mountjoy, E.; Sollis, E.; et al. The NHGRI-EBI GWAS Catalog of Published Genome-Wide Association Studies, Targeted Arrays and Summary Statistics 2019. *Nucleic Acids Res.* 2019, 47, D1005–D1012. [CrossRef]
- 40. Kichaev, G.; Bhatia, G.; Loh, P.-R.; Gazal, S.; Burch, K.; Freund, M.K.; Schoech, A.; Pasaniuc, B.; Price, A.L. Leveraging Polygenic Functional Enrichment to Improve GWAS Power. *Am. J. Hum. Genet.* **2019**, *104*, 65–75. [CrossRef]
- 41. Loth, D.W.; Soler Artigas, M.; Gharib, S.A.; Wain, L.V.; Franceschini, N.; Koch, B.; Pottinger, T.D.; Smith, A.V.; Duan, Q.; Oldmeadow, C.; et al. Genome-Wide Association Analysis Identifies Six New Loci Associated with Forced Vital Capacity. *Nat. Genet.* 2014, 46, 669–677. [CrossRef]
- 42. Shrine, N.; Guyatt, A.L.; Erzurumluoglu, A.M.; Jackson, V.E.; Hobbs, B.D.; Melbourne, C.A.; Batini, C.; Fawcett, K.A.; Song, K.; Sakornsakolpat, P.; et al. New Genetic Signals for Lung Function Highlight Pathways and Chronic Obstructive Pulmonary Disease Associations across Multiple Ancestries. *Nat. Genet.* 2019, 51, 481–493. [CrossRef] [PubMed]
- 43. Sakornsakolpat, P.; Prokopenko, D.; Lamontagne, M.; Reeve, N.F.; Guyatt, A.L.; Jackson, V.E.; Shrine, N.; Qiao, D.; Bartz, T.M.; Kim, D.K.; et al. Genetic Landscape of Chronic Obstructive Pulmonary Disease Identifies Heterogeneous Cell-Type and Phenotype Associations. *Nat. Genet.* **2019**, *51*, 494–505. [CrossRef] [PubMed]
- 44. McKay, J.D.; Hung, R.J.; Han, Y.; Zong, X.; Carreras-Torres, R.; Christiani, D.C.; Caporaso, N.E.; Johansson, M.; Xiao, X.; Li, Y.; et al. Large-Scale Association Analysis Identifies New Lung Cancer Susceptibility Loci and Heterogeneity in Genetic Susceptibility across Histological Subtypes. *Nat. Genet.* 2017, 49, 1126–1132. [CrossRef] [PubMed]
- 45. Lutz, S.M.; Cho, M.H.; Young, K.; Hersh, C.P.; Castaldi, P.J.; McDonald, M.-L.; Regan, E.; Mattheisen, M.; DeMeo, D.L.; Parker, M.; et al. A Genome-Wide Association Study Identifies Risk Loci for Spirometric Measures among Smokers of European and African Ancestry. *BMC Genet.* **2015**, *16*, 138. [CrossRef] [PubMed]
- 46. Nelson, P.T.; Estus, S.; Abner, E.L.; Parikh, I.; Malik, M.; Neltner, J.H.; Ighodaro, E.; Wang, W.-X.; Wilfred, B.R.; Wang, L.-S.; et al. ABCC9 Gene Polymorphism Is Associated with Hippocampal Sclerosis of Aging Pathology. *Acta Neuropathol.* **2014**, 127, 825–843. [CrossRef]
- 47. Penney, M.E.; Parfrey, P.S.; Savas, S.; Yilmaz, Y.E. A Genome-Wide Association Study Identifies Single Nucleotide Polymorphisms Associated with Time-to-Metastasis in Colorectal Cancer. *BMC Cancer* **2019**, *19*, 133. [CrossRef]
- 48. Pilling, L.C.; Kuo, C.-L.; Sicinski, K.; Tamosauskaite, J.; Kuchel, G.A.; Harries, L.W.; Herd, P.; Wallace, R.; Ferrucci, L.; Melzer, D. Human Longevity: 25 Genetic Loci Associated in 389,166 UK Biobank Participants. *Aging* **2017**, *9*, 2504–2520. [CrossRef]
- 49. Wright, K.M.; Rand, K.A.; Kermany, A.; Noto, K.; Curtis, D.; Garrigan, D.; Slinkov, D.; Dorfman, I.; Granka, J.M.; Byrnes, J.; et al. A Prospective Analysis of Genetic Variants Associated with Human Lifespan. *G3 Genes* **2019**, *9*, 2863–2878. [CrossRef]
- 50. Bønnelykke, K.; Matheson, M.C.; Pers, T.H.; Granell, R.; Strachan, D.P.; Alves, A.C.; Linneberg, A.; Curtin, J.A.; Warrington, N.M.; Standl, M.; et al. Meta-Analysis of Genome-Wide Association Studies Identifies Ten Loci Influencing Allergic Sensitization. *Nat. Genet.* 2013, 45, 902–906. [CrossRef]
- 51. Herold, C.; Hooli, B.V.; Mullin, K.; Liu, T.; Roehr, J.T.; Mattheisen, M.; Parrado, A.R.; Bertram, L.; Lange, C.; Tanzi, R.E. Family-Based Association Analyses of Imputed Genotypes Reveal Genome-Wide Significant Association of Alzheimer's Disease with OSBPL6, PTPRG, and PDCL3. *Mol. Psychiatry* 2016, 21, 1608–1612. [CrossRef] [PubMed]
- 52. Leng, S.; Liu, Y.; Weissfeld, J.L.; Thomas, C.L.; Han, Y.; Picchi, M.A.; Edlund, C.K.; Willink, R.P.; Gaither Davis, A.L.; Do, K.C.; et al. 15q12 Variants, Sputum Gene Promoter Hypermethylation, and Lung Cancer Risk: A GWAS in Smokers. *J. Natl. Cancer Inst.* 2015, 107, djv035. [CrossRef] [PubMed]
- 53. Sherva, R.; Tripodis, Y.; Bennett, D.A.; Chibnik, L.B.; Crane, P.K.; de Jager, P.L.; Farrer, L.A.; Saykin, A.J.; Shulman, J.M.; Naj, A.; et al. Genome-Wide Association Study of the Rate of Cognitive Decline in Alzheimer's Disease. *Alzheimers Dement* **2014**, *10*, 45–52. [CrossRef]

Antioxidants 2022, 11, 802 16 of 17

54. Lawrenson, K.; Song, F.; Hazelett, D.J.; Kar, S.P.; Tyrer, J.; Phelan, C.M.; Corona, R.I.; Rodríguez-Malavé, N.I.; Seo, J.-H.; Adler, E.; et al. Genome-Wide Association Studies Identify Susceptibility Loci for Epithelial Ovarian Cancer in East Asian Women. *Gynecol. Oncol.* 2019, 153, 343–355. [CrossRef] [PubMed]

- 55. Manichaikul, A.; Peres, L.C.; Wang, X.-Q.; Barnard, M.E.; Chyn, D.; Sheng, X.; Du, Z.; Tyrer, J.; Dennis, J.; Schwartz, A.G.; et al. Identification of Novel Epithelial Ovarian Cancer Loci in Women of African Ancestry. *Int. J. Cancer* 2019, 146, 2987–2998. [CrossRef]
- 56. Visconti, A.; Duffy, D.L.; Liu, F.; Zhu, G.; Wu, W.; Chen, Y.; Hysi, P.G.; Zeng, C.; Sanna, M.; Iles, M.M.; et al. Genome-Wide Association Study in 176,678 Europeans Reveals Genetic Loci for Tanning Response to Sun Exposure. *Nat. Commun.* 2018, 9, 1684. [CrossRef] [PubMed]
- 57. Zeng, Y.; Nie, C.; Min, J.; Chen, H.; Liu, X.; Ye, R.; Chen, Z.; Bai, C.; Xie, E.; Yin, Z.; et al. Sex Differences in Genetic Associations With Longevity. *JAMA Netw. Open* **2018**, *1*, e181670. [CrossRef]
- 58. Karlsson Linnér, R.; Biroli, P.; Kong, E.; Meddens, S.F.W.; Wedow, R.; Fontana, M.A.; Lebreton, M.; Tino, S.P.; Abdellaoui, A.; Hammerschlag, A.R.; et al. Genome-Wide Association Analyses of Risk Tolerance and Risky Behaviors in over 1 Million Individuals Identify Hundreds of Loci and Shared Genetic Influences. *Nat. Genet.* **2019**, *51*, 245–257. [CrossRef]
- 59. Ray, M.E.; Wistow, G.; Su, Y.A.; Meltzer, P.S.; Trent, J.M. AIM1, a Novel Non-Lens Member of the Betagamma-Crystallin Superfamily, Is Associated with the Control of Tumorigenicity in Human Malignant Melanoma. *Proc. Natl. Acad. Sci. USA* **1997**, 94, 3229–3234. [CrossRef]
- 60. Ferreira, M.A.; Vonk, J.M.; Baurecht, H.; Marenholz, I.; Tian, C.; Hoffman, J.D.; Helmer, Q.; Tillander, A.; Ullemar, V.; van Dongen, J.; et al. Shared Genetic Origin of Asthma, Hay Fever and Eczema Elucidates Allergic Disease Biology. *Nat. Genet.* **2017**, 49, 1752–1757. [CrossRef]
- 61. Ferreira, M.A.R.; Mathur, R.; Vonk, J.M.; Szwajda, A.; Brumpton, B.; Granell, R.; Brew, B.K.; Ullemar, V.; Lu, Y.; Jiang, Y.; et al. Genetic Architectures of Childhood- and Adult-Onset Asthma Are Partly Distinct. *Am. J. Hum. Genet.* **2019**, *104*, 665–684. [CrossRef] [PubMed]
- 62. Martin, L.J.; Gupta, J.; Jyothula, S.S.S.K.; Butsch Kovacic, M.; Biagini Myers, J.M.; Patterson, T.L.; Ericksen, M.B.; He, H.; Gibson, A.M.; Baye, T.M.; et al. Functional Variant in the Autophagy-Related 5 Gene Promotor Is Associated with Childhood Asthma. *PLoS ONE* 2012, 7, e33454. [CrossRef] [PubMed]
- 63. McAlinden, K.D.; Deshpande, D.A.; Ghavami, S.; Xenaki, D.; Sohal, S.S.; Oliver, B.G.; Haghi, M.; Sharma, P. Autophagy Activation in Asthma Airways Remodeling. *Am. J. Respir. Cell Mol. Biol.* **2019**, *60*, 541–553. [CrossRef] [PubMed]
- 64. Pham, D.L.; Kim, S.-H.; Losol, P.; Yang, E.-M.; Shin, Y.S.; Ye, Y.-M.; Park, H.-S. Association of Autophagy Related Gene Polymorphisms with Neutrophilic Airway Inflammation in Adult Asthma. *Korean J. Intern. Med.* **2016**, *31*, 375–385. [CrossRef] [PubMed]
- 65. Acosta-Herrera, M.; Kerick, M.; González-Serna, D.; Myositis Genetics Consortium; Scleroderma Genetics Consortium; Wijmenga, C.; Franke, A.; Gregersen, P.K.; Padyukov, L.; Worthington, J.; et al. Genome-Wide Meta-Analysis Reveals Shared New Loci in Systemic Seropositive Rheumatic Diseases. *Ann. Rheum. Dis.* 2018, 78, 311–319. [CrossRef] [PubMed]
- 66. Bentham, J.; Morris, D.L.; Graham, D.S.C.; Pinder, C.L.; Tombleson, P.; Behrens, T.W.; Martín, J.; Fairfax, B.P.; Knight, J.C.; Chen, L.; et al. Genetic Association Analyses Implicate Aberrant Regulation of Innate and Adaptive Immunity Genes in the Pathogenesis of Systemic Lupus Erythematosus. *Nat. Genet.* 2015, 47, 1457–1464. [CrossRef]
- 67. Langefeld, C.D.; Ainsworth, H.C.; Cunninghame Graham, D.S.; Kelly, J.A.; Comeau, M.E.; Marion, M.C.; Howard, T.D.; Ramos, P.S.; Croker, J.A.; Morris, D.L.; et al. Transancestral Mapping and Genetic Load in Systemic Lupus Erythematosus. *Nat. Commun.* **2017**, *8*, 16021. [CrossRef]
- 68. Martin, J.-E.; Assassi, S.; Diaz-Gallo, L.-M.; Broen, J.C.; Simeon, C.P.; Castellvi, I.; Vicente-Rabaneda, E.; Fonollosa, V.; Ortego-Centeno, N.; González-Gay, M.A.; et al. A Systemic Sclerosis and Systemic Lupus Erythematosus Pan-Meta-GWAS Reveals New Shared Susceptibility Loci. *Hum. Mol. Genet.* 2013, 22, 4021–4029. [CrossRef] [PubMed]
- 69. Laufer, V.A.; Tiwari, H.K.; Reynolds, R.J.; Danila, M.I.; Wang, J.; Edberg, J.C.; Kimberly, R.P.; Kottyan, L.C.; Harley, J.B.; Mikuls, T.R.; et al. Genetic Influences on Susceptibility to Rheumatoid Arthritis in African-Americans. *Hum. Mol. Genet.* **2019**, *28*, 858–874. [CrossRef]
- Márquez, A.; Vidal-Bralo, L.; Rodríguez-Rodríguez, L.; González-Gay, M.A.; Balsa, A.; González-Álvaro, I.; Carreira, P.; Ortego-Centeno, N.; Ayala-Gutiérrez, M.M.; García-Hernández, F.J.; et al. A Combined Large-Scale Meta-Analysis Identifies COG6 as a Novel Shared Risk Locus for Rheumatoid Arthritis and Systemic Lupus Erythematosus. *Ann. Rheum. Dis.* 2016, 76, 286–294. [CrossRef]
- 71. Mitchell, J.S.; Li, N.; Weinhold, N.; Försti, A.; Ali, M.; van Duin, M.; Thorleifsson, G.; Johnson, D.C.; Chen, B.; Halvarsson, B.-M.; et al. Genome-Wide Association Study Identifies Multiple Susceptibility Loci for Multiple Myeloma. *Nat. Commun.* **2016**, *7*, 12050. [CrossRef] [PubMed]
- 72. Saad, M.N.; Mabrouk, M.S.; Eldeib, A.M.; Shaker, O.G. Studying the Effects of Haplotype Partitioning Methods on the RA-Associated Genomic Results from the North American Rheumatoid Arthritis Consortium (NARAC) Dataset. *J. Adv. Res.* **2019**, *18*, 113–126. [CrossRef] [PubMed]
- 73. Al Olama, A.A.; Kote-Jarai, Z.; Berndt, S.I.; Conti, D.V.; Schumacher, F.; Han, Y.; Benlloch, S.; Hazelett, D.J.; Wang, Z.; Saunders, E.; et al. A Meta-Analysis of 87,040 Individuals Identifies 23 New Susceptibility Loci for Prostate Cancer. *Nat. Genet.* **2014**, *46*, 1103–1109. [CrossRef] [PubMed]

Antioxidants **2022**, 11, 802

74. Conti, D.V.; Darst, B.F.; Moss, L.C.; Saunders, E.J.; Sheng, X.; Chou, A.; Schumacher, F.R.; Olama, A.A.A.; Benlloch, S.; Dadaev, T.; et al. Trans-Ancestry Genome-Wide Association Meta-Analysis of Prostate Cancer Identifies New Susceptibility Loci and Informs Genetic Risk Prediction. *Nat. Genet.* **2021**, *53*, 65–75. [CrossRef] [PubMed]

- 75. Schumacher, F.R.; Al Olama, A.A.; Berndt, S.I.; Benlloch, S.; Ahmed, M.; Saunders, E.J.; Dadaev, T.; Leongamornlert, D.; Anokian, E.; Cieza-Borrella, C.; et al. Association Analyses of More than 140,000 Men Identify 63 New Prostate Cancer Susceptibility Loci. *Nat. Genet.* 2018, 50, 928–936. [CrossRef]
- 76. Xu, D.; Wang, X.; Yan, S.; Yin, Y.; Hou, J.; Wang, X.; Sun, B. Interaction of PTPRO and TLR4 Signaling in Hepatocellular Carcinoma. *Tumor Biol.* **2014**, *35*, 10267–10273. [CrossRef]
- 77. Xu, Y.; Li, J.; Wang, P.; Zhang, Z.; Wang, X. LncRNA HULC Promotes Lung Squamous Cell Carcinoma by Regulating PTPRO via NF-KB. *J. Cell. Biochem.* **2019**, 120, 19415–19421. [CrossRef]
- 78. Schuliga, M. NF-KappaB Signaling in Chronic Inflammatory Airway Disease. Biomolecules 2015, 5, 1266–1283. [CrossRef]
- 79. Võsa, U.; Claringbould, A.; Westra, H.-J.; Bonder, M.J.; Deelen, P.; Zeng, B.; Kirsten, H.; Saha, A.; Kreuzhuber, R.; Kasela, S.; et al. Unraveling the Polygenic Architecture of Complex Traits Using Blood EQTL Metaanalysis. *bioRxiv* 2018, 447367. [CrossRef]