Pharmacogenetic meta-analysis of genome-wide association studies of LDL cholesterol response to statins

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<td>Published Version</td>
<td>doi:10.1038/ncomms6068</td>
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We validate the most promising signals in a further 22,318 statin recipients and identify two loci, and

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The 3-hydroxymethyl-3-methylglutaryl coenzyme A (HMG-CoA) reductase inhibitors, also known as statins, are widely prescribed and are highly effective in the management and prevention of cardiovascular disease. Statin therapy results in a lowering of low-density lipoprotein cholesterol (LDL-C) levels by up to 55% and a 20–30% reduction of cardiovascular events. Despite the clinical efficacy of statins in a wide range of patients, interindividual variability exists with regard to LDL-C lowering response as well as efficacy in reducing major cardiovascular events. The suggestion that some of this variability may be due, in part, to common pharmacogenetic variation is supported by previous studies that have identified genetic variants associated with differential LDL-C response to statin therapy.

A small number of genome-wide association studies (GWAS) have previously identified loci associated with statin response on a genome-wide level. A GWAS in the JUPITER trial identified three genetic loci, ABCG2 (rs2199936), LPA (rs10455872) and APOE (rs7412), that were associated with percentage LDL-C levels by up to 55% and a 20–30% reduction of cardiovascular events. Despite the clinical efficacy of statins with an additional 4.3% increase per allele in LDL-C lowering effect compared with non-carriers. The second strongest association was with a SNP on LPA on chromosome 6 (rs10455872, MAF = 0.069, β = 0.041, s.e. = 0.006, \( P = 1.95 \times 10^{-11} \); Fig. 2b), indicating a 5.9% smaller LDL-C lowering per minor allele for carriers of the SNP compared with non-carriers. Associations at both loci have previously been described. A third genome-wide significant association was found with a SNP at RICTOR on chromosome 5 (rs13166647, MAF = 0.230, \( \beta = -0.253 \), s.e. = 0.046, \( P = 4.50 \times 10^{-10} \)), although genotypes for this SNP were only available in two studies within the first stage (\( n = 2,144 \)).

**Second-stage meta-analysis.** We selected 246 SNPs with \( P < 5 \times 10^{-8} \) from 158 loci for further investigation in three additional studies comprising up to 22,318 statin-treated subjects (see Methods; Supplementary Tables 1 and 5; Supplementary Note 3). This second stage confirmed the genome-wide significant associations between variations within the APOE and LPA loci and LDL-C response, as observed in the first stage (Table 1; Supplementary Fig. 2; Supplementary Table 5). In addition, SNPs at two new loci with \( P \) values between 6.70 \( \times 10^{-7} \) and 2.26 \( \times 10^{-6} \) in the first phase were shown to be significantly associated with statin-induced LDL-C lowering treatment in the total combined meta-analysis at a genome-wide level: SORT1/CERS2/PSRC1 (rs646776, \( \beta = -0.013 \), s.e. = 0.002, \( P = 1.05 \times 10^{-9} \) and rs12740374, \( \beta = -0.013 \), s.e. = 0.002, \( P = 1.05 \times 10^{-9} \); Fig 2c) and SLC10A1 (rs2900478, \( \beta = 0.016 \), s.e. = 0.003, \( P = 1.22 \times 10^{-9} \); Fig 2d), indicating an additional 1.5% increase per allele in LDL-C lowering effect for carriers of the SORT1/CERS2/PSRC1 SNP and a 1.6% smaller LDL-C lowering per minor allele for carriers of the SLC10A1 SNP.

The six next-ranked SNPs with \( P \) values just below \( 5 \times 10^{-8} \) in the combined meta-analysis, including the two SNPs at RICTOR (rs13166647 and rs13172966), were selected for additional genotyping in the Scandinavian ASCOT participants (see Methods). None of these six SNPs reached genome-wide significance after this additional genotyping (Supplementary Table 6). Therefore, our overall genome-wide significant findings were the SNPs at APOE, LPA, SORT1/CERS2/PSRC1 and SLC10A1.

**Subfraction analyses.** To extend our results for the novel GWAS finding SORT1/CERS2/PSRC1, we performed additional association analyses, using measurements of cholesterol levels in four LDL subfractions (large, medium, small and very small) from two of the trials in GIST, CAP and PRINCE (Table 2; see Methods). The minor allele of SORT1 rs646776 was associated with greater statin-induced reductions in levels of all LDL subfractions, and there was a nonsignificant trend for larger effect sizes and greater statistical significance for lowering of small and very small LDL (Table 2). In contrast, the APOE SNP associated with greater...
whether there was an interaction between LDL-C change and JUPITER trial, additional analyses were performed to determine if there is little effect of measurement noise. Next, within the CARDS data set. Correcting our effect size estimate further in the GIST meta-analysis (\(\frac{\text{Stage 1}}{\text{Stage 2}}\)) for SNPs at the 12.2160064 rs2900478 SLCO1B1 A T Stage 1 16,749 0.165 0.016 0.003 – 1.6 2.26 \times 10^{-6} Combined 24,253 0.016 0.003 – 1.6 1.22 \times 10^{-9} 19 50107480 rs445925 APOE A G Stage 1 13,909 0.098 – 0.043 0.005 4.3 1.58 \times 10^{-18} Stage 2 3,613 0.157 – 0.088 0.011 8.8 1.41 \times 10^{-15} Combined 17,522 – 0.051 0.005 5.1 8.52 \times 10^{-29} Chr, chromosome; SNP, single nucleotide polymorphism. *Beta for difference between the natural log-transformed on- and off-treatment low-density lipoprotein cholesterol (LDL-C) levels adjusted for natural log-transformed off-treatment LDL-C, age-, sex- and study-specific covariates. The beta reflects the fraction of differential LDL-C lowering in carriers versus non-carriers of the SNP; a negative beta indicates a better statin response (stronger LDL-C reduction), a positive beta a worse statin response. Betas and P values were generated using linear regression analysis. †This percentage reflects the \(\frac{1}{4} \) extra LDL-C lowering in carriers versus non-carriers of the SNP.

LDL-C response to statins (rs445925) showed a small and non-significant association with change in very small LDL (Table 2). For the minor allele of rs2900478 (SLCO1B1), the borderline significant association with smaller magnitude of LDL-C reduction showed a trend for preferential association with larger versus smaller LDL subfractions. The lack of association of rs10455872 (LPA) with changes in LDL subfractions is consistent with evidence discussed below that this locus affects levels of lipoprotein(a) (Lp(a)) and not LDL particles. Using generalized estimating equations, we tested the association of log change in each of the LDL subfractions with interactions of the four SNPs. For very small LDL, the association with the rs646776 minor allele was significantly different from that of the other minor alleles (\(P = 0.03\) after adjustment for multiple testing).

**Effects of off-treatment LDL-C.** To demonstrate that our findings for LDL-C response to statin treatment are unlikely to be explained through associations with baseline LDL-C levels, we performed a number of additional analyses (see Methods). First, Supplementary Table 7 shows regression coefficients for baseline-adjusted and measurement noise-corrected estimates of the direct effect of genotype on on-treatment LDL-C at the strongest SNPs in the GIST meta-analysis (\(P < 1 \times 10^{-8}\)), which were available in the CARDS data set. Correcting our effect size estimate further and modelling measurement noise at baseline reduced the apparent effect only slightly for all the markers, suggesting that there is little effect of measurement noise. Next, within the JUPITER trial, additional analyses were performed to determine whether there was an interaction between LDL-C change and statin or placebo allocation. Supplementary Table 8 shows significant \(P\) values for interaction (all \(< 5 \times 10^{-2}\) for SNPs at the four genome-wide significant loci in the GIST meta-analysis, also suggesting that genetic effects on baseline LDL-C as manifested in the placebo group contribute at most only in part to genetic effects on LDL-C response in the statin group.

**Genome-Wide Conditional Analysis.** To investigate whether there were multiple SNPs within any gene and multiple loci associated with differential LDL-C lowering to statin therapy, we performed a conditional analysis across the genome using the summary statistics of the combined meta-analysis. The results of the Genome-Wide Conditional Analysis (GWCA; see Methods; Supplementary Table 9) showed 14 SNPs independently associated with statin response and these explained \(\sim 5\%\) of the variation in LDL-C response to statin treatment. Of the 14 independent SNPs, 6 were genome-wide significant in the combined GWAS meta-analysis (Supplementary Table 5).

**Previous findings.** In Supplementary Table 10, we performed a look-up in our GWAS meta-analysis for SNPs previously described in the literature (NHGRI Catalogue\(^{11}\) of Published GWAS and Candidate gene studies) to be associated with statin response, besides the loci associated at a genome-wide level in the current study. None of these SNPs was associated with statin response in our GWAS after correcting for multiple testing.

**Functional analyses.** Functional characterization of the 246 SNPs selected for the second stage was performed using a range of bioinformatics tools (see Methods). A total of 420 expression quantitative trait loci (eQTL) associations were identified across a wide range of tissues (Supplementary Data 1), which comprised 67 independent gene eQTL associations. Eleven genes, including APOE, SORT1, CELSR2 and PSRC1, showed eQTLs in liver, which considering its primary role in mediating statin-induced LDL reduction may be particularly relevant to statin response. Putative gene eQTLs were combined with genes annotated to variants in linkage disequilibrium (LD) with LDL-C response-associated variants, resulting in a list of 185 candidate gene loci, defined by 2,681 SNPs (Supplementary Data 2 and 3). To identify statin responsive genes among the candidate loci, gene expression data measured in response to statin treatment in a range of cell lines was retrieved from the Connectivity Map resource\(^{12}\) (see Methods). Five genes (APOE, BRCA1, GRPEL1, ADRB2 and ETV1) showed convincing evidence of statin responsiveness on the basis of greater than twofold differential expression in response to statin treatment. Eight genes showed suggestive evidence (1.5- to 2-fold change; TOMM40, SREBP1, PSRC1, BCL3, BCAM, ANK3, SIV1A and RANBP9; Supplementary Data 3). Finally, involvement in statin response was investigated at a pathway level using GeneGo Metacore (Thomson Reuters\(^{13}\)). Briefly, 87 literature-reported genes linked to statin response were combined with the 185 candidate gene loci reported here.
Figure 2 | Regional association plots of the genome-wide significant associations with LDL-C response after statin treatment. The plots show the genome-wide significant associated loci in the combined meta-analysis (\(n=40,914\)), the \(APOE\) locus (a), the \(LPA\) locus (b), the \(SORT1/CELSR2/PSRC1\) locus (c) and the \(SLCO1B1\) locus (d) (generated using LocusZoom (http://genome.sph.umich.edu/wiki/LocusZoom)). The colour of the SNPs is based on the LD with the lead SNP (shown in purple). The RefSeq genes in the region are shown in the lower panel. P values were generated using linear regression analysis.

Table 2 | Associations of the minor alleles of rs646776, rs445925, rs2900478 and rs10455872 with changes in LDL-C and LDL subfractions in response to statin in the combined CAP and PRINCE studies.

<table>
<thead>
<tr>
<th>Change</th>
<th>(SORT1/CELSR2/PSRC1) rs646776 (MAF 0.2)</th>
<th>(APOE) rs445925 (MAF 0.086)</th>
<th>(SLCO1B1) rs2900478 (MAF 0.16)</th>
<th>(LPA) rs10455872 (MAF 0.056)</th>
</tr>
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<td>LDL-C total</td>
<td>–0.023 0.008 0.003</td>
<td>–0.046 0.018 0.008</td>
<td>0.010 0.005 0.04</td>
<td>0.032 0.019 0.09</td>
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<td>Large LDL-C</td>
<td>–0.028 0.014 0.042</td>
<td>–0.075 0.029 0.009</td>
<td>0.02 0.008 0.01</td>
<td>0.036 0.031 0.23</td>
</tr>
<tr>
<td>Medium LDL-C</td>
<td>–0.027 0.015 0.075</td>
<td>–0.079 0.032 0.012</td>
<td>0.016 0.009 0.07</td>
<td>0.010 0.034 0.77</td>
</tr>
<tr>
<td>Small LDL-C</td>
<td>–0.047 0.018 0.009</td>
<td>–0.071 0.037 0.050</td>
<td>0.002 0.010 0.83</td>
<td>–0.024 0.039 0.54</td>
</tr>
<tr>
<td>Very small LDL-C</td>
<td>–0.034 0.009 0.00006</td>
<td>–0.022 0.017 0.202</td>
<td>0.001 0.005 0.90</td>
<td>0.008 0.019 0.67</td>
</tr>
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LDL-C, low-density lipoprotein cholesterol; MAF, minor allele frequency.
*Change: ln (on treatment) – ln (baseline) models adjusted for log (baseline variable), age, sex, body mass index, smoking(y/n) and study (CAP versus PRINCE). Betas and P values were assessed using a generalized estimating equation method.

(Supplementary Data 3). A conservative network of direct interactions was constructed between query genes (Supplementary Data 4). The network included 24 genes located in the LDL-C-associated loci (Supplementary Fig. 4). Collectively, our functional and pathway analysis confirms a strong biological and functional role in statin response for several strongly associated gene loci, including \(APOE/TOMM40/PVRL2\) and \(SORT1/CELSR2/PSRC2\).

**Discussion**

We have performed a meta-analysis of GWAS including more than 40,000 subjects, investigating genetic variants associated with variation in LDL-C lowering on statin treatment independent from associations with baseline LDL-C. We identified four loci at genome-wide significance, including the previously identified \(APOE\) and \(LPA\), and the novel GWAS loci \(SORT1/CELSR2/PSRC1\) and \(SLCO1B1\).

Nine SNPs in the \(APOE\) gene region reached genome-wide significance for LDL-C response. The minor allele of the lead SNP rs445925, which is a proxy for the apoE e2 protein variant defining SNP rs7412 (ref. 14), was associated with a larger LDL-C-lowering response to statins compared with carriers of the major allele. The magnitude and direction of the effect size was similar to previously reported findings for the rs445925 variant in
the GWAS study performed in CARDS and ASCOT and of the SNP rs7412 in JUPITER. Since the apoE e2 protein results in increased hepatic cholesterol synthesis, it may also predispose to stronger inhibition of cholesterol synthesis by statin treatment.

Three independent SNPs at LPA were significantly associated with LDL-C response to statins. The minor G allele of the lead SNP rs10455872 was associated with smaller LDL-C reduction than the major allele. This result was similar to the previous GWAS findings for this SNP in the JUPITER trial and the combined ASCOT and CARDS study. The rs10455872 SNP was strongly associated with the KIV-2 copy number variant in Lp(a), which encodes variability in apo(a) size and is responsible for 30% of variance in Lp(a) levels. Furthermore, rs10455872 was shown to be strongly associated with plasma Lp(a) levels. Standard assays of LDL-C, as well as the Friedewald formula, include cholesterol that resides in Lp(a).

Carriers of this LPA variant are characterized by higher Lp(a) levels and a larger proportion of their measured LDL-C resides in Lp(a) particles. Since statin therapy does not reduce the number of Lp(a) particles, their presence attenuates the measured LDL-C response to statins.

Two SNPs at SORT1/CLESR2/PSRC1 (rs646776 and rs12740374) on chromosome 1p were associated with an enhanced statin LDL-C response. A similar association was previously observed in a large candidate gene study in HPS, however, we demonstrate this finding now first at a genome-wide significance level. The minor allele of rs12740374 has been shown to generate a binding site for the transcription factor C/EBPa18. Transcription results in upregulation of hepatic expression of three genes at this locus, SORT1, CELSR2 and PSRC1 (ref. 18), which we also showed in our eQTL analysis (Supplementary Data 1). Of these, SORT1 is most notable, in that it encodes the multifunctional intracellular trafficking protein sortilin, which has been shown to bind tightly to apoB. Sortilin-induced lowering of plasma LDL-C results from two mechanisms: reduced secretion of apoB-containing precursors, and, perhaps of greater importance, increased hepatic LDL uptake via binding to sortilin at the cell surface, with subsequent internalization and lysosomal degradation. Notably, the minor allele of rs646776 is preferentially associated with lower levels of small and very small LDL (Table 2), suggesting that sortilin is of particular importance for regulating levels of these particles. Smaller LDL subfractions have been shown to be relatively enriched in particles with reduced LDL receptor binding affinity and cellular uptake, a property that may contribute to their associations with increased risk for cardiovascular disease.

This property may also underlie the diminished efficacy of statins for reduction of these particles (Supplementary Fig. 3), since statins act to reduce LDL-C levels to a large extent by increasing LDL receptor expression as a result of upregulation of the transcription factor SREBP2, whereas SORT1 is not regulated by this mechanism. Hence, the greater statin-mediated reduction of LDL-C among carriers of the rs646776 minor allele could be attributed to relative depletion of LDL particles dependent on sortilin for clearance and hence a residually greater proportion of those LDL particles whose uptake is more dependent on the LDL receptor than on sortilin.

Notably, the strong association of rs646776 with statin-induced reductions in small and very small LDL particles contrasts to the weaker associations of changes in these particles with rs445925, likely the result of differing mechanisms underlying the effects of these SNPs on statin response. As noted above, rs445925 is a proxy for the SNP defining the apoE e2 protein variant that is thought to predispose to heightened statin response as a result of greater statin inhibition of cholesterol synthesis and hence upregulation of SREBP and LDL receptor activity.

The SLCO1B1 rs2900478 minor allele was associated with a smaller LDL-C reduction in response to statin treatment. SLCO1B1 encodes the organic anion-transporting polypeptide OATP1B1 and facilitates the hepatic uptake of statins. SNP rs2900478 is in strong LD (r² = 0.89) with rs4149056, which represents the Val174Ala substitution resulting in complete loss of function. In the HPS trial, which used simvastatin, this candidate gene SNP was associated with a 1% lower LDL-C reduction per allele. Single-dose studies have shown that the observed area under the curve of plasma level of active simvastatin after a dose of 40 mg was 221% higher in rs4149056 CC homozygotes compared with rs4149056 TT homozygotes, as compared with atorvastatin 20 mg (144% higher for CC versus TT) and rosuvastatin 40 mg (117% higher for CC versus TT). This finding results from the slower hepatic uptake of statins caused by the genetic variant, which would also be expected to result in a reduction in the cholesterol-lowering effect. In a GWAS of the genetic risk factors for simvastatin-induced myopathy, SLCO1B1 showed the strongest association. This property may also underlie the diminished efficacy of statins for reduction of these particles (Supplementary Fig. 3), since statins act to reduce LDL-C levels to a large extent by increasing LDL receptor expression as a result of upregulation of the transcription factor SREBP2, whereas SORT1 is not regulated by this mechanism. Hence, the greater statin-mediated reduction of LDL-C among carriers of the rs646776 minor allele could be attributed to relative depletion of LDL particles dependent on sortilin for clearance and hence a residually greater proportion of those LDL particles whose uptake is more dependent on the LDL receptor than on sortilin.

In the current study, we combined the results of 6 randomized clinical trials and 10 observational studies in the first stage. This approach resulted in combining several types of statins, since different statins were studied in the trials and within the observational studies (Supplementary Table 2). This, and the variation in statin dosage during follow-up for an individual, is a limitation of the current study, since, for example, the impact of the SLCO1B1 variant on statin pharmacogenetics is known to be highly dependent on statin type and dose. To correct for between-study variance, we used a fixed effect meta-analysis with inverse variance weighting. Since we observed that the SLCO1B1 variant on statin pharmacogenetics is known to be highly dependent on statin type and dose, we used a fixed effect meta-analysis with inverse variance weighting. Since we observed that the SLCO1B1 gene was genome-wide significantly associated with LDL lowering, this highlights the thoroughness of our analytical approach, in which the analyses were correctly adjusted for the type and dose of statins used (Supplementary Table 3). Moreover, a comparison of the estimates of the SNPs between the RCTs (where there are no intra-individual differences in dosages) with the estimates of the SNPs in the observational studies showed large homogeneity between the estimates in the various study designs (Supplementary Fig. 2), indicating that our adjustment for dosage seems to be sufficient within this study.
control for possible associations with off-treatment LDL-C levels, analyses were adjusted for the natural log-transformed off-treatment LDL-C level. An additive genetic model was assumed in the GWAS analysis. Meta-analysis of the imputed SNPs, regression analysis was performed on expected allele dosage. Analyses were additionally adjusted for age-, sex- and study-specific covariates (for example, ancestry principal components or country). Analyses in the observational studies were, if available, additionally adjusted for the statin dose by the natural logarithm of the dose equivalent as defined in Supplementary Table 3. This table shows the dose equivalent per statin type; dividing the statin dosage of an individual by the dose equivalent shown in Supplementary Table 3 will give the adjusted statin dosage.

Quality control and meta-analysis. Centrally, within each study, SNPs with MAF < 1% or imputation quality < 0.3 were excluded from the analysis. QQ-plots were assessed for each study to identify outliers and genomic inflation (Supplementary Fig. 1). The software package METAL was used for performing the meta-analysis (http://www.sph.umich.edu/csg/abecasis/Metal/index.html). A fixed effects, inverse variance weighted approach was used. Using an inverse variance weighted meta-analysis will give smaller weights to studies with large s.e. To correct for possible population stratification, genomic control was performed by adjusting the within-study findings and the meta-analysis results for the genomic inflation factor.

Second stage. SNPs with $P$ values $< 5 \times 10^{-8}$ in the first stage-meta-analysis were selected for further investigation in a second stage. A maximum of two SNPs per locus were selected, based on statistical significance, except for the APOE locus, for which all genome-wide significant associated SNPs were selected for validation. A total of 208 SNPs, within 10 independent loci, were selected for the second stage, which was performed in the JUPITER trial, HPS study and the Rotterdam Study, which all had GWAS data and response to statin treatment available. For 2 of the 246 SNPs, a proxy was used in the JUPITER trial, and 31 SNPs were not available, nor was a proxy SNP. HPS provided data on 151 directly genotyped SNPs from the GWAS and iPLEX experiments, including 48 of the 103 and 103 proxy SNPs ($r^2 > 0.8$). Analysis in HPS was not adjusted for ln baseline LDL-C levels. In addition, the number of subjects with data varied from SNP-to-SNP and ranges from $\sim 4000$ for variants with GWAS data to $\sim 18000$ for some candidate genes. Results of the first and second stage were combined using fixed effects, inverse variance weighted meta-analysis and analysed by METAL. As a third stage, six SNPs with $P$ values $5 \times 10^{-8} < P < 5 \times 10^{-7}$ in the combined meta-analysis were selected for additional genotyping in the Scandinavian participants of the ASCOT study. Kaspar assays were designed for four of the SNPs using the KBioscience Primerpicker software, and oligos were provided by Integrated DNA Technologies (http://eu.idtdna.com/site). Full Kaspar methodology is available from LGC SNP genotyping (http://www.lgcgenomics.com/genotyping/kasp-genotyping-reagents/). Two SNPs (rs981844 and rs13166647) were genotyped using Taqman assays supplied by Life Technologies (http://www.lifetech.com/uk/en/home.html) using the standard Taqman protocol. Results of the additional genotyping were combined with results from the first and second stages using a fixed effects, inverse variance weighted meta-analysis and analysed by METAL.

Determination of changes in LDL subfractions. LDL subclasses were analysed as described previously22 using non-denaturing gradient gel electrophoresis of fasting plasma samples taken at baseline and after 6 weeks of simvastatin 40 mg per day (CAP study, n = 579) or 12 weeks of pravastatin 40 mg per day (PRINCE study, n = 1284). Aliquots of 0.01 ml of whole plasma were mixed 1:1 with a sampling buffer of 20% sucrose and 0.25% bromophenol blue. Electrophoresis of samples and size calibration standards was performed using 2–14% polyacrylamide gradients at 150 V for 3 h following a 15-min pre-run at 75 V. Gels were stained with 0.07% Sudan black for 1 h and stored in 0.81% acetic acid, 4% methanol solution until they were scanned by computer-assisted densitometry for determination of areas of LDL IVb (22.0–23.2 nm), LDL IVA (23.3–24.1 nm), LDL IIb (24.2–24.6 nm), LDL IIa (24.7–25.5 nm), LDL IIb (25.6–26.4 nm), LDL IIa (26.5–27.1 nm) and LDL I (27.2–28.5 nm). The cholesterol concentrations of the subfractions (mg dL$^{-1}$ plasma) were determined by multiplying percent of the total stained LDL area for each subfraction by the LDL-C for that sample. For genetic association analyses, subfractions were grouped into large LDL (LDL I + IIa + IIb), small LDL (LDL IIIb), and very small LDL (LDL IVA + IIVb) as described previously22. A generalized estimating equation method was used to test the association of log change with the interaction of the four SNPs by LDL subfraction.

Effect of off-treatment LDL-C. Effects of genetic variation on treatment response as measured by on-treatment LDL-C could be mediated through effects on the off-treatment LDL-C. To evaluate whether genetic on-treatment LDL-C likely reflects residual effect on off-treatment LDL-C, it is necessary to adjust for the off-treatment LDL-C levels and to correct the maximum likelihood estimate of the adjusted effect of genotype on on-treatment value for the noise in off-treatment values (the noise is both random measurement error and intra-individual variation in usual LDL-C). This analysis was only possible when not all individuals in the CARDS and JUPITER studies had baseline measurements were available. From the rules of path analysis, we calculated the direct effect of genotype on on-treatment trait value as $\beta = \alpha - (1 - \rho)\beta$, where
β is the coefficient of regression for on-treatment trait value on genotype adjusted for measured off-treatment value. s is the coefficient of regression of baseline LDL on on-treatment trait value including bias correction between replicate measurements of off-treatment variables and δ is the coefficient of regression for on-treatment value on observed off-treatment value. For these calculations, we used ρ = 0.8 as a plausible value for the intraclass correlation based on the within-person correlation in LDL-C values taken over two off-treatment visits in CARD5. The interaction of candidate SNPs with statin versus placebo allocation was assessed in the JUPITER trial, since this study was not involved in the first-stage meta-analysis. Regression models were applied to the combined population of statin- and placebo-treated subjects by including extra terms encoding placebo allocation and the product of placebo allocation with SNP minor allele dose.

GWCA using Genome-Complex Trait Analysis. There may be multiple causal variants in a gene and the total variation that could be explained at a locus may be underestimated if only the most significant SNP in the region is selected. To identify independent SNPs, we ideally can perform a conditional analysis, starting with the top associated SNP, across the whole genome followed by a stepwise procedure of selecting additional SNPs, one by one, according to their conditional P values. Such a strategy would allow the discovery of more than two associated SNPs at a locus. To identify independent SNPs across the genome-wide data, we used an approximate conditional and joint analysis approach implemented in Genome-Complex Trait Analysis (GCTA) software (http://www.complextraitgenomics.com/software/gcta/). We used summary-level statistics from the first- and second-stage complex meta-analysis and LD corrections between SNPs estimated from CARD5 GWAS data. SNPs on different chromosomes or more than 10 Mb distant are assumed to be in linkage equilibrium. The model selection process in GCTA starts with the most significant SNP in the single-SNP meta-analysis across the whole genome with P value < 5 x 10⁻⁸. In the next step, it calculates the P values of all the remaining SNPs conditional on the top SNP that have already been selected in the model. To avoid problems due to colinearity, if the squared multiple correlations between a SNP to be tested and the selected SNPs(s) is larger than a cut-off value, such as 0.9, the conditional P value for that SNP will be set to 1. Select the SNPs with minimum conditional P value that is lower than the cut-off P value. Fit all the selected SNPs jointly in a model and drop the SNPs with the P value that is greater than the cut-off P value. This process is repeated until no SNPs can be added or removed from the model.

Pathway analysis and construction of a statin response network. Genes showing evidence of association (based on direct association or LD (HapMap CEU r²>0.8)) were reviewed for evidence of involvement in statin response at a pathway level using GeneGo MetaCore (Thomson Reuters (portal.genego.com)). A statin response network was constructed in two stages. First, all genes with a literature-reported involvement in statin response (based on Medical Subject Headings (MeSH)) were identified using GeneGo MetaCore (Supplementary Data 3). Second, these genes were combined with all genes in associated loci (including genes in LD) and a network was constructed based on direct interactions only. By including direct interactions only, we created a comprehensive network of direct gene interactions that have been consistently linked to statin response in the literature.

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β is the coefficient of regression for on-treatment trait value on genotype adjusted for measured off-treatment value. s is the coefficient of regression of baseline LDL on on-treatment trait value including bias correction between replicate measurements of off-treatment variables and δ is the coefficient of regression for on-treatment value on observed off-treatment value. For these calculations, we used ρ = 0.8 as a plausible value for the intraclass correlation based on the within-person correlation in LDL-C values taken over two off-treatment visits in CARD5. The interaction of candidate SNPs with statin versus placebo allocation was assessed in the JUPITER trial, since this study was not involved in the first-stage meta-analysis. Regression models were applied to the combined population of statin- and placebo-treated subjects by including extra terms encoding placebo allocation and the product of placebo allocation with SNP minor allele dose.

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Acknowledgements

Data from the Heart Protection Study have been contributed by Heart Protection Study Collaborative Group.

PROSPER/PHASE: The Prospective Study of Pravastatin in the Elderly at Risk (PROSPER) trial was supported by an investigator-initiated grant from Bristol-Myers Squibb, USA. The study was conducted, analysed and reported independently of the company. The GWAS project PHASE has received funding from the European Union's 7th Framework Programme (FP7/2007–2013) under grant agreement HEALTH-F2-2009-223004. A part of the genotyping was funded by The Netherlands Consortium for Healthy Ageing (NHL: 050606810). Professor Dr JWJ is an established clinical investigator of The Netherlands Heart Foundation (2001 D 032).

ASCOT: The Anglo-Scandinavian Cardiac Outcomes Trial (ASCOT) trial was funded by an investigator-initiated grant from Pfizer, USA. The study was investigator led and was conducted, analysed and reported independently of the company. The GWAS project PHASE has received funding from the European Union’s Seventh Framework Programme (FP7/2007–2013) under grant agreement HEALTH-F2-2009-223004. A part of the genotyping was funded by The Netherlands Consortium for Healthy Ageing (NHL: 050606810). Professor Dr JWJ is an established clinical investigator of The Netherlands Heart Foundation (2001 D 032).

CARDS: We thank the other investigators, the staff and the participants of the CARDS study. A full list of CARDS investigators can be found in original CARDS paper (2011). CARDS was funded by grants to the Universities of London and Manchester by Pfizer, Diabetes UK and the Department of Health.

PARC: This research was supported by the National Institutes of Health: grant U19 HL069757 from the National Heart, Lung, and Blood Institute, and grant UL1TR000124 from the National Center for Advancing Translational Sciences.

TNT: The TNT study was funded by Pfizer, who also provided support for genotyping.
Author contributions


Additional information
Supplementary Information accompanies this paper at http://www.nature.com/naturecommunications

Competing financial interests: B.M.P. serves on the Data and Safety Monitoring Board of a clinical trial funded by the device manufacturer (Zoll LifeCor). N.P. and A.S. received funding from Pfizer for the extended follow-up of the ASCOT UK participants. D.I.C. and P.M.R. received research support for independent genetic analysis in JUPITER from AstraZeneca. F.N. and B.J.B. have employment, stock and stock options in AstraZeneca, a for-profit company engaged in the discovery, development, manufacture and marketing of proprietary therapeutics such as rosuvastatin, but do not consider that this creates any conflict of interest with the subject–matter of this publication. R.M.K. serves on the Merck Global Atherosclerosis Advisory Board. The remaining authors declare no competing financial interests.

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How to cite this article: Postmus, I. et al. Pharmacogenetic meta-analysis of genome-wide association studies of LDL cholesterol response to statins. Nat. Commun. 5:5068 doi: 10.1038/ncomms6068 (2014).

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