Rare Genetic Variants of Large Effect Influence Risk of Type 1 Diabetes

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Most replicated genetic determinants for type 1 diabetes are common (minor allele frequency [MAF] >5%). We aimed to identify novel rare or low-frequency (MAF <5%) single nucleotide polymorphisms with large effects on risk of type 1 diabetes. We undertook deep imputation of genotyped data followed by genome-wide association testing and meta-analysis of 9,358 type 1 diabetes case and 15,705 control subjects from 12 European cohorts. Candidate variants were replicated in a separate cohort of 4,329 case and 9,543 control subjects. Our meta-analysis identified 27 independent variants outside the MHC, among which 3 were novel and had MAF <5%. Three of these variants replicated with $P_{replication} < 0.05$ and $P_{combined} < P_{discovery}$. In silico analysis prioritized a rare variant at 2q24.3 (rs60587303 [C], MAF 0.5%) within the first intron of *STK39,* with an effect size comparable with those of common variants in the *INS* and *PTPN22* loci (combined [from the discovery and replication cohorts] estimate of odds ratio [$OR_{combined}$] 1.97, 95% CI 1.58–2.47, $P_{combined} = 2.9 \times 10^{-9}$). Pharmacological inhibition of *Stk39* activity in primary murine T cells augmented effector responses through enhancement of interleukin 2 signaling. These findings provide insight into the genetic architecture of type 1 diabetes and have identified rare variants having a large effect on disease risk.

Type 1 diabetes accounts for 5–10% (1) of diabetes cases, affecting ~20 million individuals worldwide, and

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represents the majority of diabetes diagnoses in individuals <20 years of age (2,3). Its prevalence is consistently rising worldwide at an annual rate of ~2–5% (3,4) and it is estimated that by 2050, 5 million people, among whom more than half a million youths, will be living with type 1 diabetes in the U.S. (5). Type 1 diabetes is a chronic autoimmune disorder caused by destruction of the insulin-producing pancreatic β-cell, which generally occurs in genetically susceptible individuals (6) and may be precipitated by environmental factors (7). Thus, understanding the genetic determinants of type 1 diabetes and their effects can provide a better understanding of the pathophysiology of the disease and enable new treatment approaches, with potentially important public health benefits.

Our knowledge on the genetic architecture of type 1 diabetes has expanded substantially with the emergence of genome-wide association studies (GWAS). In the pre-GWAS era, the few genetic loci established to contribute to type 1 diabetes risk were identified primarily through linkage studies, such as the human leukocyte antigen (HLA) class II genes in the MHC, or through candidate gene studies, such as the genes encoding insulin (INS), cytotoxic T-cell–associated protein 4 (CTLA4) (8), protein tyrosine phosphatase, nonreceptor type 22 (PTPN22) (9), and interleukin 2 receptor α (IL2RA) (10). In comparison, recent GWAS comprising thousands of type 1 diabetes cases have identified 57 loci associated with risk of type 1 diabetes (11–13). However, with a few exceptions (14), the identified variants by GWAS are common (defined as variants with a minor allele frequency [MAF] >5%) and have modest effects on type 1 diabetes risk (odds ratios [ORs] <1.5) (13) compared with those of the previously identified HLA, INS, and PTPN22 variants (ORs >6 for the HLA and >2 for the INS and PTPN22 loci, respectively). Evaluation of rare and low-frequency variants for association with type 1 diabetes is an important area, and a recent study (15) showed the utility of rare variants for identifying potential causal genes in type 2 diabetes. In addition, understanding the biology of most GWAS loci remains challenging, as fine mapping and functional validation are typically lacking (13). Furthermore, the small effect sizes attributed to most common variants decreases the ability to dissect their function through approaches such as genome editing via CRISPR-Cas9, since the anticipated effect sizes on relevant phenotypes would be smaller than variants of larger effect. Therefore, larger effect size variants may help us to better understand the genetic pathways that increase risk of type 1 diabetes.

It has been shown that known loci explain ~80% of the heritability of type 1 diabetes (16), with the HLA variants accounting for the largest portion of this variance (17). Therefore, about 20% of the genetic risk of type 1 diabetes remains unexplained (13). The rest of this unidentified genetic component has been attributed to undetected susceptibility loci (17), possibly due to the inability of past studies to interrogate loci containing low-frequency

or rare genetic variants (defined as variants with an MAF ≤5% and >1% or ≤1%, respectively), despite the strong effects that some of them may have. Interestingly, among the 57 known type 1 diabetes loci, only 3 loci include low-frequency or rare variants, specifically in the tyrosine kinase 2 (TYK2), interferon induced with helicase C domain 1 (IFIH1), and RNA binding motif protein 17 (RBM17) (in the same locus as IL2RA) genes, which were identified mainly through fine mapping of previously known autoimmune loci (14,18). The recent availability of large human whole-genome sequencing data sets has enabled the interrogation of rare genetic variation by imputation from directly genotyped data, allowing identification of rare single nucleotide polymorphisms (SNPs) with large effects on complex traits (19,20). Here, we sought to apply these recent advances in genomics to type 1 diabetes, with the aim of identifying additional low-frequency and rare loci of large effect. To do so, we undertook a GWAS of ~9 million SNPs in 9,358 type 1 diabetes case and 15,705 control subjects from 12 cohorts of predominantly European descent and replicated our findings using de novo genotyping in a separate cohort of 4,329 type 1 diabetes case subjects from the Type 1 Diabetes Genetics Consortium (T1DGC) and 9,543 control subjects from the UK Biobank. In addition, potential biological effects of the top low-frequency locus were explored using in vitro functional experiments.

RESEARCH DESIGN AND METHODS

Cohorts and Overview of GWAS

For our ascertained case-control association study, similar to a previous type 1 diabetes GWAS (11), we used data from multiple type 1 diabetes case cohorts and control cohorts. In the discovery stage, the cohorts who were genotyped on Affymetrix or Illumina platforms were pooled separately and genotypes were imputed using the Haplotype Reference Consortium reference panel (21), which allows improved imputation of rare variants. Next, association studies were performed separately for each one of the two platform types. The summary statistics of the two association studies were then meta-analyzed to generate the final discovery GWAS estimates (Supplementary Fig. 1). Individual-level genotype data for the discovery meta-analysis were drawn from 12 cohorts of predominantly European descent totaling, before quality control, 9,684 type 1 diabetes case and 17,153 control subjects. Specifically, among 3,173 type 1 diabetes case subjects genotyped on the Affymetrix 500K array, 1,173 subjects were from the Genetics of Kidneys in Diabetes (GoKinD) study and 2,000 were from the Wellcome Trust Case Control Consortium (WTCCC). These were then compared with 5,998 similarly genotyped control subjects from WTCCC, specifically, 1,999 subjects from the type 2 diabetes (T2D) study, 2,001 subjects from the hypertension (HT) study, and 1,998 individuals from the bipolar disorder (BD) study. Among the 6,511 type 1 diabetes case subjects genotyped on Illumina arrays (HumanHap550 or

Human1-2M-DuoCustom_v1_A), 514 individuals were from McGill University, 483 from Children's Hospital of Philadelphia (CHOPTDT), 1,385 from the Diabetes Control and Complications Trial–Epidemiology of Diabetes Interventions and Complications (DCCT-EDIC) cohort, and 4,129 from T1DGC. These were compared with 9,745 similarly genotyped control subjects recruited from TwinsUK ($n = 2,249$), and two WTCCC studies (2,836 individuals from the 1958 British Cohort [58BC] and 2,633 individuals from the U.K. National Blood Service sample [NBS], respectively). In the replication stage, we used 4,329 type 1 diabetes case subjects from T1DGC and 9,543 randomly selected control subjects of white-British ancestry from the UK Biobank (22).

All participating studies in the GWAS meta-analysis were approved by the institutional review boards and the ethics committees of the respective institutions. Written informed consent was obtained from each participant in accordance with institutional requirements and the Declaration of Helsinki principles.

For a detailed description of the discovery study cohorts, see Supplementary Data and Supplementary Table 1.

Quality Control and Assessment of Population Stratification

Genotype quality assessment was performed according to published guidelines (23). This quality control removed individuals with problematic sex assignment, increased genotype missingness, increased proportion of identity by descent, and extreme heterozygosity rate. It also removed low-quality genetic variants, by retaining only array SNPs with an MAF >1%, missingness <0.05, and Hardy-Weinberg equilibrium $P > 1 \times 10^{-5}$. In the CHOPTDT case-parent trios cohort, we retained the single type 1 diabetes case per trio for association analysis, as the model used does not adjust for familial relatedness. A detailed description of the quality-control pipeline appears in the Supplementary Data. All individuals from cohorts genotyped on the same platform (Affymetrix or Illumina) were merged into a single data set, with only SNPs retained that were in common between all cohorts being merged (337,727 and 456,168 markers for Affymetrix- and Illumina-based arrays, respectively). Population stratification was assessed using EIGENSTRAT, version 6.0.1 (24). This assessment was performed for the merged cohorts genotyped by the same platform that passed quality control (Supplementary Table 1 [N(total) = 25,063]). For the Affymetrix- and Illumina-based data sets, 52,598 and 99,742 SNPs, respectively, were used as input into the analysis for population stratification, which were those that passed the aforementioned genotype quality control, followed by further filtering steps described in the Supplementary Data. Low-frequency and rare variant associations can be prone to bias from population stratification; therefore, additional steps were taken to decrease such potential effects. Specifically, analysis for population stratification removed 268 and 545 individuals

identified as ancestral outliers from the Affymetrix- and Illumina-based arrays, respectively. The top 10 principal components for the remaining individuals were used as covariates in the GWAS to adjust for potential residual population stratification. An additional principal component analysis was conducted by projecting study samples to 2,504 samples from 1000 Genomes phase 3. This additional analysis revealed that the EIGENSTRAT-based population stratification analysis successfully removed individuals of non-European ancestry and that remaining individuals across case/control status or across individual cohorts are of European ancestry (Supplementary Fig. 2). The quality-control and population stratification analysis resulted in a total of 24,250 individuals used for genotype imputation. This included 2,903/5,678 case/control subjects and 6,093/9,576 case/control subjects for the Affymetrix- and Illumina-based data sets, respectively (Supplementary Table 1).

Genotype Imputation, GWAS, Meta-analysis, and Conditional Analysis

The Sanger Institute online service (25) was used to impute the available genotypes to the Haplotype Reference Consortium, version R1.1, on ~39 million SNPs, separately in the Illumina and Affymetrix data sets. Association testing was undertaken using logistic regression as implemented in SNPTEST, version 2.5.2 (26), on samples from the same genotyping platform and including the top 10 principal components from EIGENSTRAT (24,27) to adjust for population stratification. We then combined the association results from the Affymetrix and Illumina cohorts in a fixed effects inverse variance meta-analysis using METAL (28) to generate the discovery cohort totaling 25,063 type 1 diabetes case and control subjects. We retained SNPs with an MAF in control subjects >0.5% and those with an imputation quality score (INFO) >0.3, resulting in 9,061,522 SNPs. The MAF cutoff was decided based on a power calculation using the genetic analysis calculator (https://zzz.bwh.harvard.edu/gpc/) and the following assumptions: perfect LD between the causative variant and the markers that were genotyped, an additive genetic model, a disease prevalence of 0.0033, and an α of 1×10^{-5} (similar to previous GWAS [11,12]). We declared genome-wide statistical significance at $P \leq 1.2 \times 10^{-8}$ to account for the increased number of statistical tests compared with a common variant–based GWAS (29). Conditional analysis was performed using the GCTA-COJO package (30). Among the SNPs that remained genome-wide significant after conditional analysis, we considered as candidates for replication only variants that were not within 1 Mb of MHC and that had at least three SNPs with discovery P value <0.0001 within 40 kb, henceforth referred to as satellite SNPs (Supplementary Data).
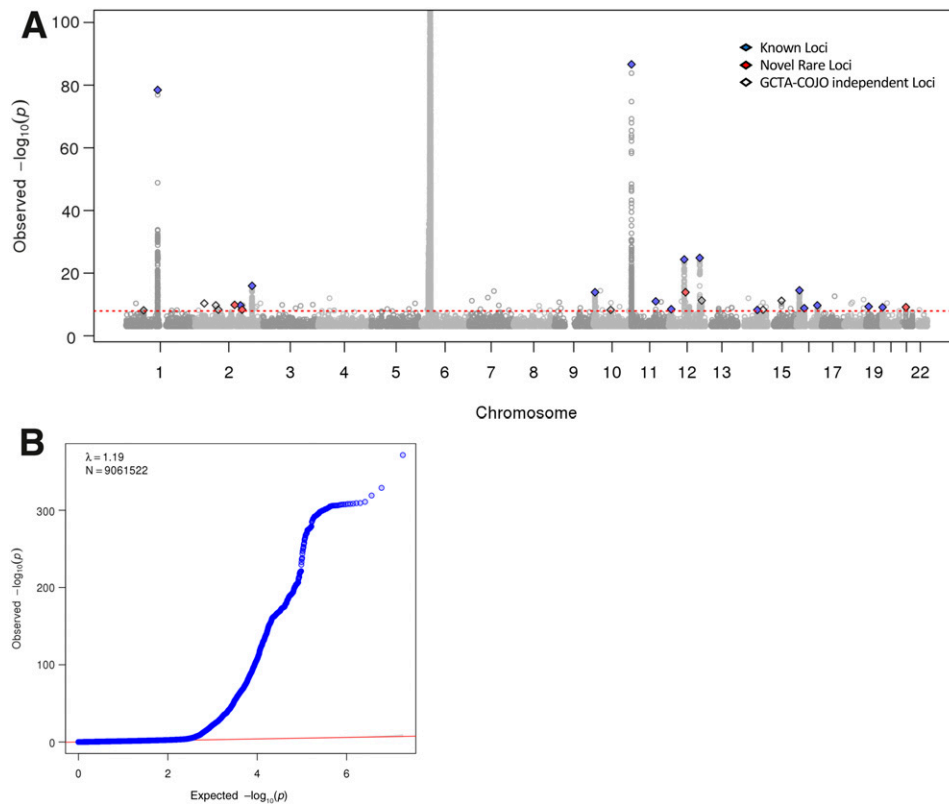
Figure 1—Discovery meta-analysis. *A*: Manhattan plot depicting genome-wide association of 9.06 million genetic variants with type 1 diabetes risk [y-axis is truncated at −log10(*P* value) of 100]. Blue diamonds represent lead independent genetic variants at known type 1 diabetes loci, red diamonds represent the novel low-frequency/rare loci, and white diamonds represent the remaining GCTA-COJO independent loci. *B*: Quantile-quantile plot depicting the observed versus expected −log10 *P* values for the genome-wide association of 9.06 million genetic variants with type 1 diabetes risk.

Replication of Discovery Association Signals

Replication de novo genotyping was performed in a cohort consisting of 4,329 type 1 diabetes case subjects from the sibling-pair set of T1DGC and 9,543 control subjects from UK Biobank. A detailed description of the replication cohort and of its assessment for population stratification is provided in the Supplementary Data. De novo genotyping of the lead SNPs for the replication in type 1 diabetes case subjects from the T1DGC was performed by LGC Genomics applying KASP genotyping. Association testing for the replication cohort was performed using GMMAT (31), using a relatedness matrix built using GEMMA (32). SNPs achieving a *P* value ≤0.05 in the replication cohort and same direction of effect were combined with the discovery cohort in a fixed effects inverse variance meta-analysis (33) to create combined estimates of OR (OR$_{combined}$) and *P* values (*P*$_{combined}$) and heterogeneity statistics from the discovery and replication cohorts.
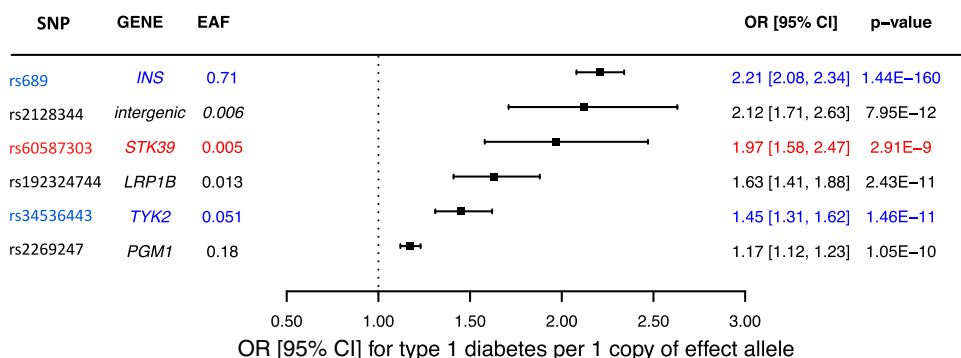
Admixture Analysis

Since low-frequency and rare variants can be strongly influenced by subtle differences in frequency across

ancestral populations, we undertook an admixture analysis using PCAdmix (34).

Specifically, the local admixture analysis was performed on 16,124 Illumina-based imputed genotypes on a 2 Mb region surrounding rs60587303 (*STK39*) (21,380 SNPs). Admixture of each individual was determined in comparison with genotype data from the European (CEU) (*N* = 99), African (YRI) (*N* = 108), and Asian (CHB/JPT) (*N* = 207) populations in 1000 Genomes phase 3. The distribution of probabilities of CEU, YRI, and CHB/JPT ancestries was stratified by dosage of the effect allele (C) at rs60587303 and type 1 diabetes case/control status.

Fine Mapping and In Silico Functional Exploration

We undertook fine mapping using FINEMAP (35) to prioritize variants at all GCTA-COJO conditionally independent loci. Putative functional targets were identified in silico as genes mapping in the same topological domain as the fine mapped SNPs or genes with fine mapped SNPs overlapping transcription factor binding sites and DNase I hypersensitivity clusters (Supplementary Data).

SNP	GENE	EAF		OR [95% CI]	p-value
rs689	*INS*	0.71		2.21 [2.08, 2.34]	1.44E−160
rs2128344	*intergenic*	*0.006*		2.12 [1.71, 2.63]	7.95E−12
rs60587303	*STK39*	*0.005*		1.97 [1.58, 2.47]	2.91E−9
rs192324744	*LRP1B*	0.013		1.63 [1.41, 1.88]	2.43E−11
rs34536443	*TYK2*	0.051		1.45 [1.31, 1.62]	1.46E−11
rs2269247	*PGM1*	0.18		1.17 [1.12, 1.23]	1.05E−10

OR [95% CI] for type 1 diabetes per 1 copy of effect allele

Figure 2—Forest plot with the effects on type 1 diabetes of the variants from the discovery and replication meta-analysis. The variants used as positive controls appear in blue. For facilitation of comparison, the novel *STK39* variant appears in red. EAF, effect allele frequency; OR, OR of type 1 diabetes after combining discovery and replication results.

Exploration of In Vitro Function of *STK39*

Murine T cells

Given the commercial availability of an antiparasitic agent, closantel, which has been shown to specifically inhibit *stk39* activity in cell lines and in mice (36), we tested the effects of this agent on cytokine responses in murine CD4[+] T cells. Cytokine secretion assays for interferon γ (IFNγ) and interleukin-2 (IL-2) were performed on activated CD4[+] T cells in the presence or absence of closantel at titrated doses (see Supplementary Data for further details).

Data and Resource Availability

The GWAS summary-level results will become available through GRASP (Genome-Wide Repository of Associations Between SNPs and Phenotypes) (https://grasp.nhlbi.nih .gov/).

RESULTS

GWAS

After quality control, imputation to 9,061,522 SNPs, and platform-specific case-control GWAS performed separately for the Affymetrix and Illumina genotyped samples, our discovery meta-analysis included a total of 9,358 type 1 diabetes case and 15,705 control subjects. The power of our meta-analysis to find variants with an MAF of 0.5% and a relative risk of 2.0 was 98% at an α of 1×10^{-5}. After controlling for population stratification, the λ for this meta-analysis was 1.19 (Fig. 1), which is similar to that reported in previous type 1 diabetes GWAS (11). Based on our criteria for prioritization of our independent lead variants (MAF in control subjects >0.5%, INFO >0.3, P value $<1.2 \times 10^{-8}$ after conditional analysis, not being in the MHC region, and presence of at least three satellite SNPs), our list of lead variants included 27 independent variants in 27 loci (Supplementary Table 3). Among these, 23 were common, mostly at known autoimmune loci ($n = 15$) reported in ImmunoBase (available from https://genetics .opentargets.org/immunobase). Five were low-frequency or rare variants, four of which were located in loci not

previously described to be associated with an autoimmune trait. One low-frequency variant (rs34536443) was located in the *TYK2* locus, which has previously been associated with type 1 diabetes risk (11).

The four novel low-frequency/rare variants were brought forward to the replication stage (Supplementary Table 4). In addition, two novel common variants with >40 satellite SNPs were tested for replication by de novo genotyping in 4,329 case and 9,543 control subjects. We used two variants, in *TYK2* (rs34536443) and *INS* (rs689), as positive controls in the replication stage. One of the two novel common SNPs (rs61944716) failed replication genotyping. Four of the five novel SNPs replicated at $P_{replication} < 0.05$. For these four variants, we combined the "discovery" and "replication" P values to create a $P_{combined}$. We considered as "replicated" the SNPs that presented a $P_{replication} < 0.05$, $P_{combined} < P_{discovery}$, and $P_{combined} \leq 1.2 \times 10^{-8}$ with consistent direction of association. Based on these criteria, three out of the four novel low-frequency/rare SNPs and the single novel common variant replicated (Fig. 2, Table 1, and Supplementary Table 5).

In Silico Functional Exploration and Fine Mapping

To prioritize variants for in vitro and in vivo functional exploration among the four novel variants that successfully replicated, we performed an in silico analysis of the four SNPs by considering their spatial proximity to putative functional elements and target genes (Fig. 3). Specifically, the top candidate genes were determined as genes within a region of elevated chromatin interactions with the lead SNP or, if lacking, nearby genes. Further, expression of these genes was assessed in type 1 diabetes–relevant cell types. These approaches converged upon *STK39*, since it resides in a region of elevated chromatin interaction with the lead SNP. The local chromatin interaction map for the *STK39* locus and its proximity to regulatory elements are shown in Fig. 3.

The lead variant with the most compelling in silico functional evidence was rs60587303 (C), a rare variant (MAF$_{control subjects}$ 0.5%) that resides in the first intron of

SNP	Candidate gene(s)	EA	EAF control subjects	$P_{discovery}$	$P_{replication}$	$P_{combined}$	OR$_{combined}$ (95% CI)
rs689*	INS	T	0.71	2.3×10^{-87}	2.3×10^{-96}	1.4×10^{-160}	2.21 (2.08–2.34)
rs2128344	Intergenic variant	A	0.0055	7.4×10^{-10}	2.5×10^{-3}	8.0×10^{-12}	2.12 (1.71–2.63)
rs60587303	STK39	C	0.0051	4.4×10^{-9}	2.4×10^{-2}	2.9×10^{-9}	1.97 (1.58–2.47)
rs192324744	LRP1B	G	0.0131	1.4×10^{-10}	5.6×10^{-3}	2.4×10^{-11}	1.63 (1.41–1.88)
rs3454443*	TYK2	G	0.0515	4.8×10^{-10}	7.0×10^{-4}	1.5×10^{-11}	1.45 (1.31–1.62)
rs2269247	PGM1	T	0.18	7.3×10^{-9}	1.7×10^{-3}	1.1×10^{-10}	1.17 (1.12–1.23)

Table 1—Main findings from the combined discovery and replication meta-analysis

Only variants with $P_{replication}$ < 0.05 and a $P_{combined}$ < $P_{discovery}$ appear in the table. EA, effect allele; EAF, effect allele frequency. *Variants used as positive controls.

the STK39 gene. With an OR$_{combined}$ of 1.97 (95% CI 1.58–2.47, $P_{combined} = 2.9 \times 10^{-9}$), the magnitude of its effect is comparable with that of the lead INS common variant in our analysis (rs689 [A], MAF 14%, OR 2.21, 95% CI 2.26–2.67, $P_{combined} = 1.44 \times 10^{-160}$). rs60587303 overlaps a DNase I hypersensitivity cluster of 68 cell types, as well as a cluster of transcription factor binding sites (Fig. 3). Statistical fine mapping experiments also prioritized rs60587303 as one of the five top plausibly causal SNPs at the 2q24.3 locus (Fig. 3). Another low-frequency variant was located in the second intron of the LDL receptor–related protein 1B gene (LRP1B). With an MAF$_{control subjects}$ of 1.3%, rs192324744 (G) had an OR$_{combined}$ of 1.63 (95% CI 1.41–1.87, $P_{combined} = 2.4 \times 10^{-11}$). Fine mapping also prioritized this variant in the 2q22.2 locus (Supplementary Fig. 4), but there was less compelling in silico functional evidence from the TAD (topologically associating domain) analysis. The third low-frequency variant that successfully replicated was intergenic (rs2128344 [A]) at the 21q22.1 locus, with an MAF$_{control subjects}$ of 0.55% and an OR$_{combined}$ of 2.12 (95% CI 1.71–2.63, $P_{combined} = 8.0 \times 10^{-12}$). In silico functional evidence in support of this variant was lacking. Finally, the single common variant that successfully replicated was an SNP in the 7th intron of the phosphoglucomutase 1 (PGM1) gene. rs2269247 (T) had an MAF$_{control subjects}$ of 18% and an OR$_{combined}$ of 1.19 (95% CI 1.12–1.26, $P_{combined} = 7.3 \times 10^{-9}$). Fine mapping prioritized this variant at the 1.p31.3 locus, and this SNP appeared to be in the same TAD as PGM1 (Supplementary Fig. 4).

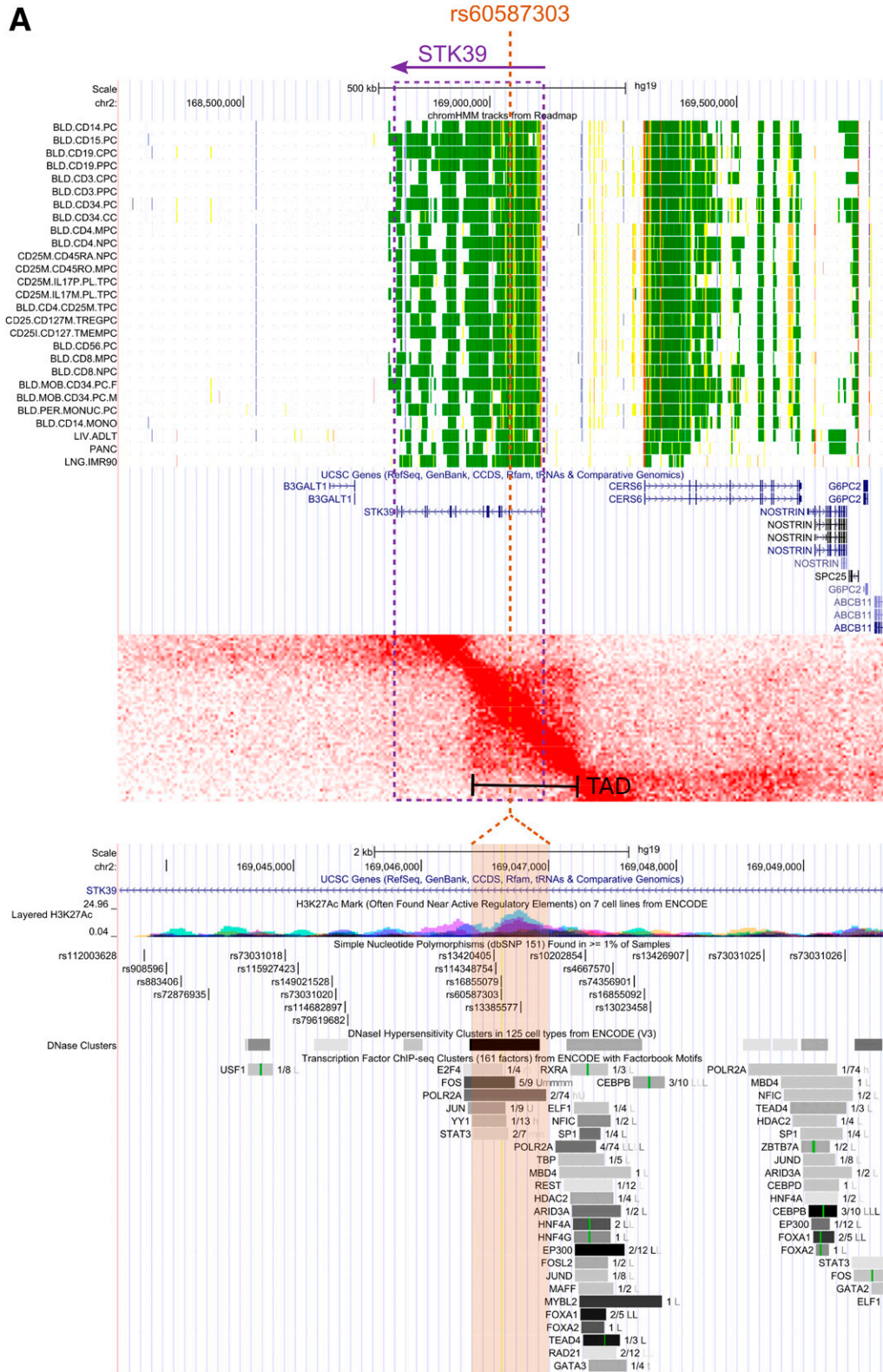## Assessment for Population Stratification and Admixture Analysis

Since rare and low-frequency variants are more prone to confounding by population stratification than common variants, we undertook a principal component analyses separately in the Affymetrix and Illumina discovery cohorts and in the replication cohort. While the population structure between case and control subjects is unlikely to be similar, given that case and control subjects come from different cohorts, our analysis found no evidence for ancestral differences between case and control subjects in the discovery Affymetrix data (Supplementary Fig. 2A), in the Illumina data (Supplementary Fig. 2B), or in the replication cohort (Supplementary Fig. 3). Moreover, using seeds from the 1000 Genomes phase 3 data set, our principal component analysis demonstrated that the outliers removed by EIGENSTRAT lie outside the 1000 Genomes European superpopulation, whereas the inliers largely overlap or are in close proximity to the European superpopulation in the Affymetrix, Illumina, and replication data (Supplementary Figs. 2 and 3).

We also undertook an admixture analysis, where we queried the MAF of the rs60587303 (C) in different ethnicities in the 1000 Genome phase 3 release V3+. We found that its MAF varied by ancestry (East Asian MAF 0.250, American MAF 0.030, African MAF 0.248, European MAF 0.007, and South Asian MAF 0.053). Since this

Figure 3—The *STK39* locus. *A*, top: A regional view of the 2q24.3 locus in the UCSC Genome Browser with tracks showing chromatin state in various immune cell types (green means active). From this, we can see that STK39 is active in immune cells but also nearby genes such as *CERS6*. *A*, middle: Topological associated domains for the *STK39* region. Deeper red color indicates that there is increased pairwise interaction within the genomic interval. A topologically associated domain, a region of increased interaction, is clearly visible that encompasses both the associated variant, rs60587303, and the promoter of *STK39* but excludes *CERS6*. *A*, bottom: Zoomed-in view of region around rs60587303 shows clear overlap with active regulatory elements containing numerous transcription factor binding sites and open chromatin sites in 68 cell types. *B*: Regional Manhattan and fine mapping plots centered on rs60587303. Top panel depicts the results from the discovery meta-analysis of a region centered on rs60587303. This genetic variant is the lead signal and is supported by

B
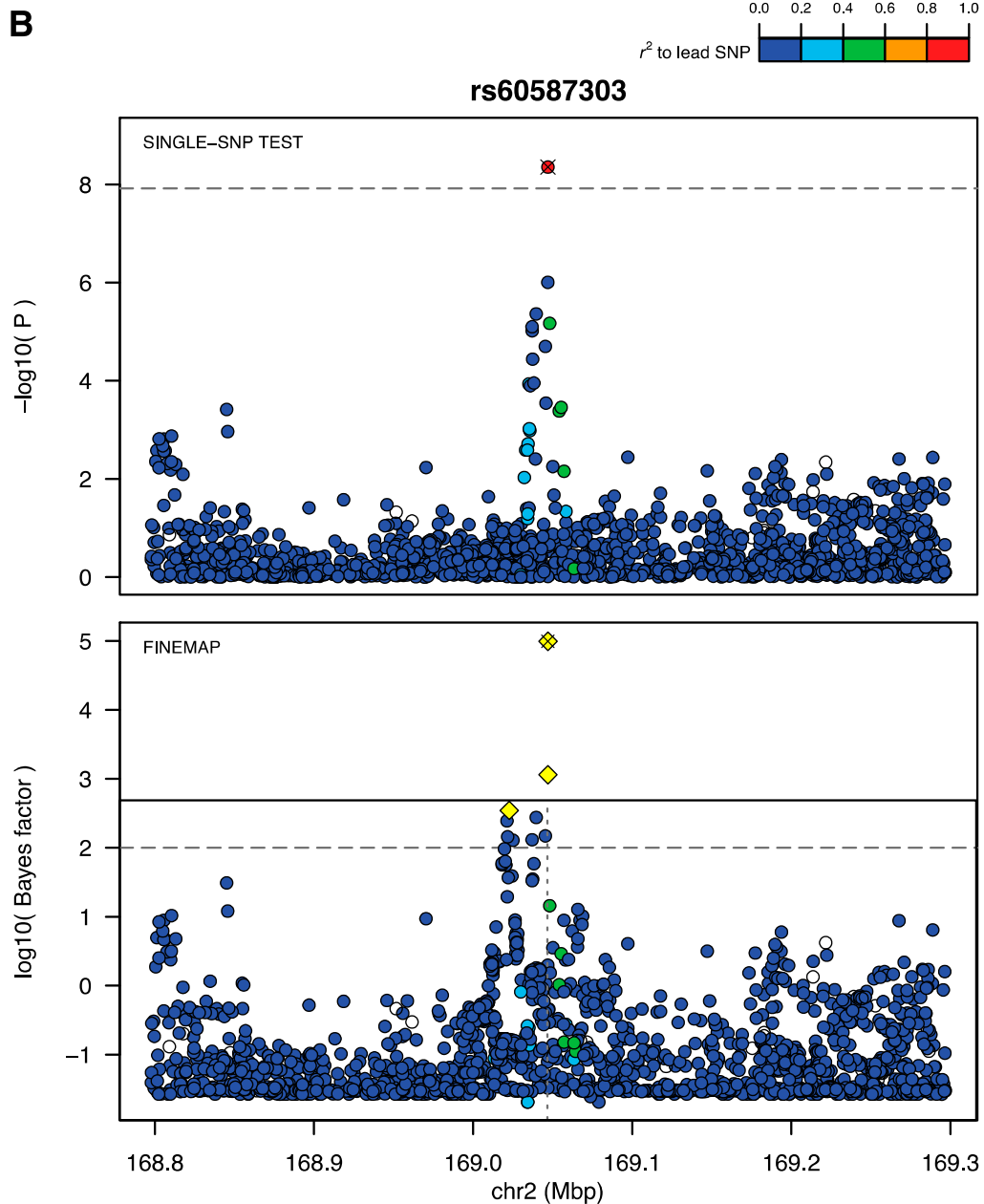
Figure 3—Continued

variant is common in East Asians and Africans, but almost absent in Europeans, we undertook an admixture analysis in our GWAS population to interrogate whether there was an enrichment of Asian or African descent among case subjects, which could have influenced the association signal from the *STK39* variant. The distributions of probabilities of CEU, YRI, and CHB/JPT ancestries were stratified by dosage of the effect allele (C) at rs60587303 and case/control status (Fig.

4). This analysis showed that the type 1 diabetes case subjects of our GWAS had less African or Asian admixture compared with control subjects. This strongly decreases the probability that this finding has arisen due to population stratification or admixture because these effects would bias results at rs60587303 near *STK39* toward the null. Interestingly, when we looked at the MAF of rs60587303 in European subpopulations available from the gnomAD database

multiple genome-wide suggestive genetic variants. In the bottom panel, statistical fine mapping of this further locus supports rs60587303 as the lead putatively causal genetic variant (yellow diamond with ×), accompanied by two highly correlated genetic variants of lower log10 Bayes factor (open yellow diamonds). chr, chromosome.
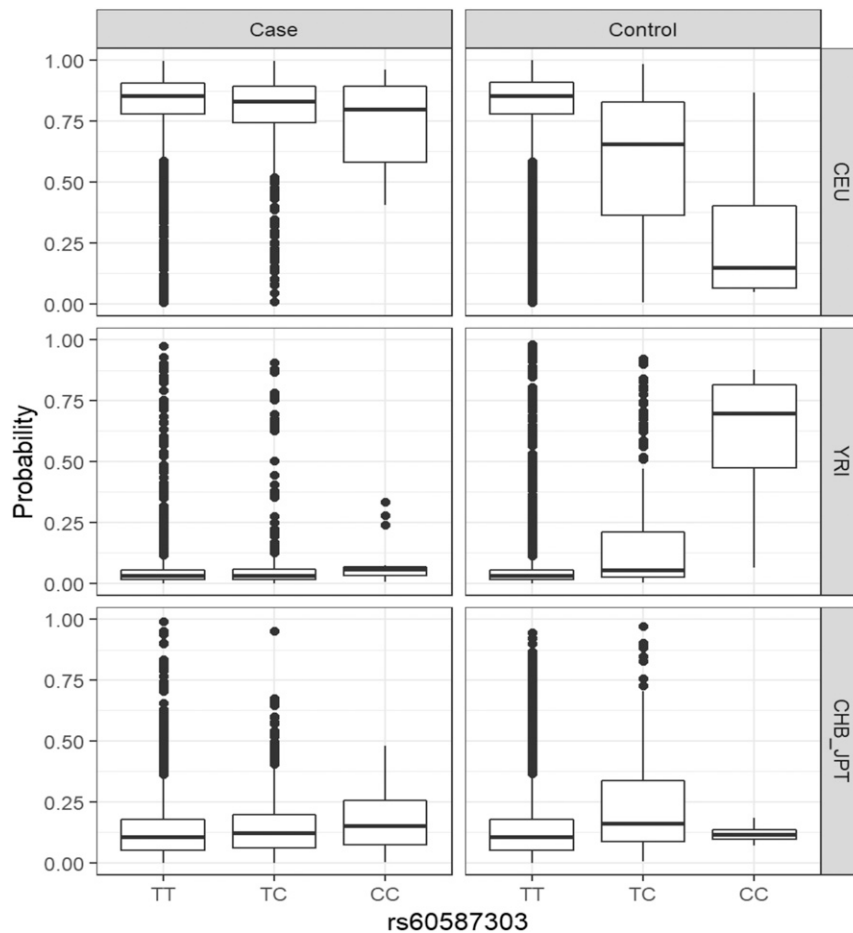
Figure 4—Admixture analysis for rs60587303, showing the probability of European (CEU), African (YRI), and Asian (CHB/JPT) ancestry of the individual from the Illumina platform from our discovery meta-analysis, further stratified by type 1 diabetes case/control status and alleles at rs60587303. Admixture analysis was conducted for a 2 Mbp region centered on rs60587303. We observed limited non-CEU ancestry for case subjects, whereas there is an elevated number of individuals with likely YRI ancestry among control subjects who carry one or more minor alleles at rs60587303.

(version 2) (https://gnomad.broadinstitute.org/variant/2 -169046632-T-C?dataset=gnomad_r2_1) we obtained the following results: Ashkenazi Jewish, 0.03793; European (Finnish), 0.01900; and European (non-Finnish), 0.009853. In the newest version, version 3, of gnomAD (https://gnomad .broadinstitute.org/variant/2-168190122-T-C?dataset= gnomad_r3), which is not overlapping with the previous version, we obtained the following results: Ashkenazi Jewish, 0.03101; European (Finnish), 0.01518; European (non-Finnish), 0.006926; and Amish, 0.000. These results suggest differences in MAF in different European subpopulations, and in particular, the MAF is double in the Finnish population compared with the non-Finnish European population. This is an interesting observation, considering Finland has the highest rate of type 1 diabetes in the world.

In Vitro Functional Exploration of Differential Stk39 Activity in T Cells

We next sought to explore the functional effects of *Stk39* using a commercially available specific STK39 inhibitor

(closantel) (36) to determine whether inhibition of *Stk39* activity would affect murine T cell activation and functions in vitro. In T-cell receptor–activated, primary freshly isolated murine CD4$^+$ T cells, treated with titrated concentrations of closantel, STK39 inhibition had no significant impact on T-cell activation or proliferation at doses that did not affect cell viability. However, we observed that closantel treatment enhanced the secretion of IFNγ and IL-2 by effector T (T$_{EFF}$) cells. Closantel also increased the level of expression of the IL-2 receptor α chain (CD25), the high-affinity binding component of the functional IL-2 receptor, indicating that closantel might augment the sensitivity of activated T cells to IL-2 (Fig. 5).

DISCUSSION

In an effort to discover new loci harboring not previously identified low-frequency and rare variants, we have carried out a large GWAS for type 1 diabetes, including the largest number of SNPs to date. Our analysis revealed the presence of three novel low-frequency/rare variants, the
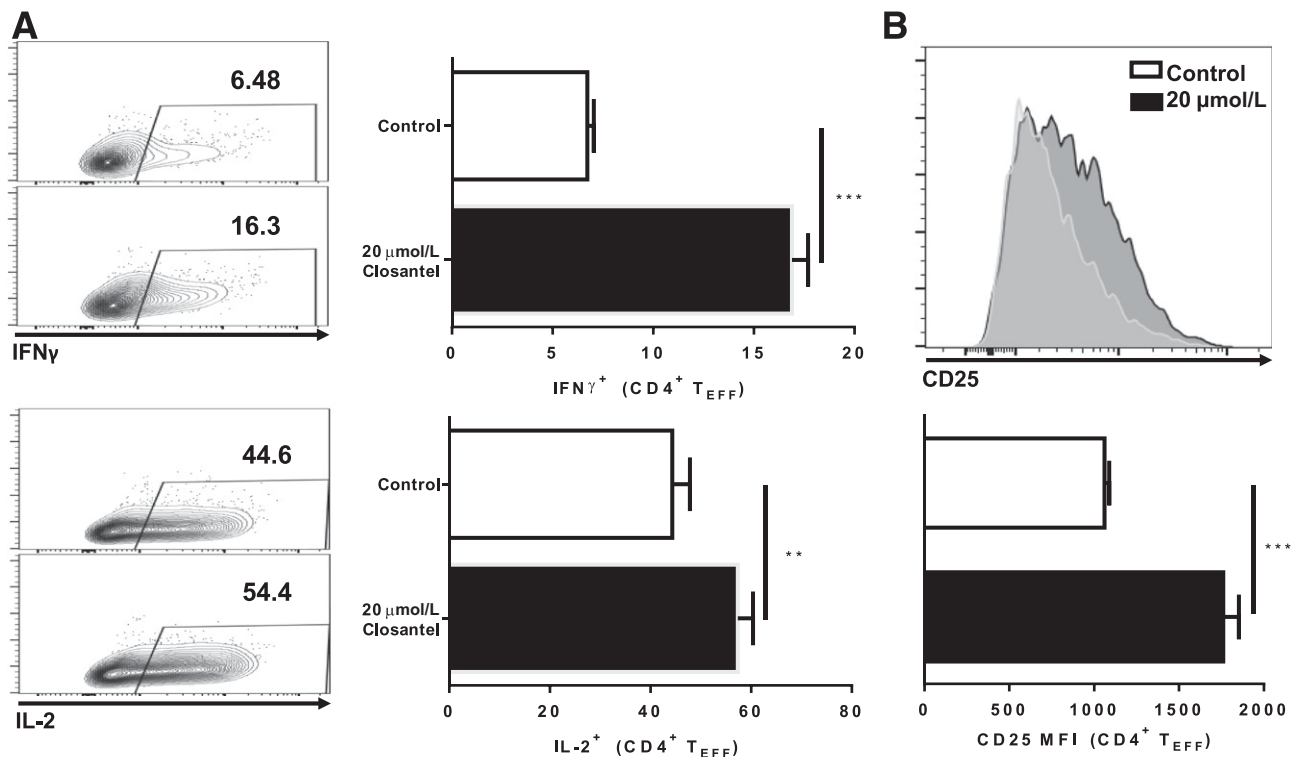
Figure 5—*STK39* inhibition regulates T_{EFF} functions. *A*: Secretion of IFNγ and IL-2 by T_{EFF} cells 72 h following anti-CD3 activation in the presence of indicated concentrations of closantel. Gated on viable CD4$^+$ Foxp3$^-$ cells. *B*: Expression of cell surface CD25 on T_{EFF} cells 72 h following activation in the presence of indicated concentration of closantel. Gated on viable CD4$^+$ Foxp3$^-$ cells. Plots shown from one representative experiment of three, done in triplicate. Error bars represent SD for that experiment. Unpaired parametric *t* test done for all comparisons. *$P \leq 0.05$; **$P \leq 0.005$; ***$P < 0.0005$.

intergenic variant rs2128344, the rs60587303 in *STK39*, and the rs192324744 in *LRP1B*—all validated by replication using de novo genotyping and all with ORs ≥1.5, effects comparable with those of the lead non-MHC common variants at *INS* and *PTPN22* loci. Functional exploration of the *STK39* locus provided evidence supporting a role for *STK39* in type 1 diabetes.

Our in silico exploration approach prioritized rs60587303 in the *STK39* gene for our in vitro experiments. Specifically, carrying one risk allele of this variant appears to approximately double the risk of type 1 diabetes in individuals of European ancestry. This gene encodes a serine/threonine kinase that is thought to function in the cellular stress response pathway (37). Although not previously associated with autoimmunity, STK39 is linked in protein-protein interaction networks to protein kinase C θ (PRKCQ), which then interacts with CD28 (38). The IL2RA and PRKCQ loci on chromosome 10 are well-replicated type 1 diabetes GWAS gene loci. Our in vitro experiments using a cellular murine model of immunity provided evidence that STK39 could be involved in T-cell activation and effector functions. Pharmacological inhibition of *STK39* in vitro appeared to enhance inflammatory responses from T_{EFF}, providing a mechanistic hypothesis for a possible role of *STK39* in type 1 diabetes. We emphasize that further functional validation of *STK39*'s role in immunity is required.

Additional association signals were identified from variants near *LRP1B* and *PGM1*—genes with known roles in metabolism: specifically, *LRP1B* encodes the LDL receptor protein 1B, which has been previously involved in tumor suppression pathways (39). *PGM1* encodes the phosphoglucomutase-1 enzyme, which catalyzes the transfer of phosphate between the 1 and 6 positions of glucose (40). The novel *PGM1* variant (rs2269247) identified in our study is in linkage disequilibrium with a variant (rs2269241) in the same locus, previously shown to present a genome-wide suggestive *P* value for type 1 diabetes (12). These findings provide rationale for further functional studies investigating the role of both *LRP1B* and *PGM1* genes in type 1 diabetes pathophysiology.

Our study has limitations. Similar to previous type 1 diabetes genetic association studies (11,18), the case-control design of our GWAS meta-analysis did not allow for matching of case subjects to control subjects within the same European population because of the lack of availability of control samples in each participating case cohort. Instead, we matched case subjects to control subjects from different cohorts of similar ancestry. Also, case and control samples were not matched for demographics, such as age and sex. This approach could induce bias from population stratification; however, control for population stratification was applied. Also, most studies

included adult individuals, and most cases of type 1 diabetes are manifested in childhood and early adulthood, making the likelihood of misclassification of control subjects very low. Moreover, the likelihood of similar population stratification issues being present in discovery and replication is low. Thus, given that both discovery and replication cohorts showed similar effects, the probability that both were biased by population stratification in the same direction is unlikely. Further, in the case of *STK39*, the increased allele frequency in non-Europeans should have biased our results toward the null, since control subjects were demonstrated to have a higher component of admixture from non-Europeans. On the other hand, differences in allele frequency of the STK39 variant within European populations (for instance, in the Finnish population compared with the general European population) could present residual population stratification, but the likelihood that this phenomenon has biased both the discovery and replication results is very low. Although we applied a liberal imputation INFO cutoff of 0.3 to select variants to include in our GWAS, all results replicated in separate cohorts using direct genotyping, which does not depend on imputation. Finally, ideally, the design of this study should have included, along with imputed GWAS data, exome chip or whole-exome sequencing data, which provide more insight on rare variants. Unfortunately, to date, large-scale exome studies, providing adequate statistical power to study less common diseases, such as type 1 diabetes, are not available.

In summary, our findings demonstrate the utility of deep imputation to enable the characterization of low-frequency and rare genetic variation, offering new insights into the pathophysiology of type 1 diabetes and enabling the identification of new potential drug targets.

Author Contributions. V.F. collected data and undertook all the bioinformatics analyses. D.M. wrote the first draft of the manuscript. S.R. collected data. L.M. and M.-C. T. were involved in the replication experiment. R.I. undertook the in vitro follow-up studies. H.-Q.Q., J.P.B., S.F., A.G., H.H., and C.Po. contributed study samples. J.B.R., C.Po., and C.Pi. conceived the experiments. All co-authors reviewed and edited the manuscript. J.B.R. is the guarantor of this work and, as such, had full access to all the data in the study and takes responsibility for the integrity of the data and the accuracy of the data analysis.

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