Effects of Metformin on Metabolite Profiles and LDL Cholesterol in Patients With Type 2 Diabetes

Diabetes Care 2015;38:1858–1867 | DOI: 10.2337/dc15-0658

OBJECTIVE
Metformin is used as a first-line oral treatment for type 2 diabetes (T2D). However, the underlying mechanism is not fully understood. Here, we aimed to comprehensively investigate the pleiotropic effects of metformin.

RESEARCH DESIGN AND METHODS
We analyzed both metabolomic and genomic data of the population-based KORA cohort. To evaluate the effect of metformin treatment on metabolite concentrations, we quantified 131 metabolites in fasting serum samples and used multivariable linear regression models in three independent cross-sectional studies (n = 151 patients with T2D treated with metformin [mt-T2D]). Additionally, we used linear mixed-effect models to study the longitudinal KORA samples (n = 912) and performed mediation analyses to investigate the effects of metformin intake on blood lipid profiles. We combined genotyping data with the identified metformin-associated metabolites in KORA individuals (n = 1,809) and explored the underlying pathways.

RESULTS
We found significantly lower (P < 5.0E-06) concentrations of three metabolites (acyl-alkyl phosphatidylcholines [PCs]) when comparing mt-T2D with four control groups who were not using glucose-lowering oral medication. These findings were controlled for conventional risk factors of T2D and replicated in two independent studies. Furthermore, we observed that the levels of these metabolites decreased significantly in patients after they started metformin treatment during 7 years’ follow-up. The reduction of these metabolites was also associated with a lowered blood level of LDL cholesterol (LDL-C). Variations of these three metabolites were significantly associated with 17 genes (including FADS1 and FADS2) and controlled by AMPK, a metformin target.

CONCLUSIONS
Our results indicate that metformin intake activates AMPK and consequently suppresses FADS, which leads to reduced levels of the three acyl-alkyl PCs and LDL-C. Our findings suggest potential beneficial effects of metformin in the prevention of cardiovascular disease.

Type 2 diabetes (T2D) is a chronic disease with diminished response to insulin and relative insulin deficiency (1). Patients with T2D mostly take metformin as first-line oral treatment to lower their glucose levels and to improve insulin sensitivity (2). Despite metformin’s use as an antihyperglycemic agent for more than 50 years, its
primary mode of action is not yet completely understood (3). Inside a cell, metformin apparently inhibits complex I of the mitochondrial electron transport chain and thereby reduces the cellular energy status and upregulates the cytoplasmic 5′-AMPK pathway (3). Activated AMPK stimulates catabolic processes (glycolysis and fatty acid oxidation) and inhibits anabolic pathways (gluconeogenesis and fatty acid synthesis). So far, six metformin targets are documented in the DrugBank (4) database, including the AMPK complex and five metformin transporters. Furthermore, metformin was reported to have several possible pleiotropic effects, resulting in reduced risks for both cancer (5) and cardiovascular disease (CVD) (6), as well as reduced levels of LDL cholesterol (LDL-C) (7,8).

Metabolomic studies have detected metabolite profile changes during the development of T2D (9–12) and identified concentration differences caused by various physiological and environmental factors such as age (13), sex (14), smoking status (15), and alcohol consumption (16). Several metabolomic studies attempted to unravel the physiological effects of metformin (17–21). However, they either used technologies covering only small sets of metabolites or examined relatively few participants (e.g., 20 healthy volunteers [18], 15 patients [17,19], 31 patients [20], and 24 patients treated with glipizide and 23 patients with metformin [21]). As interindividual genetic variations contribute to diverse metabolite profiles and different drug responses, combining metabolomics and genomics may help to understand the mechanisms underlying the action of medications (22–25).

In this study, we discovered metformin treatment–associated metabolites in the Cooperative Health Research in the Region of Augsburg (KORA) cohort (26,27). We confirmed our finding in longitudinal KORA data and replicated them in two independent studies: the Erasmus Rucphen Family Study (ERF) (28) and the Netherlands Twin Register (NTR) (29). The biologically relevant pathways for the identified metabolites and their associated genes were further analyzed in organ-specific protein–metabolite interaction networks (30,31). Additionally, we assessed the effects of metformin treatment on LDL-C levels.

**RESEARCH DESIGN AND METHODS**

An overview of the analysis work flow is shown in Fig. 1.

**Ethics Statement**

All participants gave written informed consent. The KORA study was approved by the ethics committee of the Bavarian Medical Association, Germany; the ERF study by the medical ethics board of the Erasmus MC Rotterdam, the Netherlands; and the NTR study by the Central Ethics Committee on Research Involving Human Subjects of the VU University Medical Center, Amsterdam, the Netherlands.

**KORA Cohort**

KORA is a population-based cohort study conducted in Southern Germany (26). The baseline survey 4 (KORA S4) consists of 4,261 individuals (aged 25–74 years) examined between 1999 and 2001. During the years 2006–2008, 3,080 participants took part in the follow-up survey 4 (KORA F4). Clinical data for each participant were retrieved from medical records. Based on physician-validated and self-reported diagnosis (9,26), fasting glucose and 2-h postglucose load, and information on medications (Table 1), we excluded 1) patients suffering from type 1 and steroid-induced diabetes (n = 9), 2) patients with T2D treated with both metformin and insulin (n = 15), 3) patients taking glucose-lowering oral medication other than metformin (n = 25), and 4) patients lacking clear information on treatment (n = 1). Furthermore, participants with overnight nonfasting blood samples (n = 16) or isolated impaired fasting glucose (n = 112) were excluded. We previously showed that impaired fasting glucose and impaired glucose tolerance (IGT) should be considered two different phenotypes (9). In KORA F4, we focused on five groups: 1) patients with metformin-treated T2D...
(mt-T2D), 2 patients with T2D with insulin treatment (it-T2D), 3 patients with T2D without glucose-lowering treatment (non-antidiabetes drug treated [ndt-T2D]), 4) participants with prediabetes with IGT, and 5) healthy individuals with normal glucose tolerance (NGT) (Table 1).

Replication Studies
The ERF includes 3,000 living descendants of 22 couples who had at least six children baptized in the community church around 1850–1900. The participants are not selected based on any disease or other outcome. Details about the genealogy of the population have previously been provided (28).

Owing to the limited number of it-T2D patients in these two replication studies ($n = 3$ and $n = 9$, respectively), this group is not included in the statistical analyses in these two replication studies.

Initially, we had contacted a third potential replication study, the Estonian Genome Center of the University of Tartu (EGCUT). However, only two mt-T2D participants with available metabolomics data were available in this cohort; results from the EGCUT study are therefore not shown.

Figure 1—Flowchart of the study design.
Blood Sampling
In the KORA cohort study, blood was drawn into S-Monovette serum tubes (Sarstedt AG & Co., Nümbrecht, Germany) in the morning between 8:00 A.M. and 10:30 A.M. after at least 8 h of fasting. Tubes were gently inverted twice, followed by 30 min resting at room temperature to obtain complete coagulation. For serum collection, blood was centrifuged at 2,750 rpm for 15 min. Serum was filled into synthetic straws, which were stored in liquid nitrogen (−196°C) until the metabolomics analyses (9,23).

In the ERF and NTR, the overnight fasting serum samples were drawn for metabolite profiling. Details about the sampling in these two cohorts were described in previous publications (28,32).

Metabolomics Measurement
The serum samples from participants in the baseline KORA S4 and follow-up KORA F4 study were measured with the AbsoluteDQp180 and AbsoluteDQp150 kits (Biocrates Life Sciences AG, Innsbruck, Austria), respectively. The assay procedures were previously described in detail (27). For KORA S4 and F4, identical quality-control procedures (9,13), which are explained in details in our previous publications, were used. In KORA F4, 131 metabolites of the initially targeted 163 metabolites passed all quality-control criteria: hexose (H1), 24 acylcarnitines, 14 amino acids, 13 sphingomyelines, 34 phosphatidylcholines (PCs), diacyl (aa), 37 PCs acyl-alkyl (ae), and 8 lysoPCs. In total, 124 metabolites overlapped between KORA S4 and F4, including H1, 21 acylcarnitines, 14 amino acids, 13 sphingomyelines, 33 PC aas, and 34 PC aes, as well as 8 lysoPCs.

The metabolite measurements for both replication studies (ERF and NTR) were performed using the same platform (AbsoluteDQp150 kit) as in the KORA F4 study. Additionally, in ERF, PC ae C36:4, PC ae C38:5, and PC ae C38:6 were measured in the full set of serum samples by a targeted liquid chromatography–mass spectrometry method. The measurement is performed on a UPLC-ESI-Q-TOF (Agilent 6530; Agilent Technologies, San Jose, CA) mass spectrometer using reference mass correction. Chromatographic separation was achieved on an ACQUITY UPLC HSS T3 column (1.8 mm, 2.1 * 100 mm) with a flow of 0.4 mL/min over a 16-min gradient. The metabolites were detected in full scan in the positive ion mode. The raw data were processed using Agilent MassHunter Quantitative Analysis software (version B.04.00; Agilent Technologies).

Measured concentration values of all analyzed metabolites are reported in micromolar (µM) and were natural-log transformed, and the distributions were subsequently standardized with mean of zero and an SD of 1 for all analyses unless otherwise indicated.

Single Nucleotide Polymorphism Genotyping, Imputation, and Genes
In KORA F4, we carried out genotyping using the Affymetrix 6.0 GeneChip array (Affymetrix, Santa Clara, CA). Imputation was performed with Impute (http://mathgen.stats.ox.ac.uk/impute/), version 0.4.2 (reference HapMap phase 2, release 22). We only used autosomal single nucleotide polymorphisms (SNPs) with a
minor allele frequency >5%, call rate >95%, and imputation quality >0.4. For the phenotype set enrichment analysis (PSEA), we only mapped those SNPs to a gene that were either in its transcribed region or in its flanking region (110 kb upstream, 40 kb downstream). Gene information was downloaded from the UCSC (University of California, Santa Cruz) genome browser (http://genome.ucsc.edu). The SNP gene mapping was described in detail previously (25). In total, 20,801 genes were analyzed.

**Statistical Analysis**
To evaluate the effect of metformin treatment on metabolites, we used multivariable linear regression models with the metabolite concentration values as outcome and the grouping variable as predictor. Each metabolite was assessed individually. To include potential confounders, we adjusted for two sets of covariates: 1) age and sex as the crude model and 2) age, sex, BMI, physical activity, alcohol intake, smoking, systolic blood pressure (BP), levels of HDL cholesterol (HDL-C), triglycerides, HbA1c, and fasting glucose as well as the use of statins, β-blockers, ACE inhibitors, and angiotensin receptor blockers (ARBs) as the full model (Table 1). To account for multiple testing, we used Bonferroni correction and considered only those metabolites with a P < 0.05/131 = 3.8E-04 to be statistically significantly different in KORA F4. Meta-analysis of the three studies was performed using random effect models, using a restricted maximum-likelihood estimator.

In the KORA S4 to F4 longitudinal study, we used linear mixed-effect models. We adjusted for the two sets of covariates as described above while assigning a random offset to each of the individual participant in the longitudinal study. Additionally, using linear regression models on the KORA data set, including two time points (S4 n = 1,335 and F4 n = 2,763) (9), we calculated the residuals of the metabolite concentrations adjusted for age, sex, BMI, physical activity, alcohol intake, smoking, systolic BP, HDL-C, triglyceride, fasting glucose, and HbA1c. The significance of the changes in the metabolite concentrations between the two time points (S4 and F4) was tested using a linear mixed-effect model with the covariates at two time points.

PSEA is a gene-based approach to analyze the associations of genome-wide SNP data with multiple phenotypes in a combined way (25). The significance of enrichment was calculated based on 10,000 permutations (limited by computational restrictions), while setting the significance level at P < 1.0E-04 (lowest possible P value owing to the permutation number).

Mediation analysis (33) was conducted to model the identified metabolites as mediators for the association between metformin treatment and LDL-C and total cholesterol in the longitudinal KORA data. The mediation effects of each single metabolite and their summed concentration were tested with crude and fully adjusted multivariable linear regression models.

All statistical analyses were performed in R (version 3.0.1 [http://cran.r-project.org/]).

**Pathway Analysis**
With use of a bioinformatical approach, a network was constructed by retrieving pairwise connections between candidate metabolites, PSEA-identified genes, intermediate proteins, and known metformin target genes (9,31). Information on protein-protein interactions was extracted from STITCH (30). Known metformin target genes were retrieved from the DrugBank (4). In our network, we only considered the shortest paths (allowing one intermediate protein, confidence score >0.7) connecting the protein encoded by the genes identified in PSEA with the metformin target genes.

**RESULTS**

**Metabolites Associated With Metformin Treatment**
We found six metabolites including three acyl-alkyl PCs, two diacyl (aa) PCs, and one amino acid to have significantly lower concentrations in the 90 mt-T2D patients compared with the 169 ndt-T2D individuals in KORA F4 (Table 2). For example, for the metabolite PC ae C36:4, we observed that the fully adjusted effect estimate was −0.66 with P = 4.92E-07; i.e., the PC ae C36:4 level in the mt-T2D group was 0.66 SD lower than the ndt-T2D group.

We further investigated whether the observed differences are specifically for metformin treatment or just reflect the progress of T2D in general. The concentrations of the six metabolites are significantly lower in mt-T2D than in the NGT and IGT groups (Supplementary Table 4). In contrast, none of the six metabolites showed a significantly different concentration in the pairwise comparisons among the four groups without metformin treatment, i.e., NGT, IGT, ndt-T2D, and it-T2D (Supplementary Table 4).

For sensitivity analysis, we tested the associations of the six metabolites after adding the duration of T2D to the fully adjusted model. The three acyl-alkyl PCs (PC ae C36:4, PC ae C38:5, and PC ae C38:6), which are composed of at least one polyunsaturated fatty acid (PUFA), remained significantly different in the
<table>
<thead>
<tr>
<th>Metabolite</th>
<th>Replication NTR</th>
<th>NTR meta-analysis</th>
<th>Replication ERF</th>
<th>ERF meta-analysis</th>
<th>Discovery KORA</th>
<th>KORA meta-analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>PC aC C38:0</td>
<td>10.38E-07</td>
<td>1.00</td>
<td>10.38E-07</td>
<td>1.00</td>
<td>10.38E-07</td>
<td>1.00</td>
</tr>
<tr>
<td>PC aC C38:2</td>
<td>10.38E-07</td>
<td>1.00</td>
<td>10.38E-07</td>
<td>1.00</td>
<td>10.38E-07</td>
<td>1.00</td>
</tr>
<tr>
<td>PC aC C38:4</td>
<td>10.38E-07</td>
<td>1.00</td>
<td>10.38E-07</td>
<td>1.00</td>
<td>10.38E-07</td>
<td>1.00</td>
</tr>
<tr>
<td>PC aC C38:5</td>
<td>10.38E-07</td>
<td>1.00</td>
<td>10.38E-07</td>
<td>1.00</td>
<td>10.38E-07</td>
<td>1.00</td>
</tr>
<tr>
<td>PC aC C38:6</td>
<td>10.38E-07</td>
<td>1.00</td>
<td>10.38E-07</td>
<td>1.00</td>
<td>10.38E-07</td>
<td>1.00</td>
</tr>
</tbody>
</table>

**Table 2: Metabolites associated with metformin treatment in patients with T2D**

For the three acyl-alkyl PCs, we observed consistent results in both replication studies (ERF and NTR), i.e., significantly lower levels were observed in T2D individuals compared with normal T2D individuals (Supplementary Fig. 2). Additionally, a meta-analysis of the three replicate metabolites for the ERF study (Supplementary Fig. 2) yielded consistent results for the three replicate metabolites. For the three replicate metabolites, which are not associated with the other three metabolites, we explored the effects of the three acyl-alkyl PCs on the association between metformin treatment and the three highly intercorrelated metabolites (Supplementary Table 6). These findings confirmed our observations in the cross-sectional study.
fully adjusted models ($P < 0.05$) (Fig. 2E and Supplementary Table 7). In particular, metformin was associated with a decrease in LDL-C levels of 11.83 mg/dL. We therefore focused on the analysis of LDL-C and total cholesterol.

After adding the three metabolites to the full model, the direct association between metformin treatment and LDL-C levels was not significant anymore ($P = 0.25$) (Fig. 2F and Supplementary Table 8A). Based on longitudinal analysis, we found consistent results as reported above (Table 2); i.e., significantly reduced levels of the three metabolites in the metformin-treated patients were observed (e.g., for the summed metabolite concentration $P = 2.16E-05$) (Fig. 2F and Supplementary Table 8B). Furthermore, we found significant positive associations between LDL-C and each of the three metabolites as well as their summed concentration after adjusting for metformin treatment (e.g., for the summed metabolite concentration $P = 6.87E-12$) (Fig. 2F and Supplementary Table 8C). This means that these associations of the metformin-associated metabolites with LDL-C are independent of metformin treatment. Finally, for each of the three metformin-associated metabolites (and their summed concentration), the mediation effects on the association between metformin treatment and the LDL-C levels were significant in both models (Table 3). For instance, the summed concentration of the metabolites mediates 3.43 mg/dL reduction in LDL-C level, which accounts for 29% of the total effect of metformin on LDL-C (Table 3).

To rule out the potential effect of statin intake, we performed a sensitivity analysis by excluding individuals taking statin at baseline KORA S4 and/or follow-up F4. The mediation effects of the summed concentration were also significant for the associations between metformin and LDL-C level (Supplementary Table 8B). However, although the crude and full model showed similarly significant mediation effects for total cholesterol (Supplementary Table 8D and E and Table 3), after excluding statin users from the analysis, the effects on total cholesterol were not significant anymore with respect to the fully adjusted model ($P < 0.05$) (Supplementary Table 9B).

**Seventeen Genes Are Linked to Metformin-Associated Metabolites and Pathway Analysis**

To identify genes associated with the three metabolites, we applied PSEA on these metabolites in a subset of KORA F4 individuals ($n = 1,809$) with available genotyping data and metabolite profiles. We found 17 genes with an enrichment of SNPs in their transcribed or spliced region ($P < 1.0E-04$) (Supplementary Table 10). These genes belong to five clusters, one of them containing 12 genes located on chromosome 11. A literature search revealed disease phenotypes associated with these 17 genes. Six genes, namely, FADS1, FADS2, FADS3, MYRF, BEST1 and RAB3IL1, are associated with T2D or its comorbidities, including retinopathy and...
coronary artery diseases (for references, see Supplementary Table 10).

To explore potentially related pathways, we used a bioinformatics approach, integrating the 17 identified genes with 6 known metformin target genes (4) into a protein-protein interaction network (9,30,31). For 3 of the 17 genes, there was no record for *Homo sapiens* in the STITCH (30); therefore, we investigated the interaction of the remaining 14 genes with the 6 metformin targets (Supplementary Table 11). *AMPK* was found to be linked to *FADS1* and *FADS2* through interacting proteins (leptin and sterol regulatory element–binding protein 1c [SREBP1c]). A manual evaluation of these interactions in a literature research showed organ specificity, mainly referring to liver and hypothalamus (Fig. 2G). The AMPK complex is inhibited by leptin and metformin in the hypothalamus, whereas it is activated by metformin and leptin in the liver. (References for each interaction are provided in the Supplementary Table 12).

**CONCLUSIONS**

We found significant concentration differences for three metabolites (PC ae C36:4, PC ae C38:5, and PC ae C38:6) in the blood of patients with T2D under metformin treatment and replicated them in two independent studies. We identified SNP variations in 17 genes (including *FADS1* and *FADS2*) that were associated with the three metabolites. Based on these genes, we built an interaction network to investigate the underlying mechanisms of metformin treatment and identified the organ-specific AMPK pathway. We further found that the reduced LDL-C levels in metformin-treated patients with T2D were mediated partially by the three acyl-alkyl PCs. Sensitivity analyses were performed to consider the duration of diabetes and statin use.

The levels of metabolites depend on multiple modifiable factors, such as lifestyle and environment (9–11,13–16). We therefore considered a number of confounding effects, e.g., physiological parameters (age, sex, BMI, and systolic BP), lifestyle (physical activity, alcohol intake, and smoking), glucose levels (HbA1c and fasting glucose), lipid levels (HDL-C and triglycerides), and medication usage (statins, β-blockers, ACE inhibitors, and ARBs). Additionally, intermediates or end products of metabolism are influenced by underlying genetic factors (23,24). In our study, phenotypes and genotypes are available for each person (*n* = 1,809); we thus used genotype set enrichment analysis (25). Our combined analysis of genetic and metabolomic data enabled us to identify genes associated with the three metabolites and supported the identification of an organ-specific pathway. The observation of significantly lower levels of the three metformin-associated metabolites (polyunsaturated acyl-alkyl PCs) in the mt-T2D patients can be explained by metformin’s effects on AMPK in the liver (Fig. 2G and Supplementary Table 12). In the hepatocyte, metformin increases the AMP-to-ATP ratio and thus leads to the activation of AMPK. Activated AMPK blocks SREBP1c, a transcription factor controlling enzymes involved in the fatty acid synthesis and inhibiting the synthesis of FADS1 and FADS2 (22). This results in a reduced synthesis of unsaturated fatty acids and consequently lower acyl-alkyl PC concentrations. Leptin occupies a central position in the network (Fig. 2G) and affects the FADS complex via three different interactions. In the liver, leptin not only activates AMPK, thereby suppressing SREBP1c and downregulating FADS1 and FADS2, but can also directly inhibit both SREBP1c and FADS2 (34). Metformin and leptin exert opposite effects in the hypothalamus and in the liver (for references, see Supplementary Table 12), but further studies are required to better understand the organ-specific metformin effects in humans.

Recently, clinical practice guidelines have recommended the usage of metformin as first-line therapy in T2D patients with heart failure (1,2). Our observation of lower blood levels of LDL-C in metformin-treated patients points toward a beneficial effect of metformin for the prevention of CVD. A meta-analysis of randomized clinical trials shows that metformin treatment results in lowered LDL-C levels in newly diagnosed T2D patients (8). Similar results were also reported in patients without T2D in an epidemiological study (7). Here, we observed that metformin treatment leads to lowered LDL-C levels, an effect mediated most likely through metformin-mediated reduction of FADS

<table>
<thead>
<tr>
<th>Table 3—Mediation effects of the three metabolites for the association between metformin treatment and reduction of LDL-C and total cholesterol</th>
<th>Crude model</th>
<th>Full model</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Effect estimate (95% CI)</strong></td>
<td><strong>Explained effect (%)</strong></td>
<td><strong>Effect estimate (95% CI)</strong></td>
</tr>
<tr>
<td><strong>LDL-C</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PC ae C36:4</td>
<td>−3.05 (−4.38, −1.71)</td>
<td>2.21E-04</td>
</tr>
<tr>
<td>PC ae C38:5</td>
<td>−2.94 (−4.21, −1.67)</td>
<td>2.65E-04</td>
</tr>
<tr>
<td>PC ae C38:6</td>
<td>−5.25 (−8.11, −2.40)</td>
<td>1.34E-05</td>
</tr>
<tr>
<td>Summed concentration</td>
<td>−4.37 (−6.37, −2.37)</td>
<td>1.52E-05</td>
</tr>
<tr>
<td><strong>Total cholesterol</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PC ae C36:4</td>
<td>−5.00 (−7.77, −2.23)</td>
<td>2.63E-05</td>
</tr>
<tr>
<td>PC ae C38:5</td>
<td>−4.99 (−7.71, −2.26)</td>
<td>2.33E-05</td>
</tr>
<tr>
<td>PC ae C38:6</td>
<td>−6.99 (−11.86, −2.13)</td>
<td>8.96E-06</td>
</tr>
<tr>
<td>Summed concentration</td>
<td>−6.63 (−10.55, −2.71)</td>
<td>2.76E-06</td>
</tr>
</tbody>
</table>

The estimates of the mediation effects and *P* values were calculated using the longitudinal (KORA S4–F4) mediation analysis adjusted for the crude and full model. The mediation effects for the three metformin-associated metabolites and the summed concentration are shown. *The* summed concentration refers to the overall concentration of the three metabolites (PC ae C36:4, PC ae C38:5, and PC ae C38:6).
activity and consequently reduction of the levels of PUFA, namely, arachidonic acid (35). It has been suggested that lower levels of arachidonic acid leads to an increased membrane fluidity, thus increasing LDL-C receptor recycling (35). This hypothesis is especially strong, given that genetic variants assigned to lower activity of FADS1 and -2 were significantly associated with lower LDL-C levels (36). While certain PCs can indeed exert antidiabetic effects (37), further mechanistic studies are required to test whether lowering of these circulating lipids contributes directly to the prevention of CVDs or merely by its antidiabetic effect (1).

Beyond its common antihyperglycemic action and its effect in lowering LDL-C, metformin can potentially reduce the risk of cancer mortality and diminish the progression of cancer (38). In the current study, we have found the three metformin-associated metabolites significantly associated with two genes, *FEN1* and *C20orf94*, which are involved in DNA repair (39,40). This may partly explain that metformin has been shown to influence the prevalence of different types of carcinoma, such as gastrointestinal cancers (39) and leukemia (40).

The strength of our study is that we used three independent cohort studies to discover and replicate our observations. Importantly, all results presented in this study were independent of physiological parameters, lifestyle, glucose levels, lipid levels, and medication. We combined metabolomics and genomics data, broad literature research, and organ-specific information from animal studies to deepen the insight into the underlying mechanisms.

Our findings are limited by the observational nature of cohort studies, and the applied methods, such as the mediation analysis, are of purely statistical character, but they offer the opportunity to raise new questions for experimental confirmation studies, such as randomized controlled clinical trials to investigate, for instance, the effect of metformin on blood lipid levels of patients without diabetes.

In the present studies (KORA, ERF, NTR), the duration of T2D is based on self-reported information. Moreover, neither data on the dosage nor data on duration and compliance of the metformin treatment were available. Furthermore, it has to be mentioned that the degree of diabetes severity presumably discriminates the different groups of patients (ndt-T2D, mt-T2D, and it-T2D), which is reflected by their HbA1c and fasting glucose values (Table 1). Although the investigated metabolite panel does not represent the whole human metabolome, the comprehensive analysis of >130 metabolites from different classes represents a considerable improvement compared with previous technologies.

We found three metformin-associated metabolites, which showed no overlap with the findings of previous studies (17–21). This is likely to result from the use of different sampling matrices (plasma vs. serum), unmeasured metabolites (asymmetric dimethylarginine), or study design (glipizide treatment). Additional, our study considered considerably more potential cofounding effects in a comparably larger number of individuals than previous studies (17–21).

In conclusion, we observed that metformin treatment reduced levels of the three acyl-alkyl PC metabolites in patients with T2D. This change in the metabolic profiles may mediate lowered blood levels of LDL-C. The underlying mechanism is most likely the metformin-induced activation of AMPK and the consequent suppression of SREBP1c and FADS, which leads to reduced levels of PUFA and LDL-C. Our findings suggest a pharmaco-epidemiologic mechanism by which metformin may exert beneficial effects to prevent CVD. More importantly, our study suggests a novel approach to identify pleiotropic effects of medication using multilevel omics data.

**Acknowledgments.** The authors express their appreciation to all KORA study participants for donating their blood and time. The authors thank the staff in Augsburg conducting the KORA studies. The authors thank the staff from the Institute of Epidemiology at the Helmholtz Zentrum München and the Genome Analysis Center Metabolomics Platform, who helped in the sample logistics, data and straw collection, and metabolomic measurements, and especially J. Scarpa, K. Fasching, F. Scharl, N. Lindemann, H. Chavez, A. Sabuncti, A. Schneider, A. Ludolph, S. Jelic, and B. Langer. The authors are grateful to all general practitioners involved in ERF for their contribution. The authors thank all participants in the NTR.

**Funding.** The KORA study was initiated and financed by the Helmholtz Zentrum München–German Research Center for Environmental Health, which is funded by the German Federal Ministry of Education and Research (BMBF) and by the Free State of Bavaria. Furthermore, KORA research was supported by the European Community’s Seventh Framework Programme grants HEALTH-2009-2.2.1-3/242114 (Project OPTIMIS) and HEALTH-2013-2.2.1-1/602936 (Project GaTarDis). The German Diabetes Center is funded by the German Federal Ministry of Health (Berlin, Germany) and the Ministry of Innovation, Science and Research of the State of North Rhine-Westphalia (Düsseldorf, Germany). The diabetes part of the KORA F4 study was funded by a grant from the German Research Foundation (DFG) RA 459/3-1. This study was supported in part by a grant from the BMBF to the German Center for Diabetes Research (DZD e. V.). W.R.-M. is funded by the German Federal Ministry of Education and Research grant 03IS2061B (project Gani_Med). K.Su. is supported by Biomedical Research Program grants at Weill Cornell Medical College in Qatar, a program funded by the Qatar Foundation. The EGUCUT received support from the European Community’s Seventh Framework Programme grant B8MRI-LPC 313010, targeted financing from Estonian Government IUT20-60 and IUT24-6, Estonian Research Roadmap through the Estonian Ministry of Education and Research (3.0.3041.11-0312), the Center of Excellence in Genomics (EXCEGEN), and Development Fund from the University of Tartu (SPI1GARENG), and from an EFSD New Horizons grant. This work was also supported by the U.S. National Institutes of Health (R01DK075787). The ERF was supported by grants from the Netherlands Organisation for Scientific Research (NWO) and Erasmus MC and the Centre for Medical Systems Biology (CMSB). Telomere length assessment was supported through funds from the European Community’s Seventh Framework Programme (FP7/2007-2013), grant agreement HEALTH-F4-2007-214113 (ENGAGE). Research for the NTR was funded by the Netherlands Organisation for Scientific Research (NWO) [MagW/ZonMW grants 904-61-090, 985-10-002, 904-61-1, 480-04-004, 400-05-717; Addiction-31160008 Middelgroot-911-09-032; and Spinozepremie 56-464-14192], the Center for Medical Systems Biology (CSMB, NWO Genomics), NBIC/BioAssist/RK(2008.024), Biobanking and Biomolecular Resources Research Infrastructure (BMBRI–NL) (1BA-021-007), the VU University’s Institute for Health and Care Research (EMGO+), and the European Community’s Seventh Framework Program (FP7/2007-2013), grant HEALTH-F4-2007-214113 (ENGAGE).

**Duality of Interest.** No potential conflicts of interest relevant to this article were reported.

References