Comparative effectiveness of alternative second-line oral antidiabetic treatments on metabolic, kidney, and cardiovascular outcomes amongst people with type 2 diabetes mellitus: a cohort study using routinely collected health data

Supplementary materials

SUPPLEMENTARY METHODS

INSTRUMENTAL VARIABLE ANALYSIS

We followed a two-stage residual inclusion (2SRI) approach in the main analysis to reduce the risk of bias from unmeasured confounding and allow us to identify the average treatment effects (ATEs). We compared these estimates to those from using 2-stage least squares (2SLS) (alternative analysis).

2-stage least squares (2SLS):

In the first stage, we estimated linear probability models by regressing indicators for each of the treatments of interest (DPP4i or SGLT2i using SU as the reference category) on the instruments (TTP for either treatment), and the baseline covariates including NHS region and time period. In the second stage, we regressed the outcome of interest on the baseline covariates and the predicted probability of being prescribed each treatment obtained from the first stage. The two stages were estimated jointly so that standard errors reflected the uncertainty of both stages. However, when effects are heterogeneous, that is they vary with respect to observed or unobserved covariates, this approach estimates the *local* average treatment effects (LATE) since the effects relate to the compliers whose treatment assignment is altered by the instrument (or in the case of a continuous IV, a weighted average of LATEs), which is less relevant for decision making compared with the overall average treatment effect. We therefore consider 2SRI to be the more informative approach here since estimates relate to the full population provided the first stage model is correctly specified.

2-stage residual inclusion:

For DPP4i and SGLT2i, we estimated first-stage probit models for whether or not the patient was prescribed this treatment, as a function of the baseline covariates and the tendency to prescribe that treatment. For continuous outcomes (e.g., HbA1c at 12 months), we then estimated a second stage regression model, using ordinary least squares including the generalised residuals¹ from the first stage models, all measured baseline covariates. For the censored time-to-event outcomes (e.g., time to 3-point MACE), in the second stage we estimated Cox proportional hazards models that account for individual frailty,² in addition to covariates and the observed residuals from the first stage models.³

Variable selection:

In addition to the covariates listed, the 2SRI and 2SLS models also considered the quadratic forms of age and baseline HbA1c as well as two sets of interactions. The first set of interactions are those between baseline HbA1c with age, sex and baseline BMI. The second set of interactions are the products of the IV (for the first stage models) or the treatment indicator variables (for the second stage models) with baseline HbA1c, eGFR, BMI, systolic blood pressure and age.

To prevent overfitting the models, we used the Least Absolute Shrinkage and Selection Operator (LASSO) regression algorithm^{4, 5} to inform which of the interactions above are relevant in each case. The LASSO aims to find the set of coefficients that minimise the sum-of-squares loss function subject to a constraint on the sum of absolute values of coefficients. This results in a linear regression in which only a small number of covariates have non-zero coefficients that can then be included in the model in question. Specifically, we used the 'rigorous LASSO' approach⁶ which places a high priority on controlling overfitting, thus often producing parsimonious models.

By partialling out variables prior to penalisation, we ensure these variables are always included in the selected models and only penalise (and potentially discard) variables in the interaction sets. We use the 'rigorous LASSO' approach⁶ which places a high priority on controlling overfitting, thus often producing parsimonious models.⁷ By partialling out variables prior to penalization, we ensure these variables are always included in the selected models and only penalise (and potentially discard) variables in the interaction sets.⁷

To select the variables included in the estimation of the 2SRI models, we estimated the first and second stage models for each outcome using rigorous LASSO. The final set of covariates used to estimate effects for each outcome included all the covariates mentioned in the *Covariates* section plus the interactions that were selected in at least one model of the respective outcome. For the Cox proportional hazards models, all final selected covariates were assessed for violation of the proportional hazards assumption using Schoenfeld residuals.

Estimating treatment effects:

From the second stage models using the selected variables, we calculated the difference in the average absolute change in predicted outcomes (continuous measures) and times to event between the comparison groups, providing estimates of the treatment effect according to individual-level covariates. We aggregate these estimates to report results overall and according to whether or not patients had pre-existing CVD (at least one of previous MI, previous stroke, CHF, IHD, or unstable angina).

All standard errors were calculated with non-parametric bootstrapping as described below, and accounted for clustering of individuals within NHS region, treatment arm and censoring status.

HANDLING OF MISSING DATA, CENSORING, AND LOSS TO FOLLOW-UP

The PERMIT study uses routine linked data (CPRD and HES) which raises several challenges for the statistical analysis. Missing data may occur due to:

- Non-attendance at a GP within the requisite time period for the study outcome definition (+/- 3 months either side of timepoints 0.5, 1, 2, 3, 4 and 5 years)
- Information not being recorded during a GP visit
- Tests not being done during a GP visit

In addition to missing data, all patients are not fully followed from baseline to five years. For example, a patient enrolled in December 2020 will have 12 months follow-up to 2021 and can only be included in the analysis models for the continuous outcomes for the periods between baseline and 6 months or 1 year, as they are unobserved for subsequent timepoints. The final challenge is related to 'loss to follow-up' or 'dropouts', as a patient may stop attending GP appointments before death or censoring (end of follow-up or patient/GP stops contributing to CPRD) has occurred.

Supplementary methods table 1 presents the full list of covariates which are adjusted for in both sets of analyses, summarises the seven survival outcomes and the four continuous clinical outcomes measures at timepoints 0.5, 1, 2, 3, 4 and 5 years.

Supplementary methods table S1: Summary of (i) analysis variables adjusted for in the continuous and survival analyses, (ii) survival information included in the imputation models for the analysis variables, and (iii) continuous outcome information included in the imputation models for the analysis variables

Missing data is present in in both the continuous outcomes, and also several covariates which are used in the analysis of the continuous and survival outcomes. The percentage of missing values in the analysis covariates are available in Table 1 of the main paper. **Supplementary methods table 2** presents the percentage missing for those not censored at time *t* for each clinical measure. The longitudinal clinical measures (HbA1c, BMI, SBP, eGFR) could be unavailable at any timepoint (6 months, 1, 2, 3 or 5 years). For example, a patient could have observed HbA1c values at all time points except for year 2.

Supplementary methods table S2: Percentage of observations which are missing at time point t after accounting for censoring

Multiple imputation

We used Multiple imputation by chained equations⁸ to handle both missing values in analysis covariates and missingness in the continuous outcomes, $^{9, 10}$ which will generate five imputed datasets.

Predictive mean matching with 10 donors¹¹ was used to impute all categorical and continuous partially-observed variables to improve robustness to misspecification of the imputation model. We assumed that data were `missing at random' (MAR). For missing values in the continuous outcome measures, this assumption implies that this missingness is at random, i.e. at random conditional on all other measures in the model including all preceding and subsequent levels of the measure in question, and the levels of any measures that were available at the timepoint in question. Some measurements taken repeatedly over time, e.g., HbA1c and BMI, were missing at baseline for some individuals, and the same rationale for supporting the underlying MAR assumption would apply here as for outcomes with intermittent missingness, given that measurements for time periods prior to baseline and during the subsequent follow-up periods were available for the imputation models.

For the analysis covariates, ethnicity had the greatest proportion of missing values. Previous literature has shown that conducting a MAR analysis for ethnicity can lead to similar point estimates as implementing missing data methods under the `missing not at random' assumption.^{12, 13} Here, our base case analysis used multiple imputation for ethnicity, along with the other covariates, and we examined robustness to the assumed missing data mechanism by undertaking complete-case analysis in a sensitivity analysis.

Imputation model specification

Due to the non-linear trajectory of the continuous outcomes, all continuous measures from 6 months to 5 years were used when imputing a continuous outcome at time *t.* For example, a patient's observed HbA1c values from baseline, 6 months and 2-5 years would be used to impute their unobserved year 1 HbA1c value, in addition to any auxiliary information which would improve the imputed value. The imputation models for the analysis covariates included information on both the survival and continuous outcomes to ensure congeniality¹⁴ between the covariates and each continuous and survival outcome. The imputation models for all partially-observed covariates are specified in **Supplementary methods table 3**. Interactions included in the analysis models were treated as `just another variable'¹⁵ and imputed using MICE with PMM.

Supplementary methods table S3: Fitted imputation models for each partially-observed variable used in the continuous and survival analyses.

Analysis covariates, Survival information and Continuous outcomes are specified in Supplementary methods table 1.

Imputation model stratification and follow-up status

The imputation models were stratified by (i) treatment assignment (SGLT2i, DPP4i, SU), and (ii) status across the follow-up period ((i) a patient has died during follow-up; (ii) a patient is fully followed for 5 years, and (iii) censored as a patient no longer contributes to the study due to either reaching the end of the study monitoring period, or the patient/practice no longer contributing to CPRD). For patients who are censored, we assume that this is `completely at random' as censoring pertains to administrative reasons or due to the end of the follow-up period, which are unlikely to be related to the patient's

characteristics of interest in our analyses, such as their prognosis. For people who have died, their corresponding missing values prior to death are likely to differ to those who were alive at a given follow-up timepoint, and hence missing values for these people were imputed separately from those with full follow-up, or who stopped contributing before full follow-up was reached.

In total, 9 imputation models were used to impute each partially-observed variable depending on which treatment and follow-up status strata they belonged to. The three imputation models for patients who died (Death-SU; Death-SGLT2i; Death-DPP4i) also included a "time to death from baseline", in addition to the variables specified in **Supplementary methods table 3**, to recognise that this may be predictive of the missing outcome.

Due to the specification of the imputation models (**Supplementary methods table 3**) and the MICE¹⁶ package in R, it was not possible to restrict imputing missing continuous outcome values up to the point of death or the point of no longer contributing to the study. Instead, missing values in the continuous clinical measures were imputed for all timepoints t=0.5, 1,…, 5 years. Censoring rules were then applied post-imputation before running the statistical analyses.

Post-imputation estimation of treatment effects and confidence intervals

The relative treatment effects were estimated in each imputed dataset using two-stage residual inclusion IV (with a frailty inclusion for time-to-event outcomes when using Cox proportional hazards).³ Rubin's rules¹⁷ was applied to obtain an overall treatment effect:

$$
\hat{\bar{\theta}}_d = M^{-1} \sum_{m=1}^M \hat{\theta}_{m,d}
$$

where $d =$ (i) SGLT2i vs. SU, (ii) SGLT2i vs. DPP4i or (iii) DPP4i vs. SU. For Cox proportional hazards, Rubin's rules were applied on the log-hazard scale. The analysis model of interest was applied to each of the five multiply imputed datasets (M=5). This number of imputations was chosen as the overall analytical framework (IV residual inclusion) required that standard errors were estimated with the non-parametric bootstrap i.e. each of the nine imputation models were applied within each of the 500 bootstrap replications. The choice of M=5^{18, 19} was a balance between recognising the importance of the number of imputed datasets for improved inference and the impact on computational time when running MI, non-parametric bootstrapping, IV residual inclusion and a Cox proportional hazards model with a frailty inclusion term.

Confidence intervals for the treatment effects were estimated using bootstrap sampling (BS), stratifying by region, treatment group, death and censoring status to maintain similar sampling patterns within each bootstrap sample. The original unimputed data were bootstrapped 500 times, and within each bootstrap sample, MI was applied (BS-then-MI).^{20, 21}

Within each bootstrap sample $b = 1, ..., 500$, we took the same approach to handling missing data and implementing the analysis model, as previously specified. Rubin's rules were applied to the *M* imputed datasets of bootstrap sample *b* to get an overall treatment effect for each drug comparison *d*:

$$
\widehat{\overline{\theta}}_{b,d} = M^{-1} \sum_{m=1}^{M} \widehat{\theta}_{m,d}
$$

The 500 estimates of $\widehat {\bar\theta}_{b,d}$ was used to estimate variance and calculate *t*-based confidence intervals.

SUPPLEMENTARY TABLES

Supplementary table 1: Summary of target trial emulation

Supplementary table 2: Details of inclusion and exclusion criteria for the study population

Supplementary table 3: Details of covariate data sources and definitions

Supplementary table 4: Details of outcome data sources and definitions

Supplementary table 5: Frequency of individual drug substances within each drug class included as the treatments of interest in this study

Supplementary table 6: Time spent on second-line antidiabetic treatment, overall and stratified by treatment group

*Other types of 3rd line treatment include monotherapies with insulin, thiazolidinediones, glucagon-like peptide 1 receptor agonists (GLP1RA), and no treatment (de-prescribed).

Supplementary table 7: Describing the proportion of the study population who initiate second-line oral antidiabetic treatment during the COVID-19 pandemic, and corresponding missingness in the primary outcome by treatment group

¹Pre-COVID-19: prior to 23 March 2020 (the date of the first UK lockdown)

2COVID-19: 23 March 2020 to the end of the study follow-up for continuous outcomes (31 December 2021)

Supplementary table 8: Differences in the change in continuous clinical measures for the three second-line antidiabetic treatment comparisons for the main analysis (2SRI, bootstrap-multiple imputation)

Supplementary table 9: Crude event counts and rates (95% CI) for time-to-event kidney and cardiovascular outcomes up to 2-years follow-up

Supplementary table 10: Summary of results from main analysis for kidney, cardiovascular, and mortality time-to-event outcomes, as well as summary of results for alternative analyses for kidney, cardiovascular, and mortality outcomes

***** Base method is the main analysis (2 stage-residual inclusion (2SRI) instrumental variable analysis with multiple imputation to account for missing data, assuming data are missing at random)

** Models could not converge for MAKE outcome extended to 5-years follow-up

Supplementary table 11: Differences in the change in continuous clinical measures for the three second-line antidiabetic treatment comparisons according to CVD status prior to initiation of second-line treatment (2SRI, bootstrap-multiple imputation)

Supplementary table 12: Summary of results from the subgroup analysis comparing kidney, cardiovascular, and mortality outcomes according to CVD status prior to initiation of second-line treatment

Supplementary table 13: Differences in the change in continuous clinical measures for the three second-line antidiabetic treatment comparisons for 2SRI analysis (complete cases)

Supplementary table 14: Differences in the change in continuous clinical measures for the three second-line antidiabetic treatment comparisons for 2 stage-least squares (2SLS) instrumental variable analysis on complete cases

Supplementary table 15: Differences in the change in continuous clinical measures for the three second-line antidiabetic treatment comparisons for ordinary least squares (OLS) regression adjusted for measured confounders (complete cases)

Supplementary table 16: Standard mean differences in variables before and after propensity score weighting for the primary outcome (change in HbA1c from baseline to 1-year)

Outcome												
/ Follow	SU			DPP4i			SGLT2i			Total		
up year												
	Mean	Minimum	Maximum	Mean	Minimum	Maximum	Mean	Minimum	Maximum	Mean	Minimum	Maximum
HbA1c												
0.5	3.04	1.02	31.75	2.17	1.16	45.58	4.80	1.11	223.29	2.98	1.02	223.29
$\mathbf{1}$	2.99	1.01	35.24	2.13	1.12	69.00	5.08	1.10	113.78	2.98	1.01	112.78
$\overline{2}$	2.84	1.02	40.43	2.11	1.16	74.75	5.82	1.16	202.23	2.98	1.01	202.23
3	2.61	1.02	29.70	2.12	1.17	21.02	6.93	1.21	219.47	2.97	1.02	219.47
4	2.35	1.01	18.33	2.22	1.23	101.52	7.89	1.24	101.52	2.96	1.01	101.52
5	2.19	1.02	31.44	2.33	1.26	24.35	9.10	1.28	245.77	3.00	1.02	245.77
BMI												
0.5	3.17	1.01	39.38	2.16	1.10	33.11	4.45	1.09	78.06	2.97	1.01	78.06
$\mathbf{1}$	3.10	1.01	34.77	2.11	1.14	46.35	4.89	1.10	86.87	2.97	1.01	86.87
$\overline{2}$	2.91	1.01	33.57	2.09	1.15	32.02	5.63	1.13	232.93	2.98	1.01	232.93
3	2.68	1.03	27.67	2.10	1.16	24.82	6.62	1.21	190.69	2.98	1.03	190.69
4	2.45	1.02	25.13	2.17	1.23	20.59	7.62	1.20	288.58	2.98	1.02	288.58
5	2.22	1.02	12.91	2.31	1.23	24.33	9.01	1.28	225.04	2.02	1.02	225.04
eGFR												
0.5	3.01	1.01	32.59	2.14	1.16	48.63	4.81	1.10	220.61	2.99	1.01	220.61
$\mathbf{1}$	3.04	1.01	38.19	2.11	1.12	58.50	5.05	1.10	100.22	2.97	1.01	100.22
$\overline{2}$	2.88	1.01	35.32	2.09	1.17	81.15	5.84	1.15	210.11	2.98	1.01	210.11
3	2.66	1.01	30.92	2.09	1.16	35.24	6.91	1.20	224.47	2.98	1.01	224.47
4	2.40	1.01	18.89	2.19	1.23	23.32	7.89	1.19	105.86	2.96	1.01	105.86
5	2.23	1.02	28.32	2.29	1.22	23.98	9.01	1.23	298.99	3.00	1.02	298.99
SBP												
0.5	2.99	1.91	32.16	2.14	1.11	43.93	5.06	1.10	234.98	2.98	1.01	234.98
$\mathbf{1}$	2.97	1.01	35.40	2.12	1.16	55.75	2.12	1.16	55.75	5.22	1.10	211.14
$\overline{2}$	2.78	1.02	33.66	2.11	1.16	56.65	5.93	1.12	221.53	2.98	1.02	221.53
$\overline{3}$	2.59	1.02	27.41	2.12	1.18	50.55	7.13	1.21	209.47	2.98	1.02	209.47

Supplementary table 17: Mean, minimum, and maximum unstabilised weights by treatment arm for each continuous outcome in the inverse probability of treatment weighting (IPTW) analysis

BMI: body-mass index; DPP4i: dipeptidyl peptidase 4 inhibitors; eGFR: estimated glomerular filtration rate; HbA1c: haemoglobin A1c; SBP: systolic blood pressure; SGLT2i: sodium-glucose co-transporter 2 inhibitors; SU: sulfonylureas

Supplementary table 18: Differences in the change in continuous clinical measures for the three second-line antidiabetic treatment comparisons (inverse probability of treatment weighting (IPTW), complete cases)

			Year of follow-up							
Outcome	Comparison		0.5	$\mathbf{1}$	$\mathbf{2}$	3	4	5		
		$N =$	46,900	42,441	32,364	23,082	15,126	8,022		
		Estimate	3.29	1.31	0.09	-0.29	-0.75	-0.56		
Difference in the	DPP4i vs SU	(95% CI)	(2.97, 3.62)	(0.94, 1.68)	$(-0.35, 0.52)$	$(-0.79, 0.20)$	$(-1.36, -0.14)$	$(-1.42, 0.29)$		
change in HbA1c (mmol/mol) from		Estimate	1.73	-1.23	-1.30	-1.84	-1.13	-1.00		
baseline	SGLT2i vs SU	(95% CI)	(1.30, 2.17)	$(-1.73, -0.73)$	$(-2.00, -0.60)$	$(-2.65, -1.03)$	$(-2.23, -0.03)$	$(-2.41, 0.41)$		
	SGLT2i vs	Estimate	-1.56	-2.54	-1.38	-1.55	-0.37	-0.44		
	DPP4i	(95% CI)	$(-1.99, -1.13)$	$(-3.02, -2.05)$	$(-2.06, -0.71)$	$(-2.34, -0.76)$	$(-1.47, 0.72)$	$(-1.87, 0.99)$		
		$N =$	33,508	34,431	25,809	18,253	11,577	5,903		
		Estimate	-0.53	-0.59	-0.46	-0.52	-0.49	-0.35		
Difference in the	DPP4i vs SU	(95% CI)	$(-0.60, -0.46)$	$(-0.67, -0.52)$	$(-0.54, -0.38)$	$(-0.62, -0.41)$	$(-0.62, -0.37)$	$(-0.55, -0.14)$		
change in BMI (kg/m^2)	SGLT2i vs SU	Estimate	-1.23	-1.30	-1.08	-0.95	-0.81	-0.70		
from baseline		(95% CI)	$(-1.31, -1.15)$	$(-1.39, -1.22)$	$(-1.18, -0.97)$	$(-1.09, -0.81)$	$(-1.00, -0.63)$	$(-0.97, -0.43)$		
	SGLT2i vs DPP4i	Estimate	-0.70	-0.71	-0.62	-0.43	-0.32	-0.35		
		(95% CI)	$(-0.76, -0.64)$	$(-0.78, -0.64)$	$(-0.71, -0.52)$	$(-0.56, -0.31)$	$(-0.50, -0.14)$	$(-0.60, -0.10)$		
		$N =$	39,113	39,337	30,034	21,398	14,060	7,659		
	DPP4i vs SU	Estimate	-0.17	-0.16	0.07	-0.09	0.54	0.42		
Difference in the		(95% CI)	$(-0.39, 0.04)$	$(-0.38, 0.05)$	$(-0.19, 0.34)$	$(-0.43, 0.25)$	(0.12, 0.96)	$(-0.18, 1.03)$		
change in eGFR $(mL/min/1.73m2)$ from	SGLT2i vs SU	Estimate	0.10	0.12	1.21	1.42	1.59	2.79		
baseline		(95% CI)	$(-0.24, 0.43)$	$(-0.23, 0.47)$	(0.75, 1.67)	(0.80, 2.04)	(0.70, 2.49)	(1.72, 3.85)		
	SGLT2i vs DPP4i	Estimate	0.27	0.28	1.14	1.51	1.06	2.36		
		(95% CI)	$(-0.04, 0.58)$	$(-0.05, 0.61)$	(0.70, 1.57)	(0.90, 2.12)	(0.16, 1.95)	(1.29, 3.44)		
		$N =$	40,588	41,049	30,967	21,972	13,832	7,100		

Supplementary table 19: Differences in the change in continuous clinical measures for the three second-line antidiabetic treatment comparisons (inverse probability of treatment weighting - regression adjustment (IPTW-RA or 'weighted regression') analysis, complete cases)

Supplementary table 20: Differences in the change in HbA1c for the three second-line antidiabetic treatment comparisons (inverse probability of treatment weighting – regression adjustment (IPTW-RA or 'weighted regression'), complete cases – asymmetric trimming^{28, 29}

Supplementary table 21: Main features of the study populations and comparison groups for the PERMIT study and relevant randomised controlled trials (RCTs) that included a randomisation to either SGLT2i or DPP4i

ACEI/ARB: angiotensin converting enzyme inhibitor/angiotensin receptor blocker: BMI: body-mass index; CKD: chronic kidney disease; CVD: cardiovascular disease; DPP4i: dipeptidyl peptidase-4 inhibitor; eGFR: estimated glomerular filtration rate; GLP1-RA: glucagon-like peptide-1 receptor agonist; HbA1c: haemoglobin A1c; MACE-3: 3-point major adverse cardiovascular event; MAKE: major adverse kidney event; SGLT2i: sodium-glucose co-transporter 2 inhibitor; SU: sulfonylurea; T2DM: type 2 diabetes mellitus

¹Note that for some studies people received more than one antidiabetic treatment prior to randomisation. For these studies the sum of the percentages can exceed 100%.

Supplementary table 22: Results from main analysis of the PERMIT study and those from relevant RCTs for common endpoints

CKD: chronic kidney disease; CVD: cardiovascular disease; DPP4i: dipeptidyl peptidase-4 inhibitor; eGFR: estimated glomerular filtration rate; MACE-3: 3-point major adverse cardiovascular event; MAKE: major adverse kidney event; N/A: not applicable (in this case, the study did not include this outcome); SGLT2i: sodium-glucose cotransporter 2 inhibitor; SU: sulfonylurea; T2DM: type 2 diabetes mellitus

SUPPLEMENTARY FIGURES

Supplementary figure 1A: Directed acyclic graph (DAG) illustrating the causal relationship between the instrument, exposure, and primary outcome (change in HbA1c from baseline to 1-year follow-up)

Commentary: This directed acyclic graph illustrates that the receipt of second-line treatment is subject to unmeasured and (context- and individual-level) observed factors that confounds the link between treatment and the outcome of interest (biomarkers at 1 year). This figure suggests that the CCG's tendency to prescribe (the proposed instrumental variable) predicts the second-line treatment received by a patient registered in that CCG, but does not have a direct effect on the health outcome of interest. That is, it is assumed that the only path through which the CCGs tendency to prescribe influences the biomarkers at 1 year is through its influence in the treatment received. Thus, this reflects the explicit assumption of an IV design that the instrument is not independently associated with outcomes, unobserved confounders and individual-level confounders. The DAG allows for an association between context-level confounders (such as GP practice list size) and the IV as larger practices may have different prescription patterns compared to smaller practices. The individual-level confounders considered in this hypothesised causal diagram were classified in three broad categories: patient's socio-demographic characteristics (age, sex, etc.), baseline health status (e.g. relevant comorbidities, biomarkers and medications such as statins and renins), and baseline behaviour (alcohol and smoking status). For simplicity, this figure does not reflect all the existing correlations amongst different factors, for example the one existing between unobserved and individual-level confounders.

Supplementary figure 1B: Directed acyclic graph (DAG) illustrating the causal relationship between the instrument, exposure, and all-cause mortality (secondary outcome)

Commentary:

This DAG builds on the same structure as the previous one, but considers biomarkers at one year from intensification along with other adverse events such as MACE and hospitalisations due to heart failure as intermediate outcomes on the pathway from treatment to all-cause

mortality. It can be seen that all-cause mortality, the long-term outcome of interest, is also subject to unobserved and measured confounders, but that the only path through which the IV influences both intermediate and long-term outcomes is through its influence in the treatment received.

Supplementary figure 2A: Covariate balance plots according to levels of the instrumental variable for SU

Supplementary figure 2B: Covariate balance plots according to levels of the instrumental variable for DPP4i

Supplementary figure 2C: Covariate balance plots according to levels of the instrumental variable for SGLT2i

 ${\sf Supplementary \, figure\,3:}$ Mean change in HbA1c (mmol/mol), eGFR (mL/min/1.73m²), BMI (kg/m²), and SBP (mm Hg) from baseline during follow-up

Supplementary figure 4: Cumulative failure curve for time to 40% decline in eGFR from baseline up to 2 years follow-up by exposure status

Supplementary figure 5: Cumulative failure curve for end-stage kidney disease (ESKD) up to 2-years follow-up stratified by exposure status

Supplementary figure 7: Cumulative failure curve for heart failure hospitalisation up to 2-years follow-up by exposure status

Supplementary figure 10: Propensity score distribution before adjustment for the inverse probability of treatment weighting analysis (IPTW)

Supplementary figure 11: Propensity score distribution after adjustment for the inverse probability of treatment analysis (IPTW)

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