CCU008\_01 SAP

# Version control

|  |  |
| --- | --- |
| Version | Note |
| 1 | Initial version |

# Title (this may differ to the project title if there is more than one planned output)

The impact of the COVID-19 pandemic on the measurement of cardiovascular disease risk factor in primary care

# Lay summary and/or background

## Background

The Covid-19 pandemic had a clear impact on many aspects of health care. One of the clearest was cessation of routine face to face health checks (1) that commonly contributed to new diagnosis of common chronic cardiometabolic conditions such as type 2 diabetes, hypertension, and high cardiovascular risk. The result was reductions in diagnoses such that prescriptions of common preventative medicines were substantially reduced, as we recently showed (2). We observed a decline in the dispensing of antihypertensive medications between March 2020 and July 2021, with near half a million fewer individuals initiating treatment than expected. This decline was predicted to result in an excess of over 13 thousand CVD events in the United Kingdom. We concluded by noting that methods to identify and treat individuals who have missed treatment for CVD risk factors and remain undiagnosed are urgently required to avoid large numbers of excess future CVD events.

## The challenge

Extending the prior paper on prescriptions, we used a similar database which collects risk factor measurements in England to examine the pattern of CVD risk factor measurements over time, from before, during and after the pandemic. Such work would help determine if risk factor ascertainment were now back to expected levels or, if not, where gaps remain.

## Hypotheses

Models of care have altered with less face-to-face clinical appointments and so we hypothesised that some key measurements that require physical tests – e.g., body mass index (BMI) and blood pressure (BP) – may still be lagging behind expected levels. We also wondered whether some blood tests were also less commonly conducted given changes in where blood testing takes place in many parts of the UK, with more at central hubs and less in primary care. Such analyses are important to understanding future disease patterns and potential missed opportunities for preventative care.

## Methods

We will use the primary care data in the CVD-COVID-UK/COVID-IMPACT Consortium in England to examine the trend of risk factor measurements, and model what would the trend be after removing the effect of Covid. These will also be repeated for population subgroups.

## Significance

This study will show how Covid-19 impacted the measurement of CVD risk factors in England and if we still have reduced number of measurements in present day. This will inform if the health care service level has resumed to the expected level and identify (if any) where the shortfalls are. These will inform relevant public health policy to assist CVD prevention.

# Research hypothesis, aims and questions

* To what extent CVD risk factors measurement were reduced since the Covid-19 pandemic?
* Are they recovered to the pre-pandemic level?

# List of datasets and reasons required

|  |  |
| --- | --- |
| Data | Reasons |
| GDPPR | To count number of risk factor measurements |
| IMD – linked | To ascertain participant IMD |

# Study design with detailed definitions of study population, exposures, covariates and outcomes

This is a retrospective study including all relevant risk factor measurements from COVID-19 General Practice Extraction Service Data for Pandemic Planning and Research (GDPPR). IMD data linked using LSOA.

## Inclusion criteria

* All measurements from April 2019 to latest

## Exclusion criteria

* Measurements of people who have had a recorded death

## Outcomes

The number of RF measurements on these CVD risk factors:

* Behavioural: BMI, number of cigarettes consumed, units of alcohol consumed
* Metabolic: SBP, DBP, HbA1c, fasting glucose
* Lipid: total, LDL, HDL cholesterol, triglycerides
* Liver function: AST, ALT, GGT.

## Exposure

* Time (month/year where RF measurements were taken).

## Covariates

* age (18-39, 40-59, 60-79, >=80 years)
* sex
* linked IMD decile
* In stratified analysis, age was categorised as 18-59 and >=60 years, IMD categorised as 1st-5th, and 6th-10th deciles.
* Covid-19 restriction stringency index

# Statistical methods

All relevant risk factors measurements will be extracted from the GDPPR. For each risk factor, monthly number of measurements were calculated by age group (18-39, 40-59, 60-79, ≥80 years), sex, and IMD deciles, and was modelled using generalised additive models (GAMs) (3) with penalised splines and cyclical penalised splines for year and month effect respectively to capture their non-linear (seasonal) association with the number of risk factors (4).

The age group, sex, and IMD deciles will be modelled as categorical variables. In addition, three Covid-19 pandemic related variables were included:

1. a binary variable indicating level change since Covid-19 pandemic in UK (from March 2020),
2. a numeric variable indicating the time (in year) since the start of Covid-19 pandemic in UK,
3. the Stringency Index from Oxford COVID-19 Government Response Tracker (5) approximating the effect of Covid-19 restrictions.

The first two variables are common known as interrupted time series model to analyse changes in outcome associated to a population level intervention (6). The last variable was included to capture the additional effect of restrictions to risk factor measurements, allowing an accurate estimate of longer-term level and trend change.

Using these GAMs, we will estimate the expected number of measurements and 95% confidence intervals (CIs) if Covid-19 did not occur by setting the three pandemic related variables to 0. The missing number of measurements were then calculated as the difference between observed and expected number of measurements from the GAMs.

# References

1. Joy M, McGagh D, Jones N, Liyanage H, Sherlock J, Parimalanathan V, et al. Reorganisation of primary care for older adults during COVID-19: a cross-sectional database study in the UK. British Journal of General Practice. 2020;70(697):e540-e7.

2. Dale CE, Takhar R, Carragher R, Katsoulis M, Torabi F, Duffield S, et al. The impact of the COVID-19 pandemic on cardiovascular disease prevention and management. Nature Medicine. 2023:1-7.

3. Wood SN. Generalized additive models: an introduction with R. Boca Raton, FL: CRC press; 2017.

4. Ho FK, Cole TJ. Non-linear predictor outcome associations. BMJ Medicine. 2023;2(1).

5. Hale T, Angrist N, Goldszmidt R, Kira B, Petherick A, Phillips T, et al. A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). Nature Human Behaviour. 2021;5(4):529-38.

6. Kontopantelis E, Doran T, Springate DA, Buchan I, Reeves D. Regression based quasi-experimental approach when randomisation is not an option: interrupted time series analysis. BMJ. 2015;350.