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Technical appendix: The long-term impacts of new care models on hospital use: an evaluation of the Integrated Care Transformation Programme in Mid-Nottinghamshire

Findings from the Improvement Analytics Unit

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About this technical appendix

This technical report provides supplementary information relating to the evaluation of the long-term impacts of the Mid-Nottinghamshire Better Together Integrated Care Transformation Programme (ICTP) conducted by the Improvement Analytics Unit. It supports the Health Foundation's briefing that considers the findings of the analysis.

This appendix focuses in particular on the following elements of the study

- Sources of data
- Selecting GP practices for the donor pool
- The synthetic control method
- The risk adjustment undertaken
- The limitations of the study

The briefing is available from: https://www.health.org.uk/publications/reports/the-long-term-impacts-of-new-care-models-on-hospital-use-midnotts

Sources of data

CCG and GP Practice reference data

Data relating to key characteristics of CCGs and GP practices were collected from publicly available sources and mapped to produce a monthly series of data for all CCGs and GP practices in England between April 2011 and March 2019 (Table 1). Variables are available at either GP practice level or Lower Super Output Area (LSOA) level. Variables available at LSOA level are mapped to GP practice level according to the LSOA of registered patients. Variables available at GP practice level are mapped to CCG level according to the registered population size of each GP practice in the CCG.

Table 1: Publicly available reference data characterising CCGs and GP Practices. Variables are collected from indicated source at indicated date and mapped to produce annual series of data across the study period at both GP practice and CCG level. Variables are used for comparing between CCGs and GP practices and for risk adjustment as part of the population (POP) group, as indicated. NOTE: For comparing between CCGs, variables are calculated for individuals registered with a GP practice in the CCG and aged over 18 years; for comparing between GP practice, variables are calculated for individuals registered with the GP practice and aged over 18 years; for risk adjustment, variables are calculated for the individuals registered with the GP practice and aged over 18 years in the main analysis, and over 65 years only for the subgroup analysis.

Variable	Description	Used for: Comparing		Used for: Risk adjustment	Date of collection	Level of collection	Source
		CCG	GP	POP			
Population size	Number of registered population			X	Annual 2011–2019	GP practice	NHS Digital. *Number of patients registered at a GP practice.* 2011–2019
Proportion of all ages	Proportion of registered population for age categories 0–4, 5–14, 15–44, 65–74, 75–89, 90+	X					
Proportion of ages aged over 18 years	Proportion of registered population aged over 18 years for age categories 18–24, 65–74, 75+		X	X			
Proportions of gender	Proportion of registered population who are male	X	X	X			
Proportion of ethnicity	Proportion of registered population for self-reported ethnicities white, black, Asian and mixed	X	X	X	2011	GP practice	Office for National Statistics. Census 2011
Proportion of 3rd level education	Proportion of registered population with at least third level education (two or more A levels or equivalent)	X	X	X			
Population density	Number of persons per hectare in the nearest electoral ward	X	X				

Variable	Description	Used for:			Date of collection	Level of collection	Source
		Comparing		Risk adjustment			
		CCG	GP	POP			
Index of multiple deprivation (IMD) score		X	X		2015	LSOA	Department for Communities and Local Government. *English indices of deprivation.* 2015
Health deprivation and disability score		X	X				
Income deprivation affecting older people score		X	X				
Rate of full-time equivalent general practitioners	Number of full-time equivalent general practitioners per 1,000 registered population	X	X		2015	GP Practice	NHS Digital. *General and personal medical services* 2015
Rate of care home beds	Rate of care home beds (residential and nursing) per 1,000 registered population	X	X		2015	GP Practice	Care Quality Commission. *Register of Care Homes*
QOF achievement scores	% of maximum available achievement score for all QOF achievement measures*		X		Annual 2011-2019	GP Practice	NHS Digital. Quality Outcome Framework. 2013–2019
QOF disease prevalence	QOF prevalence for atrial fibrillation, coronary heart disease, cardiovascular disease, hypertension, peripheral arterial disease, stroke and transient ischaemic attack, asthma, COPD, cancer, chronic kidney disease (18+ only), diabetes, palliative care, osteoporosis (50+ only) and rheumatoid arthritis (16+)†		X				

* Excluding atrial fibrillation, heart failure and palliative due to lack of variation.

† Excludes QOF prevalence for heart failure due to lack of variation.

Activity data

Hospital activity data were obtained from de-identified (ie anonymised in line with the Information Commissioner's Office code of practice on anonymisation) Secondary Uses Service (SUS) data. SUS is a national, person-level database that is closely related to the widely used Hospital Episode Statistics (HES). It is used to support the NHS in the delivery of health care services and to trigger reimbursement for secondary care activity. The Improvement Analytics Unit has access to these data for its work and processes them in a secure environment based at the Health Foundation. All data are de-identified, meaning that they have been stripped of fields that can directly identify a patient, such as name, full date of birth and address. The NHS number is replaced with a pseudonym, which is used to link records for the same individual over time. The overall approach to information governance has been scrutinised by the programme oversight group and by information governance experts at NHS Digital.

Patient-level monthly activity counts for selected impact metrics[*] as well as additional counts relating to the demographics, disease prevalence, comorbidity and activity of patients with hospital use each month (Table 2) were collected between April 2011 and March 2019 for all patients aged over 18 years and registered at Mid-Nottinghamshire and donor pool GP practices. Counts were aggregated to CCG level by summing across all patients registered with a GP practice in the CCG and to GP practice level by summing across all patients registered with the GP practice. Aggregated count data were then converted to rates, proportions and averages as indicated in Tables 2 and 3 to enable comparison across CCGs and GP practices.

Only activity data for patients who are registered with a GP practices in Mid-Nottinghamshire or the donor pool are included. A&E visits for a patient who left before being seen or refused treatment, or where the visit is a duplicate, are excluded. Outpatient appointments where the patient did not attend, or where the outpatient appointment is a duplicate, are excluded. Inpatient data are structured into continuous inpatient spells (CIPS), which may consist of several consultant episodes (since patients may be under the care of multiple consultants during a hospital stay) and stays at several hospitals (if patients are transferred). Spells that are missing an admission date, or where the discharge date preceded the admission date due to data quality problems, are excluded. A&E visits, outpatient appointments and spells with gender given as other than male or female are also excluded: although these records were considered valid, they cause technical difficulties for the statistical modelling.

* For the list of impact metrics, see Table 1 in the Briefing report at: https://www.health.org.uk/publications/reports/the-long-term-impacts-of-new-care-models-on-hospital-use-midnotts.

Table 2: Additional variables derived from SUS data characterising the demographics, disease prevalence, comorbidity and activity of patients with hospital use each month. Variables are first collected at patient level per month from SUS data sources for A&E activity, inpatient (IN) activity or both. Data is then aggregated to produce monthly activity counts and converted to rates or proportions, as indicated. Variables are used for comparing between CCGs and GP practices and for risk adjustment as part of population (POP), A&E or inpatient (INP) groups, as indicated. NOTE: When used for comparison between CCGs, variables are calculated at CCG level for all individuals registered with a GP practice in the CCG and aged over 65 years only. Otherwise variables are calculated at GP practice level for all individuals registered with the GP practice and aged over 18 years for the main analysis, and over 65 years for the subgroup analysis. ACSCs=Ambulatory care sensitive conditions.

Variable	Description	SUS source	Used for:					Comment
			Comparing		Risk adjustment group			
			CCG	GP	POP	A&E	INP	
Proportion of ages	Proportion of records for age categories 18–24, 25–64, 65–74, 75+ years	ALL				X	X	
Proportion of males	Proportion of records for age categories male and female	ALL				X	X	
Proportion of ethnicity	Proportion of record for self-reported ethnicity categories white, black, Asian, mixed and other	ALL				X	X	
Rate of A&E visits	Number of A&E visits per 10,000 population	A&E	X					*
Rate of emergency admissions	Number of emergency admissions per 10,000 registered population	INP	X	X				*
Rate of emergency admissions for chronic ACSCs	Number of emergency admissions for chronic ACSCs per 10,000 registered population	INP	X					*
Rate of emergency admissions for urgent care sensitive conditions	Number of emergency admissions for urgent care sensitive conditions per 10,000 registered population	INP	X					*
Rate of elective admissions	Number of elective admissions per 10,000 registered population	INP	X	X				*

* See Table 1 in the main briefing report at: https://www.health.org.uk/publications/reports/the-long-term-impacts-of-new-care-models-on-hospital-use-midnotts.

Variable	Description	SUS source	Used for:					Comment
			Comparing		Risk adjustment group			
			CCG	GP	POP	A&E	INP	
Proportion of admissions for each primary diagnosis	Proportion of admissions for each ICD-10 Version 2015 classification code I-XXII	INP					X	Excluding codes with fewer than three cases per 10,000 activity in the month to ensure model convergence and to prevent over fitting.
Rate of Elixhauser comorbidity index	Number of inpatient admissions for patients with each Elixhauser comorbidity category per 10,000 registered population	INP		X	X			There are 31 Elixhauser comorbidity categories; here we exclude those for AIDS/HIV and obesity. Indicators for each category for each patient are calculated according to primary and secondary diagnosis ICD-10 Version 2015 classification codes (17) for all their inpatient admissions in the preceding 24 months
Proportion of Elixhauser comorbidity	Proportion of records for patients with each Elixhauser comorbidity category	ALL				X	X	As above for rate of Elixhauser comorbidity
Rate of Elixhauser comorbidity index	Number of inpatient admissions for patients with an Elixhauser index ≥2 per 10,000 registered population	ALL			X			Elixhauser index for each patient is calculated as the sum of his or her Elixhauser indices. Patients with an Elixhauser index ≥2 are classed as comorbid
Proportion of Elixhauser comorbidity index	Proportion of records with Elixhauser index ≥2	ALL				X	X	As above for rate of comorbidity index
Rate of dementia	Number of inpatient admissions for patients with a history of dementia per 10,000 registered population	INP			X			Indicator for dementia is calculated for each patient according to primary and secondary diagnosis ICD-10 Version 2015 classification codes (17) for all their inpatient admissions in the preceding 24 months
Proportion of dementia	Proportion of records for patients with a history of dementia	ALL				X	X	As above for rate of dementia

Table 3: The characteristics of the treated group (comprising 38 GP practices from Mid-Nottinghamshire) and the control group (comprising 500 GP practices) in the pre-intervention period April 2011–March 2013.

Variable	Treated group (N=38)	Control group (N=500)
Registered GP practice size	5820	6949
% Aged 18-24 years	0.025	0.025
% Aged 65-74 years	0.124	0.127
% Aged >75 years	0.085	0.09
% Third level education	0.117	0.12
% Asian ethnicity	0.01	0.02
% Black ethnicity	0.003	0.005
% White ethnicity	0.98	0.96
% Male	0.49	0.491
Number of full-time equivalent GPs per 1,000 population	3.65	5.51
Index of multiple deprivation	24.84	22.02
Health deprivation and disability score	0.38	0.21
Income deprivation affecting older people score	0.16	0.17
Population density (people/km2)	2348.1	2650.7
Rural classification	1	1
QOF achievement scores % of maximum		
Atrial fibrillation	99.64	99.78
Asthma	98.72	98.45
Blood pressure	96.44	96.31
Cancer	93.72	96.58
Coronary heart disease	97.95	99.26
Chronic kidney disease	98.33	98.04
COPD	97.51	98.5
Cardiovascular disease	89.58	96.31
Diabetes mellitus	95.62	98.23
Heart failure	97.97	98.11

Variable	Treated group (N=38)	Control group (N=500)
Hypertension	76.66	85.74
Osteoporosis	90.9	90.94
Peripheral arterial disease	97.44	97.9
Palliative care	94.13	92.43
Rheumatoid arthritis	98.94	99.37
Stroke and transient ischaemic attack	99.64	99.78
QOF disease prevalence %		
Atrial fibrillation	0.015	0.018
Asthma	0.062	0.063
Cancer	0.019	0.021
Coronary heart disease	0.042	0.041
Chronic kidney disease (>18 years only)	0.052	0.05
COPD	0.023	0.021
Cardiovascular disease	0.019	0.022
Diabetes mellitus (>17 years only)	0.063	0.063
Heart failure	0.157	0.154
Hypertension	0.002	0.002
Osteoporosis (>50 years only)	0.007	0.008
Peripheral arterial disease	0.003	0.002
Palliative care	0.008	0.008
Rheumatoid arthritis (>16 years only)	0.019	0.021
Stroke and transient ischaemic attack	0.015	0.018

Selecting GP practices for Mid-Nottinghamshire and the donor pool

Mid-Nottinghamshire GP practices

We included 38 GP practices from the 41 GP practices in Mansfield and Ashfield (M&A) and Newark and Sherwood (N&S) CCGs. These comprised the GP practices that were open at least 2 years prior to the start of the ICTP, and which remained open for the duration of the study until March 2019; three GP practices which either opened or closed during the study period were excluded.

The donor pool

The GP practices in the donor pool were selected from CCGs elsewhere in England in order to be as 'similar' (see below for how similarity is assessed) to the GP practices in Mid-Nottinghamshire in terms of both regional, ie CCG level, and local, ie GP level, influences during the 24-month pre-intervention period prior to the introduction of the ICTP.

- *Selecting comparable CCGs*
  There are 209* CCGs in England from which we excluded 30 CCGs in London, two other CCGs in Mid-Nottinghamshire and 59 CCGs participating in new care model vanguards from the potential list of similar CCGs. This is because these CCGs were likely to have very different populations, may have spillover effects, or were also implementing interventions under the new care models programme. The remaining 118 CCGs form our donor pool of CCGs. From these, we selected the 40 that were most similar to M&A CCG, and the 40 most similar to N&S CCG. This resulted in a final set of 69 distinct 'similar' CCGs. The number 40 was chosen arbitrarily to allow for a large, but manageable, sample of available GP practices for inclusion in the next step. In this set of 69 similar CCGs, there were 1,820 GP practices available as potential controls.

- *Selecting comparable GPs*
  From the 1,820 potential controls, we excluded 222 GP practices which opened or closed during the study period, 156 GP practices with registered population sizes outside the range of registered population sizes in the GP practices in Mid-Nottinghamshire, and four GP practices with patterns of key outcome variables indicative of reporting errors from the potential list of similar GP practices. The remaining 1,438 GP practices were then ordered in terms of their similarity, or distance, to each of the GP practices in Mid-Nottinghamshire. The main analysis used a donor pool comprising the first 500 most similar practices. Sensitivity analyses were run using donor pools comprising the first 250 and 1,000 most similar practices.

Table 3 summarises the key characteristics of the GP practices in Mid-Nottinghamshire and the donor pool. The table shows the averages across all 38 Mid-Nottinghamshire GP practices (intervention group) compared to the 500 most similar GP practices (donor pool)

* For data drawn March 2019.

in the pre-intervention period (April 2011–March 2013) for all publicly available GP characteristics. Good similarity between the two groups has been achieved for most of the variables expressing socio-economic characteristics, QOF achievement scores and QOF disease prevalence.

Assessing similarity

To assess similarity between units (CCGs or GP practices) in Mid-Nottinghamshire and a control group, we adapted the method used in NHS England's RightCare 'Similar 10 CCG Explorer Tool'*. That method assesses similarity by computing the squared Euclidean distances (SED) between each pair of units across a set of variables representing key characteristics of the units, with a lower SED indicating greater similarity†. The Euclidean distance represents a measure of similarity; pairs of units with shorter Euclidean distances are more similar than pairs with longer Euclidean distances.

In brief, selected variables are first standardised using inter-decile range standardisation by subtracting the median and dividing by the difference between the 90th and 10th percentiles‡. The SED is then calculated as the sum of the squares of the differences between these corresponding standardised variables. The RightCare method assesses similarity across 12 demographic indicators derived from publicly available reference sources: these include indicators relating to deprivation, population size and density, age structure and ethnic mix. To these we added other publicly available variables (see Table 1 for a complete list) as well as variables derived from SUS data which characterise the activity, disease prevalence and comorbidity of patients with hospital use each month (see Table 2 for a complete list). Annual data for each CCG or GP practice in the 2 pre-intervention years were included. When assessing similarity between pairs of CCGs, all variables were given equal weight. To allow for a more detailed comparison when assessing similarity between pairs of GP practices, we accounted for the large number of potentially related variables by weighting them according to how predictive they were of the rate of hospital admissions in 2011 and 2012 (controlling for the other variables). The weight given to each variable was determined by its squared standardised coefficient in a regression of the rate of inpatient admissions in 2012 on the variables for the preceding year.[1] The variables that received greater weights were the Quality and Outcomes Framework (QOF) achievement scores (Table 1) and the rates of elective and emergency admissions.

We applied these methods to compute the SED between all pairs of units in Mid-Nottinghamshire and a control group. We then used these pairwise SEDs to create an ordered list of control units according to their decreasing overall similarity with the Mid-Nottinghamshire units. To do this, we first selected the set of control units with smallest SED to each of the units in Mid-Nottinghamshire. These were then arbitrarily

* The 'Similar 10 CCG Explorer Tool' calculates the 10 most similar CCGs in England for a given CCG. See https://www.england.nhs.uk/publication/similar-10-ccg-explorer-tool/

† Suppose there are I units and K baseline variables. Let $\tilde{x}_{ki}$ represent the standardised version of x_{kj} where x_{kj} is the kth, baseline variable in unit i, i=1, …I, k=1,…,K. Then the SED between unit i and unit j is calculated across K baseline variables as

$$SED_{ij} = \sqrt{\sum_{k=1}^{K}(\tilde{x}_{ki} - \tilde{x}_{ki})^2} \text{ for i,j<1, i≠j.}$$

‡ The standardised value of baseline variable x_{kj} is calculated as

$$\tilde{x}_{kj} = \frac{x_{kj} - median(x_{1j}, x_{2j}, \ldots, x_{Kj})}{90th\ percentil(x_{1j}, x_{2j}, \ldots, x_{Kj}) - 10th\ percentile(x_{1j}, x_{2j}, \ldots, x_{Kj})}$$

ordered, excluding any duplicates, to create the first set of units in the list. The process was repeated for the set of control units with second smallest SED to each of the units in Mid-Nottinghamshire, and these were then added to the list. Then for the third nearest, and so on, until all control units were included in the list. This then constituted a single ordered list of the control units in terms of their decreasing similarity with units in Mid-Nottinghamshire across these variables. The top 500 units in the list were used as the donor pool for all impact metrics.

The synthetic control method

We used the Generalised Synthetic Control (GSC) method[2] to compare the hospital use (via selected impact metrics) of patients in Mid-Nottinghamshire to that of patients in the donor pool after the introduction of the ICTP. The 'synthetic control' approach, originally introduced by Abadie et al.[3,4], has several advantages over alternative approaches eg Difference-in-Differences (DiD), to evaluating population health interventions. Unlike DiD, the synthetic control approach allows for the effects of observed and unobserved predictors of an impact metric to vary over time. The central idea of the synthetic control approach is to find a weighted combination of the units in the donor pool whose mean values of an impact metric are similar to those in an intervention group in the pre-intervention period. This similarity is then assumed to extend into the post-intervention period, providing an estimate of the mean counterfactual values of the impact metric that would have been observed in the intervention group in the absence of the intervention. The synthetic control approach can provide approximately unbiased estimates provided data are available for a sufficiently long period before the intervention occurred.[4] In a health policy context, the synthetic control approach has been considered for the evaluation of various health policy initiatives.[5]

However, the synthetic control approach may provide biased estimates if assignment to the intervention is correlated with time-varying unobserved confounders;[6] or if a suitable combination of similar control units[7] cannot be found.[4,8]

Inspired by the intuitive appeal of the synthetic control approach, and driven by concerns about the limitations of the original synthetic control method, a plethora of alternative synthetic control designs have recently been proposed.[2,9,10,11,12,13,14,15] Here we use the GSC method[2] which unifies the synthetic control approach with an interactive fixed effects model under a simple framework. It can yield counterfactual estimates in scenarios where the original synthetic control method would fail to do so and can control for bias in unobserved confounders with time-varying effects. By computing a separate estimate for each unit in the intervention group, it can also account for heterogeneous treatment effects. GSC maintains the un-biasedness properties of DiD and the original synthetic control method but can provide more precise estimates than these methods if the underlying model is correctly specified.[2] In a recent comparison of synthetic control approaches, the GSC method was more efficient than alternative approaches in these circumstances.[16]

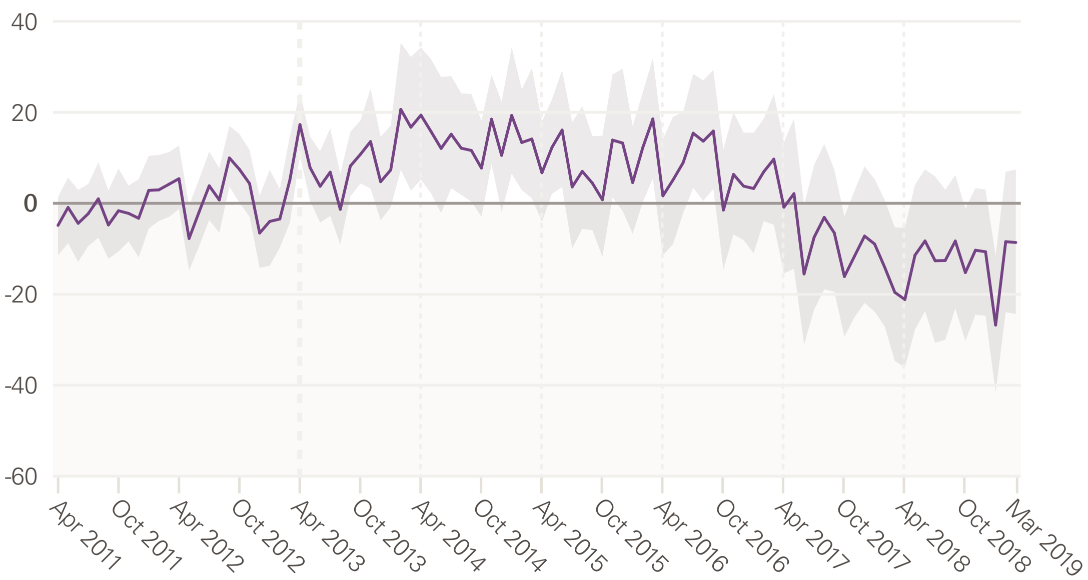
The GSC method has three steps. In the first step, the method uses data from the donor pool only to estimate a linear interactive fixed effects model for each impact metric incorporating unit-specific intercepts interacted with time-varying coefficients. This provides time-varying coefficients for all periods and unit-specific intercepts for the donor pool. In the second step, the GSC uses the estimates from the first step, as well as pre-intervention data from both the intervention group and the donor pool, to infer the unit-specific intercepts for the intervention group. We can think of this model as defining a synthetic control area which has values of the impact metric similar to those in the intervention group in the pre-intervention period. This model is then used in the third step to predict the counterfactual impact metrics in the intervention group in the post-intervention period. These counterfactual impact metrics represent the hospital use that would have been expected in each unit in the intervention group in the absence of the intervention. The difference between these and the observed impact metrics in the period following the introduction of the intervention provides estimates of the causal impact of the intervention.

We applied GSC to each impact metric separately to generate a synthetic control area, as described. These were used to estimate the impact of the ICTP on each GP practice in Mid-Nottinghamshire in each post-intervention period. These differences were then averaged over all GP practices in Mid-Nottinghamshire to provide a single monthly estimate of the impact of the ICTP on the Mid-Nottinghamshire region. Finally, the monthly estimates were averaged across each financial year to provide yearly estimates of the impact of the ICTP on hospital use in Mid-Nottinghamshire. GSC was run using the 'gsynth' package in R.*

Figures 2–5 in the main briefing report show the trends in hospital use separately for Mid-Nottinghamshire and the synthetic control area. Figure 1 in this report shows an alternative view of the same data by plotting instead the difference between the trends in hospital use for Mid-Nottinghamshire and the synthetic control area together with a 95% confidence interval.

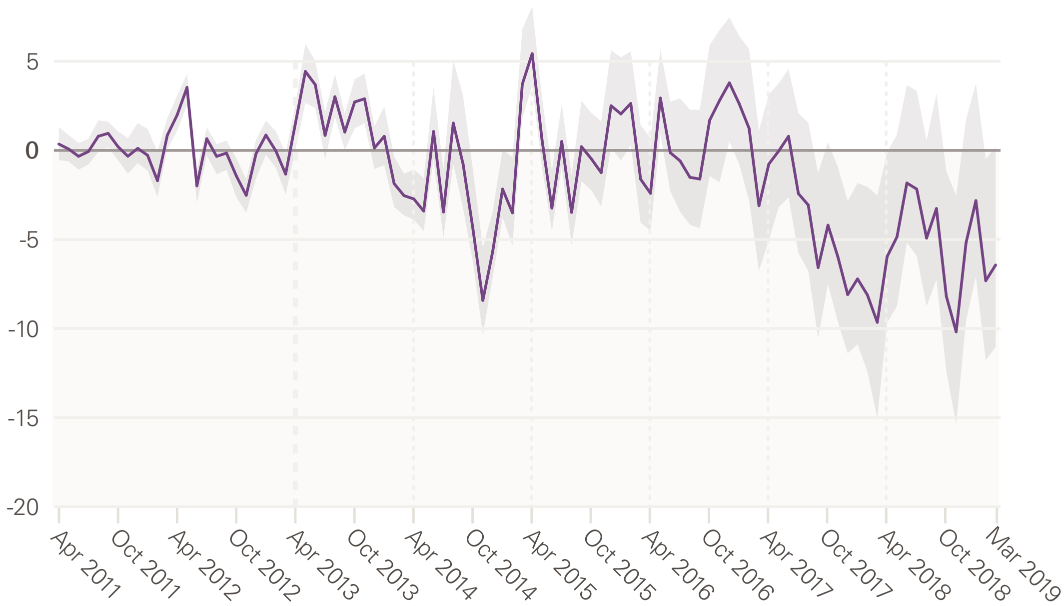
Figure 1: The impact of the ICTP on A&E visits. Plots show the difference between the true and estimated counterfactual ATT for each outcome studied. The grey shaded area indicates 95% confidence intervals.

A. Rate of A&E visits (number per month per 10,000 people aged >18 years)

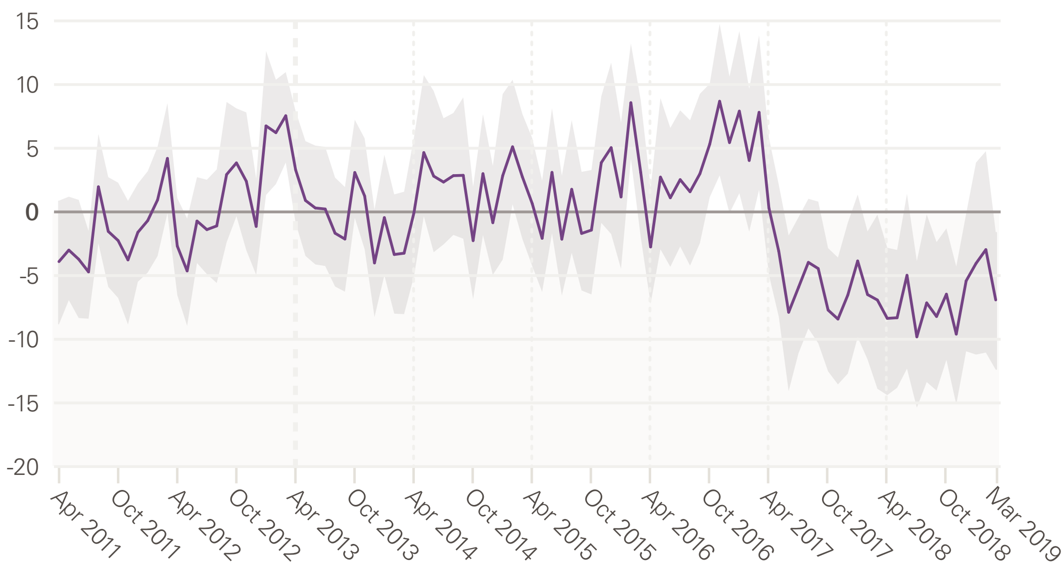


* https://cran.r-project.org/web/packages/gsynth/index.html

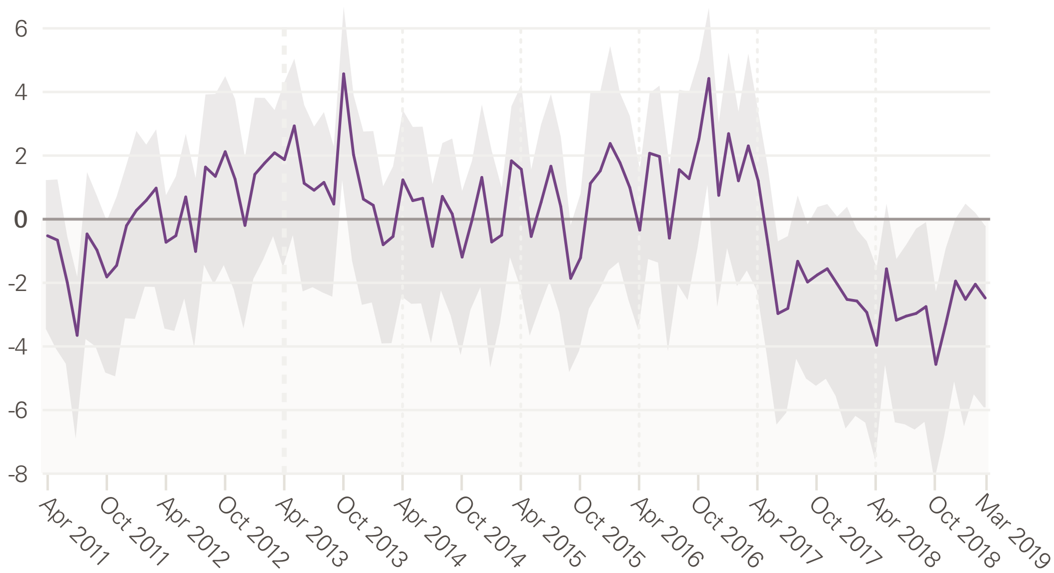
B. Proportion of patients seen within 4 hours in A&E visit (% of people aged >18 years)



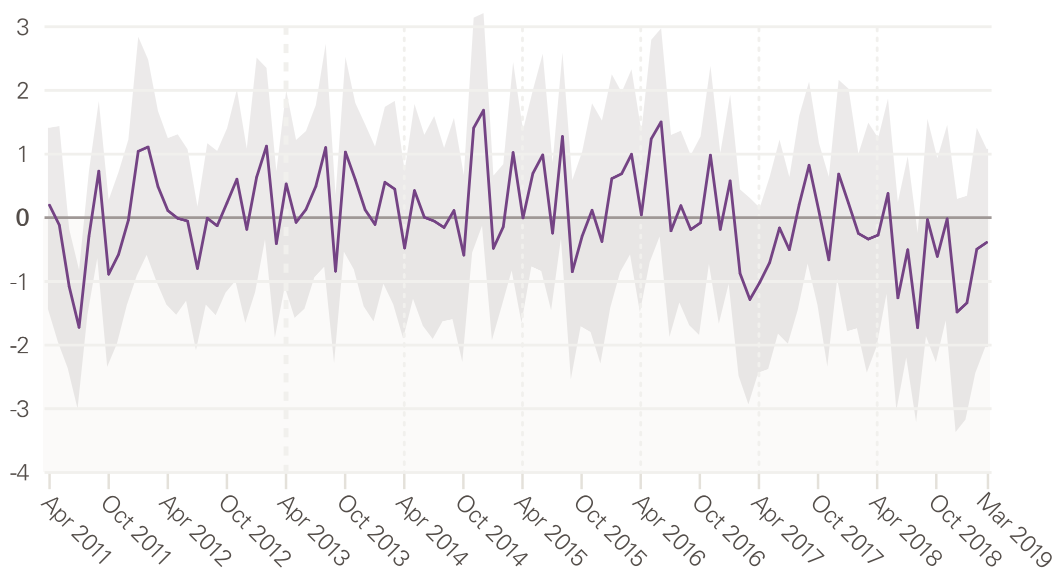
C. Rate of emergency admissions for all causes (number per month per 10,000 people aged >18 years)



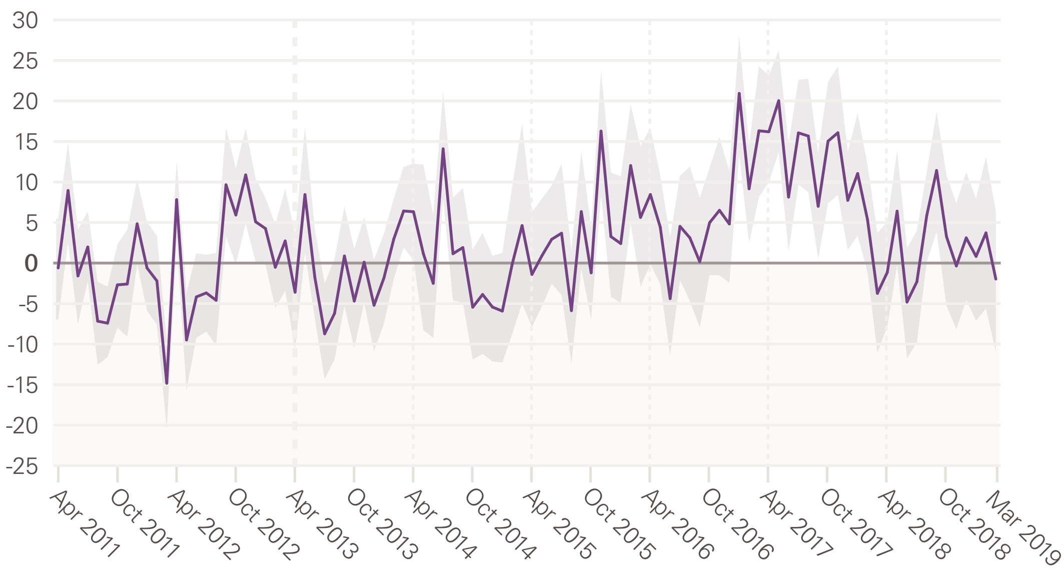
D. Rate of emergency admissions for urgent care sensitive conditions (number per month per 10,000 people aged >18 years)



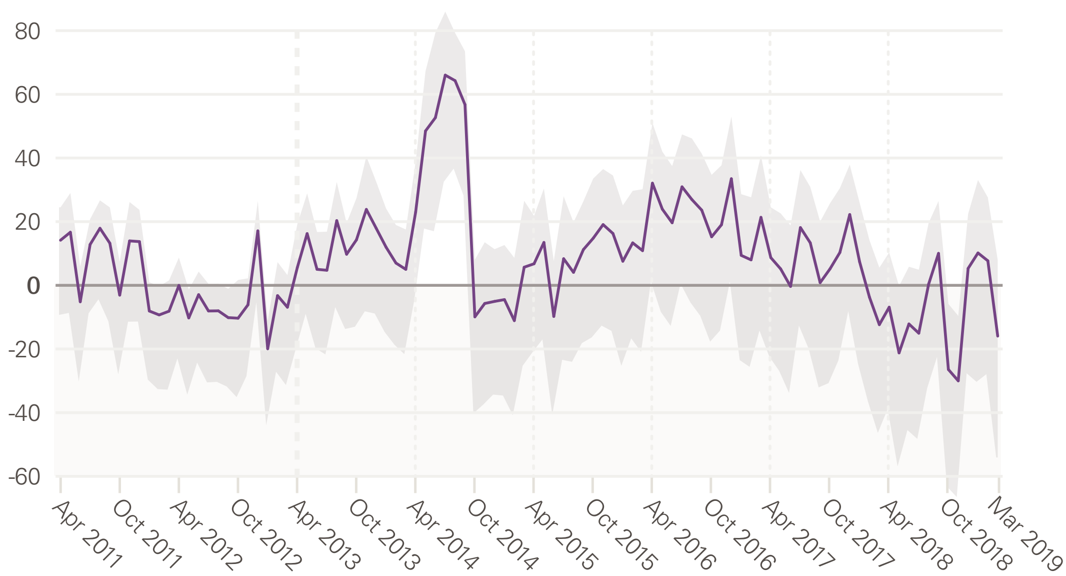
E. Rate of emergency admissions for chronic ACSCs (number per month per 10,000 people aged >18 years)



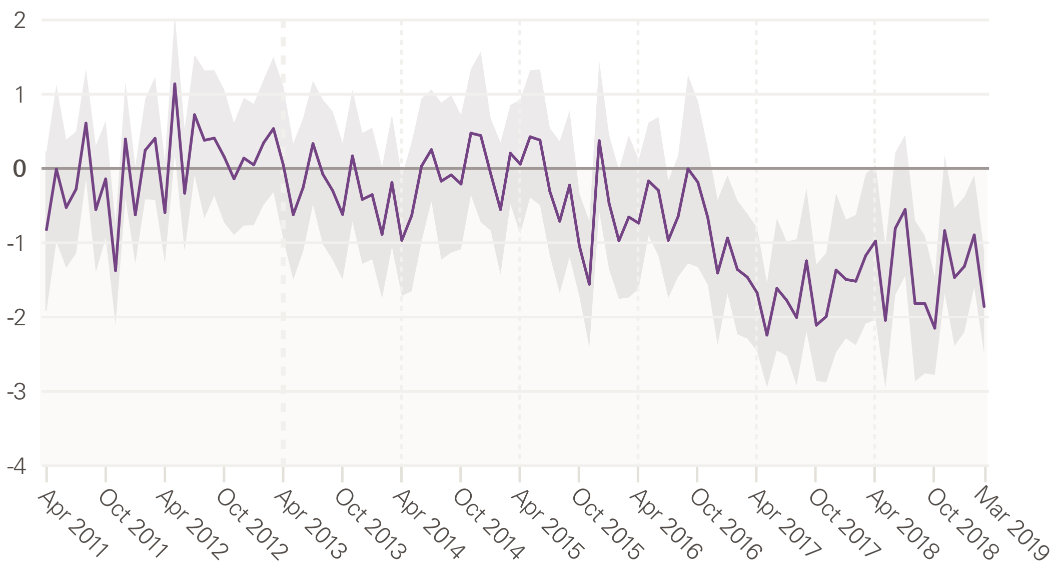
F. Rate of elective admissions for all causes (number per month per 10,000 people aged >18 years)



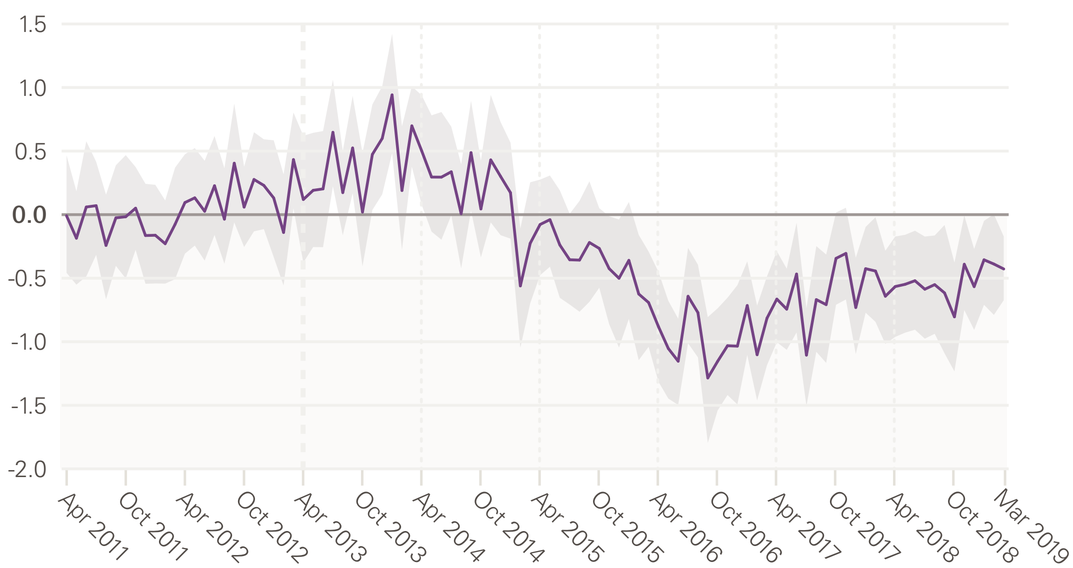
G. Rate of 1st outpatient appointments (number per month per 10,000 people aged >18 years)



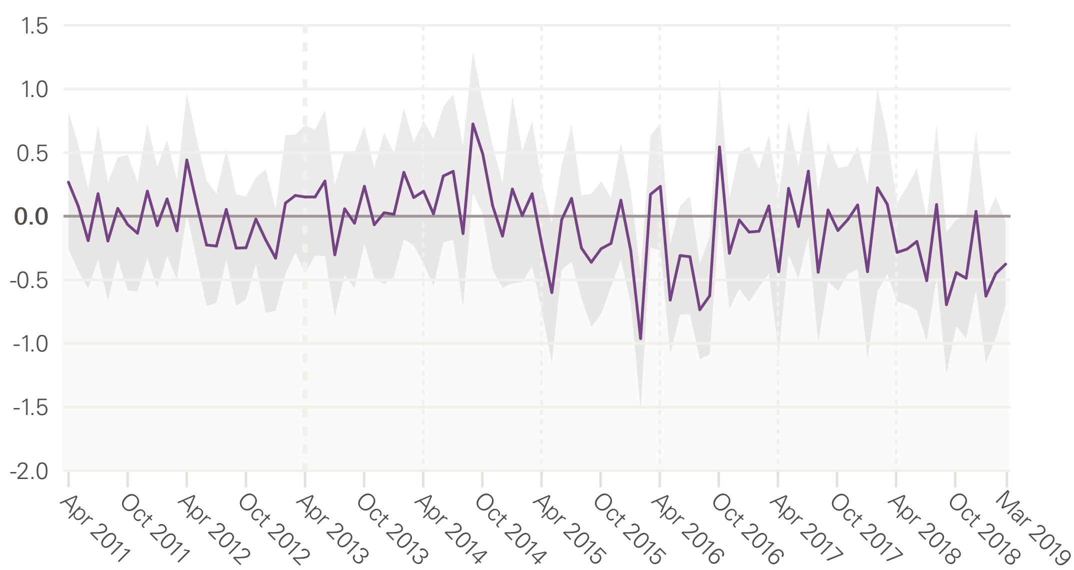
H. Rate of emergency readmissions (number per month per 10,000 people aged >18 years)



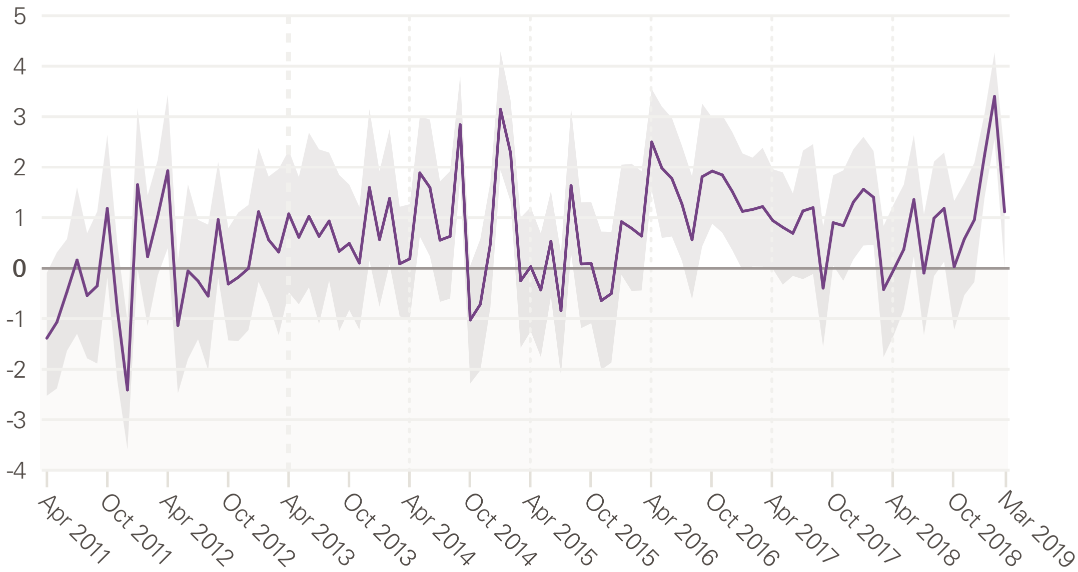
I. Average length of stay for overnight emergency admissions (days for people aged >18 years)



J. Average length of stay for overnight elective admissions (days for people aged >18 years)



K. Proportion of elective admissions with length of stay less than 1 day (% of people aged >18 years)



Risk adjustment

Impact metrics were risk adjusted for variables that reflect changes over time in the characteristics of the population at risk. For the impact metrics analysed here, there are three possible groups of risk adjustment variables:

- **Population (POP) risk adjustment.** When looking at population level impact metrics including A&E visits, inpatient admissions and outpatient attendances, all patients in the registered population are at risk. Characteristics adjusted for include population estimates of the proportion of patients by age, gender, ethnicity and education derived from publicly available information at the GP practice level (Table 1); and estimated population prevalences of patient with dementia and an Elixhauser index ≥2 derived from SUS inpatient activity (Table 2).
- **A&E risk adjustment.** When looking at impact metrics related to A&E visits, eg proportion of A&E visits where patient is seen within 4 hours, or emergency admissions following a visit to A&E, only patients attending A&E are at risk. Characteristics adjusted for include the proportion of A&E activity by age, gender, ethnicity, Elixhauser comorbidity categories[17], Elixhauser comorbidity index, and dementia (Table 2).
- **Inpatient (INP) risk adjustment.** When looking at impact metrics related to inpatient admissions, eg length of stay, or emergency readmissions, only patients with an inpatient admission are at risk. Characteristics adjusted for include proportion of inpatient activity by age, gender, ethnicity, primary diagnosis code, Elixhauser comorbidity categories, Elixhauser comorbidity index, and dementia (Table 2).

Sensitivity analysis

Considering the importance of risk adjustment by estimating effects without risk adjustment

Although it is more appropriate to risk adjust the impact metrics in order to capture the effects of any time-varying effects, we assessed the sensitivity of results to risk adjustment (Tables 4 and 5). Trends in effect were similar in the estimates with and without risk adjustment for all outcome measures except the percentage of patients seen within 4 hours of attending A&E. In this case, the GSC method identified four unobserved time-varying confounders to account for underlying variation in the characteristics of the patients attending A&E over the period. These underlying confounders were not detected in the unadjusted model confirming the importance of risk adjustment. All results presented in the briefing are risk adjusted.

Changing the start date of the ICTP when estimating the counterfactual

We assessed the sensitivity of estimates to the start date of the ICTP (Tables 6 and 7). This analysis is intended to ensure that the counterfactual accurately captures activity in the GP practices in Mid-Nottinghamshire during the pre-intervention period and that estimates are not severely impacted by slight shifts in start date. Since we also know that the GSC method is influenced by the number of pre-intervention periods, this also assesses sensitivity to changing the length of the pre-intervention period. No material differences in findings were apparent when moving the start date 3 and 6 months earlier.

Changing the size of the donor pool

Since results may also be sensitive to the number and choice of GP practices included in the donor pool, we assessed the sensitivity of estimates to changing the number of GP practices in the donor pool to the most similar 250 and 1,000 GP practices to those in Mid-Nottinghamshire (see Tables 8 and 9), rather than the 500 most similar. Although there were some marginal differences in size of impacts, the trends in the estimates of effect were similar to the original estimates for all impact metrics using 250 GP practices, and for all except rate of emergency admissions and rate of outpatient appointments when using 1,000 GP practices. In these cases, the GSC method identified one unobserved time-varying confounder leading to an implausible estimate of the impact metric in the synthetic control area.

Table 4: Risk-unadjusted estimated impact of the ICTP on hospital use in the population of the Mid-Nottinghamshire aged over 18 years, April 2013–March 2019

	Year 1 2013/14			Year 2 2014/15			Year 3 2015/16			Year 4 2016/17			Year 5 2017/18			Year 6 2018/19		
	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P
Rate of A&E visits	9.8	3.9	<0.001	14.7	5.6	<0.001	10.5	3.9	0.05	9.6	3.5	0.09	-6	-2.2	0.33	-9.4	-3.2	0.15
% A&E visits seen within 4 hours	0.1	0.1	0.55	-0.8	-0.9	0.01	4.1	4.7	<0.001	7.5	9.1	<0.001	5.2	6.5	<0.001	7.1	8.8	<0.001
Rate of emergency admissions	-0.4	-0.5	0.69	2.5	2.7	0.11	2.8	3	0.1	6.2	6.5	0.01	-2.3	-2.3	0.22	-2.8	-2.7	0.24
Rate of elective admissions	-2.1	-1.3	0.14	-0.9	-0.6	0.67	2.8	1.7	0.26	6.3	3.7	0.02	11.8	7.3	<0.001	2.5	1.5	0.37
Average LOS (days) of overnight emergency admission	0.02	0.1	0.99	0.8	4	0.14	2.7	13.1	<0.001	3.1	13.4	<0.001	1.9	7.9	0.02	2.4	8.9	<0.001
Average LOS (days) of overnight elective admission	0.7	0.8	0.05	1	1.2	<0.001	0.3	0.4	0.28	2.1	2.4	<0.001	1.5	1.7	<0.001	1.6	1.9	<0.001
Rate of 30-day emergency readmission[B]	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Rate of outpatient appointments	14.8	4.3	0.01	50.7	14.9	<0.001	109.7	37.7	0.01	147.7	50.7	0.002	140.6	57.2	0.01	150.2	54.8	0.02

A Relative (Rel.) Difference = Change in Mid-Nottinghamshire expressed as a percentage of the estimate in the synthetic control area.
B Valid synthetic control could not be found.

Table 5: Risk-unadjusted estimated impact of the ICTP on hospital use in the population of the Mid-Nottinghamshire aged over 65 years, April 2013–March 2019.

	Year 1 2013/14			Year 2 2014/15			Year 3 2015/16			Year 4 2016/17			Year 5 2017/18			Year 6 2018/19		
	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P
Rate of A&E visits	17.8	5.7	<0.001	27.2	8.2	<0.001	26.1	7.9	<0.001	31.6	9.2	<0.001	18.7	5.2	0.05	15.6	4.1	0.16
Rate of emergency admissions	-1.4	-0.7	0.68	6.2	3.1	0.11	12.2	6.3	<0.001	23.3	11.9	<0.001	7.8	3.9	0.16	7.5	3.6	0.28
Rate of emergency admissions for chronic ACSCs	0.4	1.8	0.67	0.2	0.8	0.84	1.4	6	0.25	1.9	8.2	0.09	1.9	8.3	0.15	0.04	0.2	0.98
Rate of emergency admissions for urgent care sensitive conditions	1.7	4	0.27	0.3	0.7	0.81	3.6	8.4	0.02	4.9	11.7	0.01	-0.7	-1.7	0.74	-0.5	-1.1	0.88
Rate of elective admissions	-3	-1.1	0.38	-9.3	-3.3	0.07	6.1	2.2	0.29	25.2	9.2	<0.001	44.3	16.7	<0.001	46.5	16.5	<0.001
Rate of 30-day emergency readmission	-0.2	-2	0.47	0.5	4.1	0.15	0.8	6.8	0.02	0.9	8.2	0.01	0.04	0.4	0.88	-0.3	-2.5	0.4
Rate of outpatient appointments	14.8	2.9	0.06	36.3	6.6	0.004	24.7	4.3	0.06	57.2	9.3	0.002	34.8	6.2	0.03	29.4	4.5	0.11

A Relative (Rel.) Difference = Change in Mid-Nottinghamshire expressed as a percentage of the estimate in the synthetic control area.

Table 6: Risk-adjusted estimated impact of the ICTP on hospital use in the population of the Mid-Nottinghamshire aged over 18 years, April 2013–March 2019 (start date moved 3 months earlier)

	Jan 2013 – April 2013			Year 1 2013/14			Year 2 2014/15			Year 3 2015/16			Year 4 2016/17			Year 5 2017/18			Year 6 2018/19		
	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P
Rate of A&E visits	-1.2	-0.5	0.7	9.5	3.8	<0.001	13.6	5.1	<0.001	8.7	3.2	0.08	6.1	2.2	0.24	-10.5	-3.7	0.07	-14.2	-4.7	0.01
% A&E visits seen within 4 hours	-4.3	-4.6	0.19	2.3	2.6	<0.001	-1.4	-1.6	0.23	-8.1	-8.2	0.46	-17.9	-16.6	0.19	-25.3	-22.7	0.05	-19.6	-18.1	0.07
Rate of elective admissions	2.4	1.6	0.18	-1.0	-0.6	0.55	0.6	0.4	0.78	3.8	2.3	0.09	6.6	4.0	0.01	11.3	6.9	<0.001	1.5	0.9	0.61
Rate of emergency admissions	7.7	8.8	<0.001	0.4	0.4	0.68	3.3	3.6	0.04	2.5	2.6	0.12	4.7	4.8	0.01	-4.5	-4.5	0.02	-6.2	-5.8	<0.001
Rate of 30-day emergency readmission	0.4	4.4	0.22	-0.2	-1.9	0.39	-0.1	-0.6	0.79	-0.4	-3.4	0.09	-0.7	-6.5	<0.001	-1.6	-14.4	<0.001	-1.3	-11.8	<0.001
Rate of outpatient appointments	-2.5	-0.8	0.32	12.8	3.7	0.05	50.9	14.9	<0.001	120.8	43.1	0.04	162.9	59.0	0.03	158.3	69.4	0.05	173.3	69.0	0.07

A Relative (Rel.) Difference = Change in Mid-Nottinghamshire expressed as a percentage of the estimate in the synthetic control area.

Table 7: Risk-adjusted estimated impact of the ICTP on hospital use in the population of the Mid-Nottinghamshire aged over 18 years, April 2013–March 2019 (start date moved 6 months earlier)

	Oct 2012 – April 2013			Year 1 2013/14			Year 2 2014/15			Year 3 2015/16			Year 4 2016/17			Year 5 2017/18			Year 6 2018/19		
	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P
Rate of A&E visits	0.4	0.2	0.83	9.7	3.9	<0.001	13.8	5.2	<0.001	8.9	3.3	0.06	6.3	2.3	0.22	-10.2	-3.6	0.06	-13.9	-4.6	0.01
% A&E visits seen within 4 hours	-2.0	-2.2	<0.001	-0.5	-0.5	0.02	-1.6	-1.8	<0.001	3.5	4.0	<0.001	7.5	9.2	<0.001	6.5	8.2	<0.001	8.8	11.1	<0.001
Rate of elective admissions	6.1	4.0	<0.001	0.2	0.2	0.83	1.8	1.1	0.29	5.0	3.1	0.03	7.9	4.7	<0.001	12.5	7.8	<0.001	2.8	1.7	0.28
Rate of emergency admissions	5.7	6.5	<0.001	0.9	1.0	0.38	3.8	4.1	0.01	2.9	3.1	0.07	5.1	5.2	0.01	-4.1	-4.1	0.02	-5.7	-5.4	0.02
Rate of 30-day emergency readmission	0.3	2.6	0.38	-0.2	-1.8	0.43	-0.1	-0.5	0.78	-0.4	-3.4	0.1	-0.7	-6.6	0.01	-1.6	-14.5	<0.001	-1.3	-11.9	<0.001
Rate of outpatient appointments	-0.9	-0.3	0.53	12.8	3.7	0.05	49.5	14.5	<0.001	114.0	39.7	0.05	153.8	54.0	0.04	148.6	62.5	0.06	161.2	61.2	0.09

A Relative (Rel.) Difference = Change in Mid-Nottinghamshire expressed as a percentage of the estimate in the synthetic control area.

Table 8: Risk-adjusted estimated impact of the ICTP on hospital use in the population of the Mid-Nottinghamshire aged over 18 years using 250 GP practices in the donor pool, April 2013–March 2019

	Year 1 2013/14			**Year 2 2014/15**			**Year 3 2015/16**			**Year 4 2016/17**			**Year 5 2017/18**			**Year 6 2018/19**		
	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P
Rate of A&E visits	10.2	4.1	<0.001	17.2	6.6	<0.001	13.7	5.2	0.03	13.1	4.8	0.05	-0.8	-0.3	0.9	-5.2	-1.8	0.48
% A&E visits seen within 4 hours	0.9	1.0	0.02	-0.4	-0.4	0.3	2.1	2.4	0.02	3.2	3.7	0.03	-0.9	-1.1	0.83	-1.3	-1.5	0.78
Rate of emergency admissions	-0.7	-0.8	0.59	2.1	2.3	0.19	1.0	1.1	0.54	3.4	3.4	0.1	-5.9	-5.8	<0.001	-7.0	-6.5	<0.001
Rate of emergency admissions for chronic ACSCs	0.4	4.6	0.17	0.2	1.8	0.66	0.2	2.1	0.61	0.0	0.3	0.98	-0.1	-1.4	0.66	-0.6	-6.2	0.16
Rate of emergency admissions for urgent care sensitive conditions	1.1	5.1	0.03	0.2	0.8	0.77	0.5	2.4	0.39	1.5	6.4	0.06	-2.0	-8.8	<0.001	-3.0	-12.4	<0.001
Rate of emergency admissions for non-avoidable conditions	-1.9	-2.9	0.04	1.5	2.3	0.2	0.5	0.8	0.67	1.9	2.6	0.21	-3.9	-5.3	<0.001	-3.8	-4.9	0.01
Rate of elective admissions	-1.0	-0.6	0.54	0.6	0.4	0.82	3.5	2.1	0.16	6.2	3.7	0.02	12.5	7.7	<0.001	2.6	1.6	0.47

	Year 1 2013/14			Year 2 2014/15			Year 3 2015/16			Year 4 2016/17			Year 5 2017/18			Year 6 2018/19		
	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P
Average LOS (days) of overnight emergency admissions[B]	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Average LOS (days) of overnight elective admissions	0.1	2	0.4	0.2	4.6	0.05	-0.2	-5.4	0.03	-0.2	-4.1	0.07	-0.04	-1	0.69	-0.4	-8.9	<0.001
% of emergency admissions with a LOS less than 1 day[B]	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
% of elective admissions with a LOS less than 1 day	0.9	1.0	0.02	1.0	1.2	<0.001	0.3	0.3	0.39	1.6	1.9	<0.001	0.9	1.0	0.02	1.2	1.4	0.01
Rate of 30-day emergency readmission	-0.4	-3.6	0.12	-0.2	-2.3	0.34	-0.4	-4.2	0.02	-0.8	-7.3	0	-1.8	-15.7	<0.001	-1.5	-13.3	<0.001
Rate of outpatient appointments	14.3	4.1	<0.001	28.8	7.9	<0.001	22.6	6.0	0.01	34.6	8.6	<0.001	18.0	4.9	0.09	4.0	1.0	0.85

A Relative (Rel.) Difference = Change in Mid-Nottinghamshire expressed as a percentage of the estimate in the synthetic control area.
B Valid synthetic control could not be found.

Table 9: Risk-adjusted estimated impact of the ICTP on hospital use in the population of the Mid-Nottinghamshire aged over 18 years using 1,000 GP practices in the donor pool, April 2013–March 2019.

	Year 1 2013/14			Year 2 2014/15			Year 3 2015/16			Year 4 2016/17			Year 5 2017/18			Year 6 2018/19		
	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P	Difference	Rel. Difference (%)[A]	P
Rate of A&E visits	11.4	4.6	<0.001	14.9	5.6	<0.001	8.4	3.1	0.05	2.8	1.0	0.55	-15.1	-5.3	0	-17.4	-5.7	<0.001
% A&E visits seen within 4 hours	1.5	1.7	<0.001	-2.2	-2.5	<0.001	1.7	1.9	0.01	1.5	1.7	0.11	-3.5	-3.9	0.08	-3.6	-3.9	0.21
Rate of emergency admissions	-5.9	-6.2	0.04	-7.8	-7.6	0.08	-16.2	-14.3	0.02	-18.3	-15.1	0.05	-33.4	-25.9	0	-42.8	-30.0	<0.001
Rate of emergency admissions for chronic ACSCs	0.4	4.6	0.16	0.2	2.6	0.54	0.2	2.6	0.5	0.0	-0.1	0.93	-0.2	-2.2	0.44	-0.8	-7.9	0.04
Rate of emergency admissions for urgent care sensitive conditions	1.4	6.4	<0.001	0.3	1.5	0.58	0.7	2.9	0.21	1.5	6.6	0.03	-2.0	-9.0	<0.001	-3.3	-13.6	<0.001
Rate of emergency admissions for non-avoidable conditions	-0.9	-1.5	0.28	1.9	2.9	0.08	1.5	2.2	0.12	2.6	3.7	0.04	-3.2	-4.3	0.01	-3.9	-5.0	<0.001

	Year 1 2013/14			Year 2 2014/15			Year 3 2015/16			Year 4 2016/17			Year 5 2017/18			Year 6 2018/19		
	Difference	Rel. Difference (%) [A]	P	Difference	Rel. Difference (%) [A]	P	Difference	Rel. Difference (%) [A]	P	Difference	Rel. Difference (%) [A]	P	Difference	Rel. Difference (%) [A]	P	Difference	Rel. Difference (%) [A]	P
Rate of elective admissions	0.03	0.02	0.99	1.8	1.1	0.36	4.9	3.0	0.02	8.2	4.9	<0.001	12.7	7.9	<0.001	3.4	2.0	0.15
Average LOS (days) of overnight emergency admissions	0.3	4.4	<0.001	0.2	2.0	0.09	-0.4	-4.9	<0.001	-1.0	-12	<0.001	-0.6	-7.3	<0.001	-0.5	-6.9	<0.001
Average LOS (days) of overnight elective admissions	0.1	2.9	0.2	0.2	3.8	0.09	-0.2	-4.8	0.03	-0.2	-4.2	0.07	-0.1	-1.3	0.6	-0.4	-8.8	<0.001
% of emergency admissions with a LOS less than 1 day [B]	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
% of elective admissions with a LOS less than 1 day	0.8	0.9	0.03	1.1	1.3	<0.001	0.4	0.4	0.23	1.6	1.9	<0.001	0.9	1.1	<0.001	1.1	1.2	<0.001
Rate of 30-day emergency readmission	-0.2	-2	0.36	-0.2	-1.7	0.45	-0.5	-4.8	0.01	-0.9	-7.8	<0.001	-1.9	-16.1	<0.001	-1.6	-14.2	<0.001
Rate of outpatient appointments	13.2	3.8	0.01	44.2	12.7	<0.001	81.6	25.6	<0.001	123.5	39.1	<0.001	114.4	42.0	<0.001	117.7	38.4	0.02

A Relative (Rel.) difference = Change in Mid-Nottinghamshire expressed as a percentage of the expected, as estimated in the synthetic control.
B Valid synthetic control could not be found.

Limitations

Due to constraints with national data sets, the evaluation was restricted to considering impacts on hospital use including A&E visits, emergency and elective admissions, emergency readmissions, elective and emergency length of stay and outpatient. While is was an objective of the vanguard to respond to pressures on the health system by reducing unnecessary hospital use, it would have been helpful to examine how the ICTP affects other domains, such as patient satisfaction, staff morale or improved quality of care. For a full picture of the impact of the ICTP in Mid-Nottinghamshire, the evaluation should be viewed in conjunction with the other research carried out by the local evaluator of the vanguard.

For some impact metrics (rate of emergency admissions from A&E and percentage of emergency admissions with a zero length of stay), it was not possible to find an adequate synthetic control area which accurately reflected the activity of Mid-Nottinghamshire in the pre-intervention period. Hence, it was not possible to make any conclusions about the impact of the ICTP on these measures in the post-intervention period.

For other impact metrics found to be significantly impacted by the ICTP, it is not possible to separately identify the contribution of each component of the ICTP. This is because the analysis estimates the impact of the whole suite of interventions implemented as part of the ICTP over the study period and cannot isolate the impact of each component. The interventions also evolved over time, making it harder still to determine cause and effect. We have tried to address this concern by presenting findings according to calendar year in order to isolate the impact of the ICTP in that year. Additionally, estimates may capture the impact of other changes, apart from those under the auspices of the ICTP, that occurred in the Mid-Nottinghamshire Better Together vanguard region in the post-intervention period.

Although a principled approach was used to determine which GP practices to include in the donor pool, we cannot rule out the possibility that the GP practices included were not the most appropriate ones. For instance, they may have also implemented changes whose effects could bias the estimates attributed to the vanguard. To mitigate this bias, we excluded GP practices from CCGs implementing other new care models from the donor pool and performed sensitivity analyses by reducing the size of the donor pool.

The synthetic control method assumes that similarity between observed and predicted values of the impact metrics in the pre-intervention period is indicative that the impact metrics would have been similar in the absence of the intervention in the post-intervention period. While this assumption is plausible, and we used a long pre-intervention period over which to assess similarity, this assumption is fundamentally untestable. As a result, we do not know the true counterfactual value of the impact metric. To mitigate this limitation, we assessed goodness of fit in the pre-intervention period and ran a range of sensitivity analysis varying the way the synthetic control area was selected.

Another limitation is that the true effect of patient characteristics is unknown. While we controlled for variation in relevant patient characteristics over time using a comprehensive set of observed covariates, it is possible that the risk adjustment equation was misspecified, or that unobserved covariates are not accounted for. This could lead to biased estimates of the impact of the intervention, although it should be noted that for impact metrics with significant effects, results were qualitatively similar even in the absence of risk adjustment.

A final point related to the external validity of our findings. Since the ICTP comprises multiple components evolving over time, it is unlikely that it could be easily replicated in another location and the specifics of any other implementation would need to be considered before inferring effects from this study.

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