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THE EFFECT OF MODEL UNCERTAINTY ON SMALL AREA LEVEL CAPITATION BUDGETS: AN EMPIRICAL ANALYSIS OF THE NORTHERN IRELAND CAPITATION FORMULA

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Abstract

Risk adjustment techniques are widely used to allocate resources to health plans across the world. In the UK, these techniques are used to allocate capitation based funding to geographically defined healthcare plans. New primary care led organisations are currently being established in the National Health Service servicing smaller population groups and hence it is important to assess the level of uncertainty inherent in risk adjusted capitations. We outline two types of uncertainty: uncertainty relating to the random variation in the use of healthcare services and uncertainty due to the model used to risk adjust capitation payments. In this paper we empirically estimate the effect of model uncertainty by calculating confidence intervals around capitation allocations using non-parametric bootstrapping techniques. We measure the size of this effect across a number of geographically defined areas in Northern Ireland. We illustrate that the level of model uncertainty is not related to population size. We discuss the implications of uncertainty on the setting of health plan budgets and conclude that the benefits of risk adjustment at a small area level outweigh the risks.

Background

Risk adjustment techniques are widely used across the world for allocating healthcare resources to healthcare plans. In this context the use of the term risk adjustment relates to the calculation of expected health expenditures of individuals over a fixed period of time for the purpose of setting healthcare plan budgets. Health plans can cover a wide variety of organisations from private health insurance companies, sickness funds (Netherlands, Israel), managed care organisations like HMOs (US) and capitated provider groups as in the UK [1].

Risk adjusted capitation models are widely used for allocating resources to geographically based healthcare plans across the UK [2, 3, 4]. These models estimate the expected share of resources a population will need based on the observed relationship between various population characteristics and the use of services. Due to data constraints these models are not calculated at an individual level but at small area level, often defined by postcodes. Increasingly, these models are being used to address policy goals as well as for setting plan budgets. For example, in England the capitation formula has an objective ‘to contribute to avoidable reductions in health inequalities’ whilst in Northern Ireland the capitation formula plays a key role in the Targeting Social Need (TSN) agenda.

These models are being developed and applied within an environment of continued institutional change in the UK National Health Service (NHS). Administrative structures in the NHS are currently changing with the establishment of new primary care organisations to replace or complement existing management structures. The aim of these small, locality based primary care organisations is to provide and commission services for local populations. In turn this restructuring may represent a substantial devolvement of power relative to current organisations and increasingly capitation formulae are being used to determine budgets for these organisations.

Table 1 illustrates how institutional structures have been changing across the UK and highlights the smaller population scales at which they operate.

[insert Table 1 here]

In England, primary care groups (PCGs) replaced old Health Authorities but are now on average a third of the size, whilst in Scotland and Northern Ireland similar smaller organisations have been established (however funds are not formally being devolved, but they may be for certain services in the future).

The devolvement of budgets to small populations is not a new phenomenon within the NHS. For example, in the early 1990s, the UK government established total fundholding pilots which consisted of single or a number of GP practices grouped together to purchase all services for their resident populations [5]. The requirement to devolve funding for all primary and secondary care services for these organisations highlighted the need for a robust mechanism for setting budgets at a small area level.

A number of studies have examined the potential risks associated with using capitation formula at a small area level and have focused on the risks of budgetary over- or under-spends. Martin and Smith [6] calculated the level of risk at various population sizes using the difference between the first level residuals and expected values from the acute capitation formula in England. They illustrated that the larger the degree of unexplained variation within the capitation formula the greater the degree of random variation and risk. Other methods include empirically sampling individual level data on the use of services to construct ‘synthetic’ area level expenditure to compare with area level budgets [7, 8]. In both of these approaches the researchers were concerned that due to the relative infrequency and inherent randomness of expensive healthcare events, budgets set for small populations would be subject to considerable uncertainty.

In this paper we extend this analysis by examining the issue of uncertainty in the setting of health plan budgets, rather than uncertainty related to the plans ability to manage risk associated with variations in healthcare expenditure. We develop this concept by expressing uncertainty in the capitation model by constructing confidence intervals around capitation risk adjustments. This illustrates more explicitly the uncertainty involved in setting health plan budgets, which have traditionally been presented as midpoints in the UK.

In the first section of the paper we set out a theoretical framework to distinguish between different types of uncertainty. The second and third sections outline the data and methods used to quantify model uncertainty. In the fourth section we present risk adjustments for a number of areas with associated confidence intervals and illustrate the impact of population size. The final section contains a discussion about the policy relevance of uncertainty and outlines areas for future research.

Theoretical Framework

One of the key issues in the development and implementation of any risk adjustment formula is the degree of uncertainty in the capitation allocations and the subsequent risk management issues. These two types of uncertainty can be defined and separately distinguished:

- first, what we call fundamental uncertainty, relates to uncertainty caused by unpredictable variations in medical *expenditure*; and
- second, model uncertainty, caused by uncertainty in the construction of the risk adjustment model used to determine *budgets*.

There are likely to be other sources of uncertainty impacting on the setting of health plan budgets but these are discussed later.

Fundamental Uncertainty

One source of uncertainty when setting risk adjusted budgets relates to the fundamental variation in the use of healthcare resources at an individual level. It is known that the use of healthcare varies enormously across individuals, with some individuals using very high quantities of resources and others not using any at all. These variations are due to both predictable and random elements. It has been estimated that up to 85% of expenditure is random after controlling for the effect of known risk factors at an individual level [9, 10].

It is therefore undesirable to apply average capitations to individuals because no matter how well the capitations are risk adjusted for observable factors, random and unpredictable variations will occur. Hence, decision-makers tend to apply average capitations to larger populations to reduce the probability of random fluctuations in the use of resources.

Figure 1a illustrates the uncertainty caused by random variations in the use of services, where risk relates to the difference between a capitation budget allocation and expenditure such that:

$$\left| b_t - x_t \right| > 0 \qquad [1]$$

where b_t is the capitation budget and x_t is actual expenditure in time period t.

[insert Figurse 1a and b here]

It is assumed that b_t represents an unbiased estimate of average per capita budget need. Under this assumption it can be illustrated that value of the risk or difference between expenditure and budget will tend to zero overtime:

$$\sum_{t=1}^{T} b_t - x_t \rightarrow 0 \quad \text{as} \quad t \rightarrow \infty \qquad [2]$$

The degree of random variation in x_t will also reduce as the population size within each plan increases due to the law of large numbers.

Model Uncertainty

The second source of uncertainty relates to uncertainty in the model used to generate risk adjustments. In the UK, risk adjustment modelling has focused primarily on how well various risk factors can predict current health spending. Regression models are estimated so as to generate unbiased predictions based on factors such as age, sex and socio-economic characteristics. Adjustments for age and sex are easy to estimate and are generally accepted by all parties, however, adjustments for socio-economic characteristics are more complex. In the UK, capitations are risk adjusted using an empirically estimated 'needs weight' based on the relationship between socio-economic variables and data on the use of healthcare services. It is the inherent uncertainty in this relationship which is important to quantify when considering the model uncertainty.

The effect of this uncertainty can be illustrated if we relax the assumption that b represents an unbiased estimate of average capitation need. It is then possible to identify upper and lower bound uncertainty ranges around capitation budgets. Figure 1b illustrates this with b^0 being our midpoint capitation budget estimate, varying from b^1 to b^2.

This approach explicitly recognises that there will always be a degree of error associated with the estimation of capitations using risk adjustment models. Importantly, with model uncertainty, policy makers cannot manage this risk by rolling budgets over a number of years. If a capitation budget is set at a level b^0 when the true level is b^1 then there will be a permanent mismatch between expenditure and budgets:

$$\sum_{t=1}^{T} b_t^0 - x_t \rightarrow \left| b_t^0 - b_t^1 \right| t \quad \text{as} \quad t \rightarrow \infty \qquad [3]$$

In this paper we measure the size of model uncertainty by isolating the effect of variations in the regression coefficients included in the risk adjustment model.

Data and Data Sources

We have used data from the Northern Ireland capitation formula to measure the impact of model uncertainty. The Northern Ireland formula is used to distribute resources between four Board areas using capitation techniques developed by Carr-Hill et al [11]. Each Board is allocated a budget based on its population share, adjusted for the Board's age and sex profile and a 'needs weighting' to reflect the impact of socio-economic variables. The formula is split into nine programmes of care (POCs). In five out of the nine programmes 'needs weightings' are derived from regression analysis at a small areas level. The methods and results of the formula have been published by the Capitation Formula Review Group (CFRG) [4].

We have selected two programmes of care to illustrate the impact of model uncertainty: the acute programme and the family and childcare programme. The acute formula was estimated using data on acute hospital admissions in 1994/5 and allocates approximately 40% (£650m) of healthcare resources in Northern Ireland. The family and childcare formula was estimated using data on children and family support caseload contacts and allocates approximately 6% of healthcare resources (£100m).

Each dataset contains a dependant variable defined as the actual to expected ratio of the use of services and a series of explanatory variables. The actual variables, coefficients and standard errors contained in each formulae are illustrated in Table 2.

[insert Table 2 here]

All data were provided by the Department of Health and Social Services and Public Safety (DHSSPS). The techniques used to develop each formulae are described in detail elsewhere [12, 13, 14].

The dataset contains 498 observations based on small areas or synthetic wards, with an average population of 3,170, ranging from 1,800 to 9,700. Each synthetic ward can be grouped into geographical areas of varying size, either at a Board level with an average size of 400,000 (ranging 260-630,000) or at a locality level with an average size of 32,000 (ranging from 14-150,000). There are four Boards and 27 localities within Northern Ireland (localities are usually co-terminus with district council boundaries).

Methodology

The acute and family and childcare formulae were replicated using the variables outlined in Table 2 with the following functional form:

$$u_{ih} = a + \sum_{h=1}^{H-1} d_h D_{ih} + \sum_{j=1}^{J} b_j x_{ihj} + e_{ih} \qquad [4]$$

in which e_{ih} are independently-distributed error terms with zero mean, x represents a vector of explanatory variables, u_i is an age and gender standardised measure of cost, and D a series of dummies variables for area of residence (D_{ih} = 1 if area i is in region h: D_{ih} = 0 otherwise). Both models were estimated with log linear functional forms.

Using the results from the regression analysis, we re-estimated the acute 'need weighting' or predicted values by multiplying the regression coefficients with actual values at a synthetic ward level:

$$n_{ih} = \sum_{j=1}^{J} \hat{b}_j x_{ihj} \qquad [5]$$

Standard capitation or risk adjustment methods multiply area level values (x) by the estimated midpoint coefficient values ($\hat{b}$).

In order to measure the effect of model uncertainty we relaxed the assumption that the coefficient values represent midpoints. Using non-parametric bootstrapping techniques we re-estimated the regression equation to construct an empirical distribution around each explanatory variable coefficient [15]. One hundred sets of coefficient values were simulated, and for each set, a needs weighting was calculated at a small area level. We performed the analysis using a bootstrap macro in STATA [16].

The small area level needs weight was aggregated into two levels: Board level and at a locality level. 90% confidence intervals were constructed around each Board and locality needs weight using the percentile method. The confidence intervals were translated into uncertainty intervals by expressing the percentage variation of the upper and lower bound from the mid-point.

Results

Table 3 illustrates the results of the analysis for the acute and family and childcare programmes of care. It illustrates the estimated needs weighting to be applied to each locality and Board to adjust capitations for socio-economic factors. An index value above 1.0 represents an area with an above average need for healthcare resources and vice versa. The acute needs weighting has a relatively tight distribution across localities ranging from 0.88 to 1.13, whilst the family and childcare weighting ranges from 0.49 to 1.85. The 90% confidence intervals illustrate the confidence we have in the midpoint 'needs weighting' for each locality or Board. In the acute model the intervals are very tight whilst in the family and childcare programme the estimates are subject to greater uncertainty.

Figures 2a and 2b plot locality and Board level uncertainty intervals for both programmes of care across population size. The vertical bars represent the 90% uncertainty interval for each locality or Board, where there is less than a 5% chance of the budget being over or under the upper or lower bound respectively. Interestingly we found no relationship between population size and the size of model uncertainty. This implies that budgets are as accurate at a small area level as at a Board level. This is in contrast to the literature examining the effects of fundamental uncertainty, which illustrate that the risk that expenditure deviates from budgets increases exponentially as population size falls.

It is important to note that the level of model uncertainty is not simply related to the R-squared of the risk adjustment model. The acute and family and childcare models both explain a similar proportion of the variation in the use of services, but the wide standard errors around the coefficients in the family and childcare model create greater uncertainty around the needs weighting. The high R-squared in the family model is primarily due to the 26 area level fixed effects included in the regression.

Discussion

In this paper we have outlined and distinguished between two types of uncertainty; fundamental uncertainty relating to the random variation in the use of services and model uncertainty relating to the robustness of the risk adjustment model. Previous analysis has concentrated on uncertainty for *budget-holders* associated with the unpredictable variation in the use of services. We have extended this analysis by examining the uncertainty facing *budget-setters* by relaxing the assumption that capitation budgets can be expressed as midpoints. We have presented this uncertainty by constructing confidence intervals around area level needs weightings.

We believe that this analysis has important policy implications because model uncertainty cannot be managed using similar mechanisms to those used to manage fundamental uncertainty. In fact, we consider that the uncertainty associated with random variations in the use of services may be overstated because there are a number of mechanisms available for managing demand fluctuations. These methods include the development of risk sharing agreements, by increasing the frequency of healthcare ‘events’, and the use of soft budget constraints or slack budgets.

Firstly, risk-sharing techniques are frequently used to ensure that very high cost patients do not create uncertainty for budget-holders. For example in the UK, General Practitioner prescribing budgets often incorporate an element of risk sharing because certain high-cost low-volume drugs are funded centrally. There are also a number of methods that can be used to increase ‘event’ frequencies. These include increasing the population size in each health care plan, by ‘bundling’ together a number of services (such as acute hospital, mental health and geriatric services etc) or by rolling budgets over a number of years. Clearly, event frequencies are strongly correlated with population size, but the type of service covered is also of importance. For example, for a given population, the number of pharmaceutical prescriptions dispensed will be far greater than the number of acute hospital admissions and therefore the associated uncertainty is lower. A third method for managing random variations in the use of services is to set soft budget constraints. This occurs when managers incorporate 'slack' into budgets, hold back contingency funds or cross subsidise overspends from other budgets. The NHS also has good mechanisms for absorbing periods of peak demand without the need to increase capacity, for example, waiting lists can increase and hospitals usually operate below full capacity as illustrated by bed occupancy rates below 100%.

Clearly budgets set at a very small level will create uncertainty for budget-holders but, as illustrated above, there are a number of methods available for managing this uncertainty. In general, we consider that budgets can be set with reasonable confidence at a small area level provided that event frequencies are relatively high and other sensible risk management techniques can be agreed.

The issue of model uncertainty should be seen as an equally important issue for policy makers because, as illustrated earlier in the paper, the size of this error will increase over time and cannot be managed with existing techniques. Model uncertainty can only be reduced by developing more robust risk adjustment models, either by increasing the sample size, or by improving the measurement effect of the explanatory variables. Unfortunately, it is unlikely that either of these approaches will be straightforward. It would be difficult to increase the sample size especially in small regions such as Northern Ireland, and if 'better' explanatory variables were available the researcher would most likely have already incorporated them.

Model uncertainty is also an important issue for budget-setters to consider because NHS managers are expected to balance their budgets each year. Budget underspends, or more frequently budget overspends are strictly audited and monitored. So even if budgets are set at a 'structurally incorrect' level in the short- to medium-term managers will ensure expenditure converges on the target budget.

In this paper we have only tackled one aspect of model uncertainty, defining it narrowly as the measured variation in regression coefficients. In the United States, there is a large body of literature examining the issue of model uncertainty from a number of different angles. This literature predominately examines issues associated with the predictive power of risk adjustment models, measuring the error between actual and predicted expenditure [1]. There has also been an increased use of simulation and sampling techniques to estimate model stability by repeatedly selecting random subsets of data and selecting between functional forms. For example, a paper by

Hornbrook and Goodman [17] uses multiple sampling techniques to resample their dataset to generate variations in model coefficients and also to identify the likelihood of selected variables being statistically significant. An area for further research in the UK is to consider how these techniques, developed for use with individual level data, can be applied at an area level.

A final issue we wish to raise is the extent to which as researchers we should highlight the issue of model uncertainty. Policy makers often view risk adjustment models as 'scientific' offering technical solutions to value judgements. Explicitly stating uncertainty ranges in capitation budgets may be unappealing to budget-setters especially if it undermines the confidence of budget-holders. However, the explicit recognition of uncertainty may stimulate further debate on how to improve current methods and may increase the credibility of the process, after all, those involved in the formula estimation process understand the uncertainties involved.

One conclusion we do not wish to be drawn from this debate is that it is too 'risky' to set capitation budgets at a small area level. We strongly believe that the benefits of using a capitation formula based approach to setting small area budgets will substantially outweigh any risks. Even the use of a formula with a high degree of uncertainty may provide a more equitable approach to resource allocation compared to current ad-hoc methodologies.

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TABLES AND FIGURES

Table 1. Administrative Health Care Structures

Country	Group		Average Population Size	
	Commissioning	Primary Care	Commissioning	Primary Care
England	Health Authorities	Primary Care Groups	500	150
Scotland	Boards	Local Health Care Co-operatives	350	50
Northern Ireland	Boards	Local Health and Social Groups	400	100

Table 2. Acute and Family and Childcare Formula

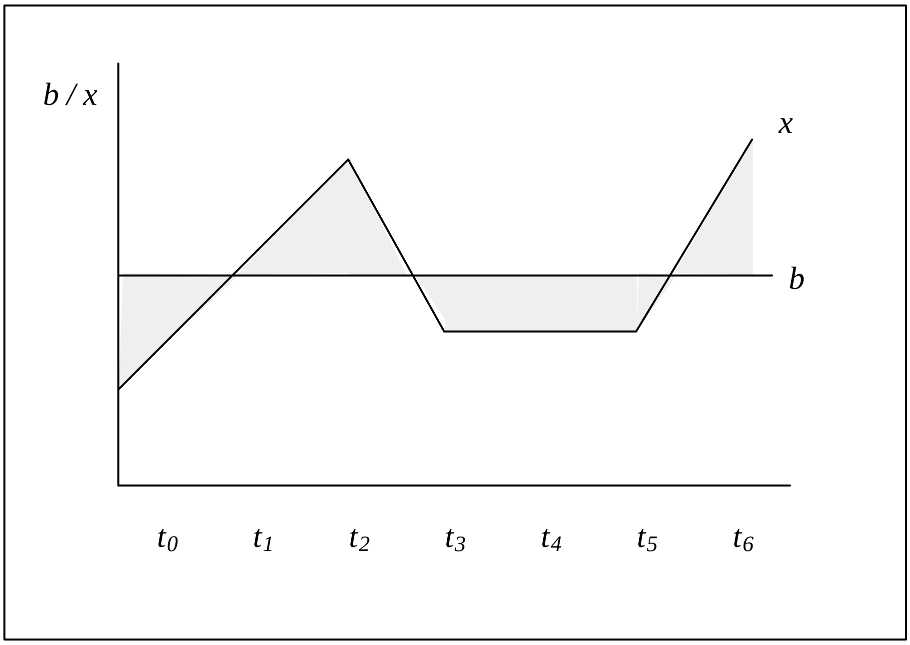
Acute Formula		Family and Child Care Formula	
Variable	Coefficient (se)	Variable	Coefficient (se)
Aged over 75 and living alone	0.107 (0.024)	Dependent children living in social rented housing	-3.693 (1.52)
1-(proportion of households claiming family credit)	-2.195 (0.379)	Families with dependent children where head of household is lone parent on income support	0.691 (0.047)
Proportion of households claiming income support	0.079 (0.019)	Children with limiting long term illness	-9.479 (4.61)
All age standardised mortality ratio	0.271 (0.038)		
Proportion of low birth weight babies	0.051 (0.016)		
R^2	0.530		0.532

Table 3. Acute and Family and Childcare Needs Weightings

Area	Needs Weighting (90%CI)					
	Family and Childcare			Acute		
	Midpoint	5%	95%	Midpoint	5%	95%
Locality						
a	0.839	0.796	0.874	0.984	0.974	0.991
b	0.620	0.570	0.661	0.934	0.926	0.943
c	0.656	0.611	0.685	1.011	1.006	1.016
d	0.749	0.711	0.782	0.937	0.932	0.943
e	0.699	0.645	0.730	0.987	0.979	0.994
f	0.578	0.527	0.614	0.934	0.927	0.941
g	1.848	1.766	1.966	1.135	1.120	1.148
h	1.0140	0.891	1.178	0.946	0.937	0.960
i	0.718	0.676	0.756	0.973	0.962	0.982
j	0.545	0.499	0.583	0.879	0.869	0.892
k	0.899	0.866	0.924	0.960	0.955	0.966
l	0.791	0.747	0.821	1.028	1.019	1.037
m	0.966	0.912	1.017	1.025	1.017	1.032
n	1.804	1.731	1.935	1.105	1.094	1.115
o	0.797	0.753	0.823	0.999	0.994	1.005
p	0.876	0.846	0.890	1.060	1.050	1.067
q	0.697	0.648	0.726	0.987	0.980	0.994
r	0.779	0.729	0.817	0.960	0.953	0.968
s	0.925	0.888	0.949	1.046	1.037	1.054
t	1.303	1.241	1.399	0.972	0.966	0.979
u	0.728	0.681	0.755	0.987	0.975	0.999
v	0.828	0.775	0.868	1.021	1.013	1.030
w	0.958	0.922	0.984	1.047	1.035	1.057
x	0.7150	0.672	0.744	0.926	0.920	0.934
y	0.493	0.445	0.534	0.888	0.877	0.902
z	0.807	0.766	0.835	1.042	1.031	1.050
aa	1.122	1.104	1.136	1.080	1.067	1.093
Board						
a	1.117	1.087	1.159	0.986	0.981	0.991
b	0.773	0.733	0.805	0.966	0.962	0.970
c	0.851	0.814	0.877	1.024	1.020	1.027
d	1.221	1.202	1.255	1.059	1.051	1.067

Figure 1. Uncertainty and Budget Setting

a.



b.

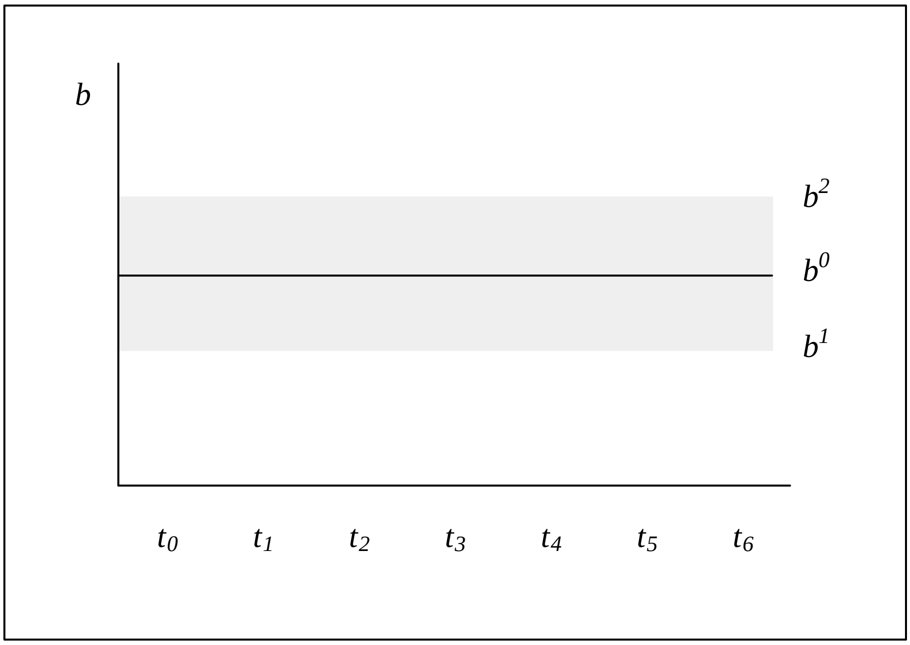
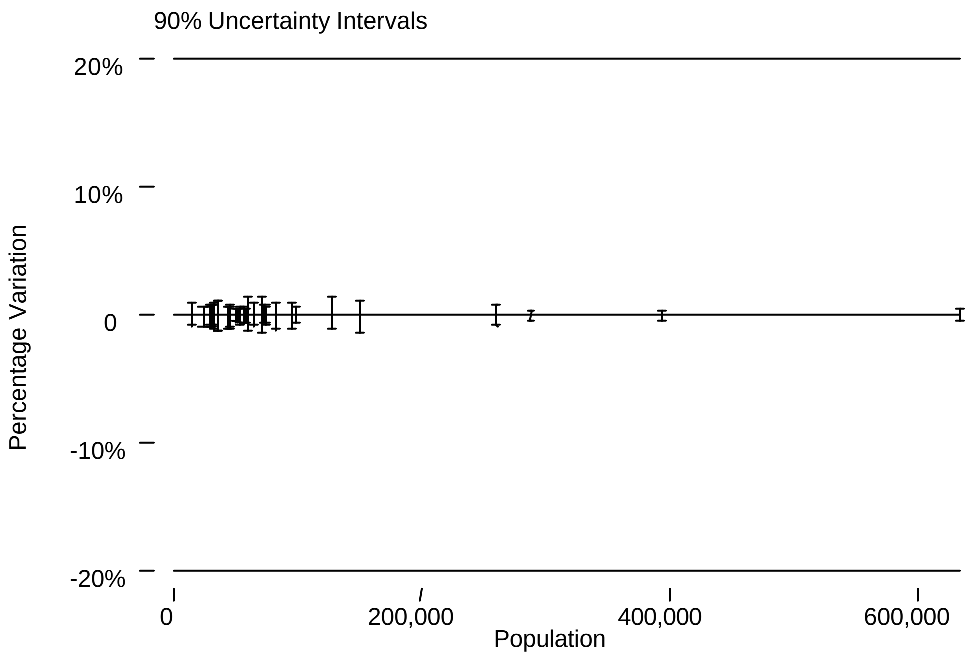


Figure 2. Percentage Variation in Budgets

a. Acute Programme



b. Family and Childcare Programme