



THE UNIVERSITY *of York*

Discussion Papers in Economics

No. 2003/15

The Effect of Practice Budget on Patient Waiting Time:
Allowing for Selection Bias

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The effect of practice budgets on patient waiting times: allowing for selection bias

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Abstract

In many health care systems primary care physicians act as ‘gatekeepers’ to secondary care. Under the UK fundholding scheme, general practices could elect to hold a budget to meet the costs of elective surgery for their patients. It was alleged the patients of fundholding practices had shorter waits for elective surgery than the patients of non-fundholders. Comparison of waiting times between fundholding and non-fundholding practices are potentially confounded by selection bias as fundholding was voluntary. We estimate the effect of a practice’s fundholding status on the waiting times of its patients for the penultimate year of fundholding using both cross sectional and difference in differences methodologies to correct for selection bias. The cross-sectional methods applied to data for the penultimate year of the fundholding scheme were: OLS, “kitchen sink” regression including variables affecting the decision to become a fundholder in the waiting time regression, propensity score matching (nearest neighbour, radius, stratification and kernel matching), instrumental variables, and two selection correction methods. Difference in difference methods compared the changes in waiting times for fundholder and non-fundholder practices before and after the abolition of fundholding, and the differences between fundholder and non-fundholder waiting times for chargeable procedures within and non-chargeable procedures without the fundholding scheme. We also construct a difference in difference in differences estimate based on the difference between procedures and over time for fundholders and non-fundholders.

All methods suggest that the effect of fundholding status was to reduce the waiting times of fundholders by 5% to 8%. The IV and selection correction methods produce positive estimates of selection bias: fundholders would have had higher waits than non-fundholders if they had not been fundholders. All other methods suggest smaller and sometimes negative selection bias.

Keywords: Budgets. Fundholding. Waiting times. Selection bias. Treatment effects.
JEL nos: I18, I11

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Acknowledgements: NPCRDC and CHE receive funding from the Department of Health. The views expressed are not necessarily those of the funders. We thank Steve Martin, Matthew Sutton and Andrew Wagner for assistance with data. We are grateful to Arild Aakvik, Vincenzo Atella, participants in the York Seminars in Health Econometrics and the 12th European Workshop on Econometrics and Health Economics for helpful comments.

1 Introduction

Like many health care systems the English National Health Service rations elective, or non-emergency, hospital care by waiting time. All patients must join the list of a general practice in order to be referred to a hospital where they will be placed on a waiting list if the hospital consultant decides that they need treatment. Around 1 million patients are on the NHS waiting list and the mean wait is 110 days.

In 1991 the UK government introduced a split between purchasers and providers of health care in the NHS [1]. Health Authorities (HAs), geographically defined entities covering on average initially about 300,000 citizens, became the main purchasers of health care. The providers of secondary care (principally hospitals) were removed from the direct control of HAs and renamed NHS Trusts. They remained within the public sector but were required to compete for contracts from purchasers in what was known as the NHS internal market.

As part of the 1991 reforms larger general practices could elect to become fundholders [2]. Fundholding practices became responsible for purchasing some elective procedures from local providers and were given an annual budget by their local Health Authority to do so. The HA thus delegated part of its budget and purchasing responsibility to those of its general practices that chose to become fundholders.

A change of government in 1997 led to a further major reform of the NHS [3]. No new fundholders were allowed from April 1998 and fundholding was abolished in April 1999. New organisations, Primary Care Trusts (PCTs), in which primary care professionals (particularly GPs) were intended to play a central managerial role, became the main purchasers of health care.¹ All practices had to join their local Primary Care Trusts. PCTs are formally responsible for health care in a geographically defined area, though their populations (around 150,000) are the populations of their constituent practices (typically numbering around 20 to 25).

One of the reasons given for abolishing fundholding was that it led to inequity. It was alleged that because of the financial incentives under fundholding, patients of fundholding practices faced shorter waiting times than patients of similar practices which chose not to become fundholders. A non-fundholding practice whose elective patients were paid for by the Health Authority could only attempt to reduce their patient's waiting time by persuading the hospital consultants to give them greater priority when patients were selected from the waiting list. Fundholding practices could, in addition, threaten to reduce provider revenue by shifting business elsewhere.

There is relatively little firm evidence on the effect of fundholding on waiting times. Studies have tended to be small scale, to lack adequate controls and to be difficult to generalise. The major problem is selection bias: because fundholding was voluntary it was difficult to disentangle the effect of the financial incentives of fundholding from

¹ Initially in April 1999 Primary Care Groups were introduced as subcommittees of their local HA but it was intended that they would progress to become separate legal entities as PCTs. By April 2002 all PCGs had become PCTs and HAs were abolished.

the unobservable characteristics of the practices that could influence both their waiting times and their decision to become fundholders. Consequently fundholders might have had different waiting times from non-fundholders even if they had not chosen to become fundholders.

Only two studies have attempted to allow for selection bias [4; 5]. Both use the difference in difference methodology of comparing the change in waiting times for practices which became fundholders with the change for practices which remained non-fundholders. Both find that the patients of fundholding practices had shorter waiting times. Dowling [4] used data from four provider Trusts in a single Health Authority over a four-year period (1992/3 to 1995/6) and two separate cross-section analyses of the differences in mean waits between the practice types at each provider. He found that there was no difference between the waiting times for patients of fundholding practices in the year before the practice became a fundholder and the waits of non-fundholders. The patients of fundholding practices in the first year after the practice became a fundholder had significantly shorter waits than those of non-fundholders. Propper et al [5] used a formal panel data difference in difference model to examine the relationship between the waiting times of individual patients and the fundholding status of their practice in a different Health Authority. They also allowed for the possible bias which could arise if a practice's decision to become a fundholder was affected by their expected future waiting time. They controlled for practice, provider and specialty effects and found that waiting times of patients in fundholding practices fell relative to non-fundholders after the practice became a fundholder but only for admissions to which the fundholding scheme applied.

We use the opportunity offered by the abolition of the voluntary fundholding regime and its replacement by the compulsory PCT scheme to examine the effect of budgetary regimes on waiting times. We have a newly constructed national data set [6] including information on mean waiting times for over 7000 practices (fundholding and non-fundholding) for the two years before (1997/8, 1998/9) and the two years after (1999/2000, 2000/1) fundholding was abolished. The fact that the 43% of practices which were standard fundholders had to switch from the fundholding regime to the PCT regime means that the difference in differences methodology has a greater chance of identifying the effect of the change in budgetary regimes compared with studies based only on data from the fundholding period when the numbers switching financial regimes in any year was much smaller. Moreover, because the end of fundholding was compulsory and we examine a period in which very few practices became fundholders there is a much reduced problem of endogenous timing of the budgetary regime change.

A number of methods have been proposed for dealing with selection bias in treatment effect models [7; 8; 9]. We first take data on waiting times for procedures covered by the fundholding scheme for a single year (1997/8) when the fundholding scheme was still in force. We estimate the effect of a practice's fundholding status using a variety of methodologies which have been suggested for application to cross-section data to correct for selection bias: "kitchen sink" regression including variables affecting the decision to become a fundholder, propensity score matching (nearest neighbour, radius, stratification and kernel matching), instrumental variables, and two variants of the Heckman selection approach.

We then use our full data set to compare such methods to the, not always feasible, alternative solution to selection bias: getting additional data which may provide information on the unobservable characteristics of practices which may be associated with waiting times and fundholding status. In our full data set we have two sources of such information. First, we can distinguish between chargeable admissions, for which a practice would have to pay if they were a fundholder and non-chargeable admissions for which neither type of practice had to pay. We use the data on non-chargeable admissions for 1997/8 to construct an estimate of the effect of fundholding status from the difference in waiting times for chargeable and non-chargeable admissions for fundholding practices and for non-fundholding practices. Second, we have data on waiting times for both types of admission after the end of fundholding and use it to estimate a temporal difference in differences model for chargeable procedures and a difference in difference in differences model of the change in the difference between chargeable and non-chargeable admissions for fundholding and non-fundholding practices.

2 Data

Data were collated from three main sources: Hospital Episodes Statistics for admissions, General Medical Statistics for practice characteristics and the database assembled for the AREA project [10] for socio-economic characteristics and provider characteristics. Details are in the Appendix. The dependent variable was the mean elective waiting time of patients admitted from a practice in a year for chargeable and non-chargeable admissions. (Results using median waiting time were very similar). Table 1 shows mean elective waiting times for the four years 1997/8 to 2000/1 for both types of admissions and gives summary statistics.

There were a number of different types of fundholder. Our interest is in the standard fundholding scheme which gave practices a budget for the purchase of certain types of elective procedures from hospital trusts. We distinguish between standard fundholders and all other practices (non-fundholders, fundholders who had budgets only for prescribing and fundholders who had budgets only for community health services such as health visiting) who we label “non-fundholders” since they had no budget for the purchase of elective care. We exclude from the analysis a small number of practices (55) which became wave 8 fundholders in April 1998 by applying to become fundholders before an official ban on new applications for fundholding status was put into effect in May 1997 [3]. The practices in the analysis are therefore those which never became standard fundholders or had become standard fundholders by April 1997.

Demographic effects are allowed for by including the age and sex proportions of the practice population as explanatory variables. The procedure is more flexible than direct or indirect standardisation and does not require recomputation of the dependent variable when the observation set changes. We also use imputed data on the socio-economic and morbidity characteristics of practice populations which may affect waiting times for patients.

Practice characteristics such as the age, gender of GPs, country of qualification, the types of clinics they offer, and their training status are used both to increase the

precision of the effects of fundholding and to provide instruments to explain fundholding status.

We use information on the characteristics of providers, such as the number of consultants and the waiting times for outpatients, since these may measure aspects of hospital decision making which affect waiting times. All the models reported are estimated with Health Authority effects. We also estimated models with provider effects to allow for differences in waiting times across providers due to unobserved differences in consultants' criteria for selecting patients from the waiting list. The results were very similar to those with HA effects and are not reported.

As Figure 1 shows, the number of admissions varied across practices thereby presenting potential heteroscedasticity problems. We dropped practices with less than five admissions, and compared models with weighted observations (where the weights were the square root of practice size) with unweighted observations. We also estimated models with robust standard errors.

3 Selection and fundholding in cross section models

3.1 Selection on observables

We first use data for the penultimate year of fundholding 1997/8 and apply a variety of cross-section methods to estimate how much of reduced waiting time associated with being a fundholder is a genuine treatment effect of the financial incentives of fundholding and how much would have occurred in any case because of unobservable characteristics of fundholding practices. We use the potential outcomes framework from the treatment effects literature [9; 11] to describe the alternative estimators. Let y_{i0} be the waiting time a practice would have if it is not a fundholder and y_{i1} the waiting time it would have if it is. Assume that potential waiting times are determined by the linear model:

$$y_{ig} = \mu_g + \alpha'_2 \mathbf{x}_i + v_{ig}, \quad \text{Ev}_{ig} = 0, \quad g = 0, 1 \quad (1)$$

where \mathbf{x}_i is a vector of observable covariates (such as practice patient population socioeconomic and morbidity characteristics, GP characteristics, local providers). Let F_i be a dummy variable with $F_i = 0$ or 1 depending on whether practice i is a non-fundholder or a fundholder. F_i^* is 0 or 1 as the latent gain F_i^* from being a fundholder is negative or non-negative:

$$F_i = 0 \text{ (or } 1) \Leftrightarrow F_i^* = \boldsymbol{\pi}' \mathbf{w}_i + u_i < 0 \text{ (or } \geq 0) \quad (2)$$

The errors in (1) and (2) are independent of the possibly overlapping vectors \mathbf{x} and \mathbf{w} of observables. Independence requires only that any unobservable variables which affect y_{ig} and F_i^* do so additively, so that the errors in the potential outcome equation are the errors from a linear projection of these unobserved variables on the observed. The coefficients on the observed variables will in general pick up the effects of the unobservable variables. Since we are interested in the effects of fundholding, rather than in obtaining unbiased estimates of the partial effects of observed variables any omitted variable bias in their coefficients does not matter.

The effect of fundholding status on a randomly chosen practice is the *average effect of treatment*:

$$ATE = E(y_{i1} - y_{i0}) = \mu_1 - \mu_0 = \alpha_1 \quad (3)$$

The concern over differences in waiting times is about horizontal equity: did patients in otherwise identical practices have shorter waiting times if the practice was a fundholder than if it was not? Hence we want to estimate the *average effect of treatment on the treated* (ATT) which is the average effect of fundholding status on waiting times of practices which choose to become fundholders:

$$\begin{aligned} ATT &= E(y_{i1} - y_{i0} | F_i = 1) = \mu_1 - \mu_0 + E(v_{i1} - v_{i0} | F_i = 1) \\ &= \underbrace{\alpha_1}_{ATE} + \underbrace{E(v_{i1} - v_{i0} | F_i = 1)}_{AATT} \end{aligned} \quad (4)$$

ATT includes the effect which a randomly chosen practice would experience (ATE) but it also includes the *average additional effect of treatment on the treated* (AATT) which arises from unobservable characteristics of practices which chose to become fundholders.

The waiting time of practice i is:

$$\begin{aligned} y_i &= (1 - F_i)(\mu_0 + \alpha'_2 \mathbf{x}_i + v_{i0}) + F_i(\mu_1 + \alpha'_2 \mathbf{x}_i + v_{i1}) \\ &= \mu_0 + (\mu_1 - \mu_0)F_i + \alpha'_2 \mathbf{x}_i + v_{i0} + F_i(v_{i1} - v_{i0}) \\ &= \alpha_0 + \alpha_1 F_i + \alpha'_2 \mathbf{x}_i + \varepsilon_i \end{aligned} \quad (5)$$

The average difference between waiting times for fundholding and non-fundholding practices, which can be estimated from (5) as the coefficient on F_i after regression of y_i on $(1, F_i, x_i)$ is:

$$\begin{aligned} E(y_i | x_i, F_i = 1) - E(y_i | x_i, F_i = 0) &= E(y_{i1} | x_i, F_i = 1) - E(y_{i0} | x_i, F_i = 0) \\ &= \mu_1 - \mu_0 + E(v_{i1} | x_i, F_i = 1) - E(v_{i0} | x_i, F_i = 0) \\ &= \alpha_1 + E(v_{i1} - v_{i0} | x_i, F_i = 1) + E(v_{i0} | x_i, F_i = 1) - E(v_{i0} | x_i, F_i = 0) \\ &= \underbrace{\alpha_1}_{ATE} + \underbrace{E(v_{i1} - v_{i0} | F_i = 1)}_{AATT} + \underbrace{E(v_{i0} | F_i = 1) - E(v_{i0} | F_i = 0)}_{\text{Selection Bias}} \end{aligned} \quad (6)$$

which is neither the effect of fundholding on fundholders nor the effect of fundholding on a randomly chosen practice. A simple comparison of the waiting times of fundholders and non-fundholders does not estimate the effect of fundholding on fundholders because part of the difference between practices which chose to become fundholders and those which did not would have been present even if no practices had been fundholders.

Since we are interested in the effect of fundholding on fundholders we want to purge estimates of selection bias. If the factors affecting the decision to become a fundholder are a subset of those in the waiting time equation (1) and the error u_i in the selection model (2) is uncorrelated with the errors v_{ig} in the waiting time equations then F_i is uncorrelated with v_{ig} . Since F_i is a (0,1) dummy the fact that it is uncorrelated with v_{ig} implies that:

$$E(v_{ig} | x_i, F_i) = E(v_{ig} | x_i) \quad (7)$$

so that selection bias is zero:

$$E(v_{i0} | x_i, F_i = 1) - E(v_{i0} | x_i, F_i = 0) = E(v_{i0} | x_i) - E(v_{i0} | x_i) = 0 \quad (8)$$

The “kitchen sink” method [7] is to use a large set of covariates which might predict fundholding in the waiting time regression in the hope that the mean independence condition (7) is satisfied. Since mean independence also implies that AATT is zero, so that $ATT = ATE$, the method identifies both the average effect of treatment and the effect of treatment on the treated.

The kitchen sink, and related regression methods, require assumptions about the functional form of the waiting time regression, as well as mean independence. Propensity score methods also rest the mean independence assumption but do not impose functional form assumptions on the regression of the errors in the potential outcome equations on the covariates. The aim is to estimate the probability that a practice is a fundholder $p_i = \Pr[F_i = 1 | \mathbf{x}_i] = p(\mathbf{x}_i)$ and then to compare the waiting times of fundholders and non-fundholders with the same probability:

$$\begin{aligned} E(y_i | p(x_i), F_i = 1) - E(y_i | p(x_i), F_i = 0) &= E(y_{i1} | p_i, F_i = 1) - E(y_{i0} | p_i, F_i = 0) \\ &= \alpha_1 + E(v_{i1} - v_{i0} | p_i, F_i = 1) + E(v_{i0} | p_i, F_i = 1) - E(v_{i0} | p_i, F_i = 0) \end{aligned} \quad (9)$$

If it is assumed that v_{i0} is conditionally independent of F_i given \mathbf{x}_i then it is also independent conditional on a function of \mathbf{x}_i . Hence the last term vanishes. Since v_{ig} are mean independent of \mathbf{x} they are mean independent of $p(\mathbf{x}_i)$ and so the middle term is $E(v_{i1} - v_{i0} | F_i = 1)$ and (9) is the effect of fundholding on fundholders with a given probability of being a fundholder. The method requires that there must be sufficient fundholder and non-fundholder practices with the same value of $p(\mathbf{x}_i)$.

When there are many covariates or they are continuous it is not possible to find practices with the same propensity score for comparison and so fundholders and non-fundholders with “similar” scores are matched and compared. Various definitions of “similar” yield different propensity matching estimators: the nearest neighbour method matches a fundholder with the non-fundholder with the nearest probability; the radius method matches with the mean of non-fundholders within a given probability radius; kernel methods match with a weighted set of non-fundholders with the weights declining with distance [12].

3.2 Selection on unobservables

3.2.1 IV estimation

There is evidence that fundholders, especially early wave fundholders, were different from non-fundholding practices [13]. Some of these differences, such as the mean age of the GPs in the practice, are observable in administrative data sets but others, such as the strength of entrepreneurial attitudes are not [14]. If the unobservable factors affecting the propensity to become a fundholder also affect waiting times as a non-fundholder then the methods considered in the previous section will not produce unbiased estimates of the effect of fundholding.

Suppose that the unobservable errors in the waiting time equations vary across practices but are not affected by whether the practice is a fundholder or not:

$$v_{i0} = v_{i1} = v_i \quad (10)$$

Then $ATT = ATE = \alpha_1$, and if we can find a set of instruments \mathbf{z} correlated with F_i but not with v_i , then we can use two stage least squares to consistently estimate α_1 .

With slightly stronger assumptions we can use a more efficient and robust IV estimator [7]. The estimator uses a probit model to estimate the binary fundholding variable $\Pr[F_i = 1|\mathbf{w}_i] = G(\mathbf{w}_i;\boldsymbol{\pi})$, where $\boldsymbol{\pi}$ are the parameters to be estimated. The predicted probabilities are then used as an instrumental variable for fundholding status in the 2SLS estimation of the waiting times model. The usual 2SLS standard errors and test statistics are valid and we also employ heteroskedasticity consistent standard errors. We do not have to ensure the model for selection is properly specified, merely that the instruments are good predictors of fundholding status.

We estimate the model using the *probit* and *ivreg2* commands in Stata version 7 [15]. To test that the instruments are correlated with treatment status we include them in the first stage regression (as opposed to the single predicted probability from the first stage probit regression of fundholding status on \mathbf{w}). We use *ivreg2* to estimate the Shea ‘partial R^2 ’ statistic and test the significance of the strength of association using the approach suggested by Davis and Kim [16]. This is a LR test of the Shea R^2 against a test statistic, computed as $(1-\exp(c.v)/T)$, where $c.v$ is the critical value from a chi-squared distribution with 1 degree of freedom, and T the sample size.

To test the over-identifying restrictions, and hence the independence of the instruments from the unobservable error process, we require an excess number of instruments. With G used as the sole instrument, the model is exactly identified but we can use the linear predictor to test this assumption by employing a one step 2SLS using all the excluded instruments. The tests can also be considered as joint tests of both correct model specification (the excluded instruments are valid instruments and correctly excluded from the estimated equation) and the orthogonality conditions. As we estimate the models using robust standard errors, *ivreg2* employs Hansen’s J statistic, which is distributed as a chi-squared with degrees of freedom equal to the number of over-identification restrictions (L-K), where L is the total number of exogenous regressors and K the number of exclusion restrictions (over-identified instruments).

3.2.2 Heckman selection model

We also allow for the endogeneity of fundholding status using Heckman’s two-step consistent estimator which does not require that the variables which explain fundholding are uncorrelated with the waiting time. We specify a probit model for the selection mechanism (treatment equation) so that u is a standard normal variate. Maintaining assumption (10), that any unobservables have the same effect on waiting times irrespective of fundholding status, $ATT = ATE$ and:

$$\begin{aligned} E[y_i | x_i, F_i = 1] - E[y_i | x_i, F_i = 0] &= E[y_{i1} | x_i, F_i = 1] - E[y_{i0} | x_i, F_i = 0] \\ &= \mu_1 - \mu_0 + E[v_i | \mathbf{x}_i, u_i \geq -\boldsymbol{\pi}'\mathbf{w}_i] - E[v_i | \mathbf{x}_i, u_i < -\boldsymbol{\pi}'\mathbf{w}_i] \\ &= \mu_1 - \mu_0 + \sigma_v \rho_{vu} \frac{\phi(-\pi w_i)}{1 - \Phi(-\pi w_i)} - \sigma_v \rho_{vu} \frac{-\phi(\pi w_i)}{\Phi(-\pi w_i)} \end{aligned}$$

$$= \underbrace{\mu_1 - \mu_0}_{ATT=ATE} + \underbrace{\sigma_v \rho_{vu} \frac{\phi(\pi w_i)}{\Phi(\pi w_i)[1 - \Phi(\pi w_i)]}}_{\text{Selection Bias}} \quad (11)$$

where σ_v, ρ_{vu} are the standard deviation of v_i and the correlation between v_i and u_i . Regression of y_i on 1, F_i , \mathbf{x}_i , $\phi_i/(1 - \Phi_i)$, $F_i \phi_i / \Phi_i(1 - \Phi_i)$ gives the coefficient on F_i as an unbiased estimate $ATT = ATE = \alpha_1$.

We use the *treatreg* command in Stata version 7 to obtain all the necessary parameters in the model. We implement both maximum likelihood and two-step estimators. The maximum likelihood estimator specifies different likelihood functions for each observation according to their fundholding status. In the two-step estimator a probit treatment model is used to obtain estimates of the inverse mills ratio for each practice depending on its fundholding. The inverse mills ratio is then included in the second stage waiting time regression. We ran the *treatreg* command using robust standard errors for the maximum likelihood estimates, and used the two-step estimator to obtain estimates of the hazard function for both fundholding and non-fundholding practices and included this as a regressor in the second stage model of practice waiting times, where the model was estimated using Huber/White robust standard errors.

3.2.3 Heterogeneous waiting times and selection

The OLS, kitchen sink, probability and matching estimators outlined in section 3.2.1 yield consistent estimates of ATT only if practices' choices of fundholding status are not affected by unobservable factors which are correlated with their waiting times if they choose to remain non-fundholders. The IV and selection correction estimators in sections 3.2.1 and 3.2.2 allow for correlation between the errors in the selection model and the waiting time model but still require that unobservable factors affecting waiting times have the same effect irrespective of fundholding status (see (10)). They rule out the possibility that the effect of fundholding status differs with the unobserved aspects of the morbidity of a practice's patients.

Relaxing assumption (10) and allowing the effect of observable characteristics to vary with fundholding regime, the expected waiting times for practices conditional on their choice of treatment are:

$$\begin{aligned} E[y_{i1} | F_i^* \geq 0] &= \mu_1 + \alpha'_{21} \mathbf{x}_i + E[v_{i1} | F_i^* \geq 0] = \mu_1 + \alpha'_{21} \mathbf{x}_i + \sigma_1 \rho_{1u} \frac{\phi(\pi' \mathbf{w}_i)}{\Phi(\pi' \mathbf{w}_i)} \\ &= \mu_1 + \alpha'_{21} \mathbf{x}_i + \alpha_{31} \lambda_1(\pi' \mathbf{w}_i) \end{aligned} \quad (12)$$

$$\begin{aligned} E[y_{i0} | F_i^* \geq 0] &= \mu_0 + \alpha'_{20} \mathbf{x}_i + E[v_{i0} | F_i^* \geq 0] = \mu_0 + \alpha'_{20} \mathbf{x}_i + \sigma_0 \rho_{0u} \frac{\phi(\pi' \mathbf{w}_i)}{\Phi(\pi' \mathbf{w}_i)} \\ &= \mu_0 + \alpha'_{20} \mathbf{x}_i + \alpha_{30} \lambda_1(\pi' \mathbf{w}_i) \end{aligned} \quad (13)$$

$$\begin{aligned} E[y_{i0} | F_i^* < 0] &= \mu_0 + \alpha'_{20} \mathbf{x}_i + E[v_{i0} | F_i^* < 0] = \mu_0 + \alpha'_{20} \mathbf{x}_i + \sigma_0 \rho_{0u} \frac{-\phi(\pi' \mathbf{w}_i)}{1 - \Phi(\pi' \mathbf{w}_i)} \\ &= \mu_0 + \alpha'_{20} \mathbf{x}_i + \alpha_{30} \lambda_0(\pi' \mathbf{w}_i) \end{aligned} \quad (14)$$

$$E\left[y_{i1} \mid F_i^* < 0\right] = \mu_1 + \mathbf{a}'_{21}\mathbf{x}_i + \alpha_{31}\lambda_0(\boldsymbol{\pi}'\mathbf{w}_i) \quad (15)$$

where $\lambda_1 = \phi / \Phi$, $\lambda_0 = -\phi / (1 - \Phi)$.

We use a version of selection correction estimator for the heterogeneous selection effect as suggested by Heckman et al [11] and Aakvik et al [17]. We

- (i) Estimate a probit regression of fundholding status on practice characteristics \mathbf{w} .
- (ii) Calculate the selection correction terms for non-fundholding status $\lambda_0(\hat{\boldsymbol{\pi}}'\mathbf{w}_i)$ and for fundholding status $\lambda_1(\hat{\boldsymbol{\pi}}'\mathbf{w}_i)$
- (iii) Fit a waiting times regression for non-fundholding practices, conditioning on observable covariates that directly effect waiting times \mathbf{x} and the selection correction term λ_0 as $\hat{y}_{i0} = \hat{\mu}_0 + \hat{\mathbf{a}}'_{20}\mathbf{x}_i + \hat{\alpha}_{30}\lambda_0(\hat{\boldsymbol{\pi}}'\mathbf{w}_i)$
- (iv) Use the estimated coefficients from the non-fundholding waiting time regression to predict the expected counterfactual outcome for each fundholding practice i :

$$\hat{y}_{i0} = \hat{\mu}_0 + \hat{\mathbf{a}}'_{20}\mathbf{x}_i + \hat{\alpha}_{30}\lambda_1(\hat{\boldsymbol{\pi}}'\mathbf{w}_i) \quad (16)$$

- (v) Calculate the estimated effect of fundholding on fundholder i as $TT_i = F_i(y_i - \hat{y}_{i0})$ and the estimated average effect of fundholding on fundholding practices by:

$$ATT = n^{-1} \sum_i F_i(y_i - \hat{y}_{i0}) \quad (17)$$

- (vi) Estimate bootstrapped standard errors and confidence intervals for the point estimate of the average effect of treatment on the treated (ATT).

3.3 Cross-section results

The cross-section results with the 1997/8 practice waiting times for chargeable admissions as the dependent variable are in Table 2. Models (not reported) with Box-Cox transformations of the dependent variable suggested that a levels specification was preferable to a log specification. Results were similar across all four types of model. The results mentioned in the text are from unweighted specification in levels.

The first model is a simple OLS cross-section regression of practice waiting times on the fundholding status of the practice and a set of covariates. The fundholding effect is statistically significant and negative, amounting to around 6% of mean practice waiting time.

The second model is a kitchen sink regression of waiting time with a number of additional covariates added to the basic OLS model. The additional variables make very little difference to the estimated effect of fundholding status. We also estimated OLS models with the probability of being a fundholder as a single control variable. The coefficients on fundholding status are very similar to the simple OLS cross-sections and are reported in Table 5.

The results from a variety of propensity matching methods for both the level and the log of mean waiting time are reported in Table 4 where the probabilities used in the matching models were estimated from the first probit model in Table 3. The

distributions of the propensity scores for fundholders and non-fundholders, is shown in Figure 3. The common support of the distributions is large (0.018 to 0.998) and only 35 out of 6171 practices had probabilities outside the common support. The log and levels models yield very similar estimates. The majority of estimates are also around 6% of mean waiting times, though that for radius matching is somewhat smaller.

The IV regressions using the predicted probability of being a fundholder as the instrumental variable are reported in Table 2. Table 3 has the supporting probit models for fundholder status. We report both the Shea R-squared and Hansen J statistics after the IV regressions. The model appears to satisfy the assumptions underpinning the IV estimation technique. The set of over-identified instruments appear to be good predictors of fundholding status. The Shea R^2 was 0.1168, which significantly exceeds the test statistic at the 99% level of 0.001 proposed by Davis and Kim [16]. The Hansen J statistics for the null of a well specified model and orthogonality of the set of instruments was 11.56, which implies we are unable to reject the null hypothesis at the 1% significance level.

The IV estimates of the fundholding effect are more negative (about -8%) than the simple OLS estimates, suggesting that fundholders would have had longer waits than non-fundholders if they had not become fundholders. The Heckman selection correction estimates in models 5 and 6 are very similar to the IV estimates.

Estimates of the heterogeneous treatment effects are shown at the bottom of Table 5. The effect of fundholding status on fundholder practices is more negative than those obtained from cross-sectional estimates assuming mean independence, but less negative than the Heckman selection model and IV estimators which assume $v_{i0} = v_{i1} = v_i$.

The simple Heckman selection correction model does not allow for the effect of unobservable practice characteristics on waiting times to differ between fundholder and non-fundholder practices. The effect of selection bias does not differ between practices who elected to become fundholders and those that remained non-fundholders. From the simple Heckman selection correction estimators, we find a significant positive coefficient on the inverse mills ratio, which implies that the effect of unobservable practice characteristics associated with both waiting times and fundholding status is to increase waiting times. Hence, our estimates of the impact of fundholder status on practices which became fundholders is more negative. The heterogeneous treatment effects estimator, however, does allow the effect of unobservable characteristics on waiting times to vary by fundholding status. The results (not in reported) from estimates of the separate waiting times models (12) and (14), show that the coefficients on the inverse mills ratios for fundholding and non-fundholding practices $\hat{\alpha}_{31}$ and $\hat{\alpha}_{30}$ differ. Both coefficients are positive, but the coefficient on $\hat{\alpha}_{31}$ is larger and more significant. This suggests that selection on unobservable characteristics that increase waiting times is greater amongst fundholder than non-fundholder practices. Hence, holding all else constant, allowing for heterogeneity in unobservable factors affecting waiting times reduces the estimate of the average effect on a randomly chosen practice.

The remainder of Table 5 summarises the regression estimates of the effect of fundholding. The unconditional mean difference in waiting times is negative (-3.1 days) but considerably smaller than any of the cross-section regression estimates, suggesting that the covariates both affect waiting time and are correlated with fundholding status. The other salient feature of the results is that the methods which attempt to allow for the effect of unobservable factors on selection yield more negative effects, suggesting that such factors both increase the waiting time of practices and their propensity to be a fundholder.

We also used cross-section data for 2000/1 to investigate the stability of the IV and Heckman estimates of selection effects. The simple OLS estimate of the effect of being an ex-fundholder in 2000/1 on waiting times for chargeable admissions compared with being an ex-non-fundholder is -0.646 (SE 0.384, t-stat -1.68). Since the fundholding scheme was abolished from April 1999, the OLS estimates suggest that unobserved fundholder characteristics work to reduce waiting times. The Heckman estimate of the ex-fundholder effect is -0.870 (SE 1.334, t-stat -0.65) and the estimate of the selection bias is 0.153 (SE 0.861, t-stat 0.178). The IV estimate of the ex-fundholder effect is -0.826 (SE 1.135, t-stat -0.73). Since ex-fundholders had no financial leverage over providers in 2000/1, the Heckman and IV estimates of a small negative and insignificant effect of having been a fundholder are plausible and similar to the OLS estimates.

One possible explanation for the difference between the positive selection bias from the Heckman/IV estimates for 1997/8 and the small negative selection bias from the same methods applied to 2000/1 is that being a fundholder led to a change in the ability to achieve lower waits for patients as fundholders learnt the system or were able to build up good relationships with hospital consultants. But this requires that there was learning over the last two years of fundholding which was in addition to any learning effects already acquired by 1997/8. Another possibility is that providers differentially changed their waiting list management between 1997/8 and 2000/1 to favour the patients of ex-fundholding practices. Since patients of fundholding practices had lower waits in 1997/8 and the aim of policy was to end such “two-tierism” this explanation seems implausible. We incline to the view that the contrast between the IV/Heckman estimates for 1997/8 and for 2000/1 is due to violation of the untestable underlying assumptions required for the IV and selection correction methods.

4 Difference in difference estimates of fundholding effects

We have two additional sources of information about practices and their waiting times which permit the application of difference in difference methods. The methods use information on differences between fundholders and non-fundholders for waiting times for types of admissions which should not be affected by fundholding status. We can thereby attempt to remove selection bias and control for factors other than the difference in financial regime that might influence practice waiting times.

4.1 Difference in differences: chargeable vs non-chargeable

We first compare the differences between the waiting times for chargeable admissions and non-chargeable admissions:

$$y_{igj} = \mu_{gj} + \alpha'_{2j} \mathbf{x}_i + v_{igj}, \quad g = 0, 1; j = c, n \quad (18)$$

where g as before indicates whether the practice is a fundholder and $j = c$ (or n) indicates that the admission is (or is not) chargeable to fundholders.

The expected difference in waiting times for fundholders and non-fundholders for type j admissions is

$$\begin{aligned} E(y_{ij} | x_i, F_i = 1) - E(y_{ij} | x_i, F_i = 0) &= E(y_{i1j} | x_i, F_i = 1) - E(y_{i0j} | x_i, F_i = 0) \\ &= \underbrace{\mu_{1j} - \mu_{0j} + E(v_{i1j} - v_{i0j} | F_i = 1)}_{ATT_j} + \underbrace{E(v_{i0j} | F_i = 1) - E(v_{i0j} | F_i = 0)}_{\text{Selection Bias}_j} \end{aligned} \quad (19)$$

Suppose that being a fundholder has no effect on non-chargeable admissions ($ATT_n = 0$) and that the selection biases for chargeable and non-chargeable admissions are equal ($\text{Selection Bias}_c = \text{Selection Bias}_n$) then a simple comparison of the differences is an unbiased estimate of the average effect of fundholding on the waiting times for chargeable procedures for fundholding practices

$$(ATT_c - \text{Selection Bias}_c) - (ATT_n - \text{Selection Bias}_n) = ATT_c \quad (20)$$

However, the assumption that fundholding had no effect on fundholder waiting times for non-chargeables ($ATT_n = 0$) may be too strong: it requires that providers were able to distinguish between cases which would receive chargeable procedures when admitted and those which would not. Hence we want to allow for this possibility in our estimation.

Letting $C_j = 0, 1$ as the admission type j is non-chargeable or chargeable

$$\begin{aligned} y_{ij} &= \mu_{0n} + (\mu_{1n} - \mu_{0n})F_i + \alpha'_{2n} \mathbf{x}_i + (\mu_{0c} - \mu_{0n})C_j \\ &\quad + [(\mu_{1c} - \mu_{0c}) - (\mu_{1n} - \mu_{0n})]F_i C_j + (\alpha'_{2c} - \alpha'_{2n})\mathbf{x}_i C_j + \varepsilon_{ij} \\ &= \beta_0 + \beta_1 F_i + \beta'_2 \mathbf{x}_i + \delta_0 C_j + \delta_1 C_j F_i + \delta'_2 \mathbf{x}_i C_j + \varepsilon_{ij} \end{aligned} \quad (21)$$

where

$$\varepsilon_{ij} = v_{i0n} + F_i(v_{i1n} - v_{i0n}) + C_j(v_{i0c} - v_{i0n}) + C_j F_i[(v_{i1c} - v_{i0c}) - (v_{i1n} - v_{i0n})] \quad (22)$$

With the general error (22) the estimated coefficients on F_i and $F_i C_j$ dummies from simple OLS estimation of (21) will pick up both the unobserved AATT component ($E(v_{i1c} - v_{i0c} | F_i = 1)$) of ATT and selection bias.

If we assume

$$v_{igj} = v_i + e_{ij}, \quad E(e_{ij} | v_i) = 0, \quad g = 0, 1, \quad j = c, n \quad (23)$$

then $\varepsilon_{ij} = v_i + e_{ij}$. The assumption implies that the selection bias for chargeables and nonchargeables is equal and that AATT is zero but, because we allow for the possibility that $\mu_{1n} \neq \mu_{0n}$, it is not strong enough to justify a simple difference in difference estimator.

Although practice specific errors v_i may be correlated with fundholding status we can estimate (21) as a panel with two observations on each unit to remove the bias induced by the correlation of the unobserved v_i with F_i . The coefficient δ_1 on $F_i C_j$ is

$ATT_c - ATT_n$ and so is the effect of the financial incentives associated with chargeable admissions. The coefficient β_1 is ATT_n so that ATT_c is the sum $\beta_1 + \delta_1$ which we would expect to be more negative than β_1 given the stronger position of fundholders, compared with non-fundholders in respect of chargeable admissions.

4.2 Temporal difference in differences

We have data for the last two years of fundholding and the first two years post fundholding so that we can also implement more conventional temporal difference in difference estimates. Analogously with the comparison of waiting times for chargeables and non-chargeables, we want to allow for the possibility that having been a fundholder has an effect on waiting times even after the abolition of the fundholding regime. We make a similar assumption about the errors, allowing them to be practice specific but not conditional on whether the practice was ever a fundholder. The waiting model for chargeable admissions in year t is

$$y_{igt} = \mu_{gt} + \mathbf{a}'_2 \mathbf{x}_{it} + v_i + e_{it}, \quad E(e_{it} | v_i) = 0 \quad g = 1, 2 \quad t = 1, \dots, 4; \quad (24)$$

and we have:

$$\begin{aligned} y_{it} &= \mu_{01} + (\mu_{11} - \mu_{01})F_i + (\mu_{0t} - \mu_{01})D_t + \mathbf{a}'_2 \mathbf{x}_{it} \\ &\quad + [(\mu_{1t} - \mu_{0t}) - (\mu_{11} - \mu_{01})]F_i D_t + v_i + e_{it} \\ &= \beta_0 + \beta_1 F_i + \beta'_2 \mathbf{x}_i + \delta_{0t} D_t + \delta_{1t} D_t F_i + v_i + e_{it} \end{aligned} \quad (25)$$

where D_t are year 2, 3, 4 dummies.

Allowing for transitional effects² in the penultimate and first post-fundholding year we focus on the coefficient δ_{14} which is the difference between the change in waiting times between 2000/1 and 1997/8 for practices which were fundholders compared with those which were not. It is the effect of the abolition of fundholding on fundholders' waiting times for chargeable admissions. Notice that we allow for the possibility that the effect of being a fundholder persisted after the end of fundholding: $\mu_{14} - \mu_{04} \neq 0$. For example, when practices became fundholders they may have learnt how to discover which providers had shorter waiting times and how to reduce the costs associated with switching patients between them. Hence some of the effect of fundholding may be permanent and some is due to the financial incentives which ceased when fundholding was abolished. The δ_{14} coefficient is the effect of fundholding which was due to financial incentives and which therefore disappeared when fundholding was abolished.

If we estimate (25) using pooled OLS the coefficient $\hat{\beta}_1$ on F_i picks up all the difference between fundholding and non-fundholding practices in 1997/8 and hence is the sum of ATT ($\mu_{11} - \mu_{01}$) and the time invariant selection bias. Hence the expected value of the sum of $\hat{\beta}_1 + \hat{\delta}_{14}$ is $(\mu_{14} - \mu_{04}) + \text{Selection Bias}$. Part of the sum is a genuine permanent "learning" effect of fundholding and part is selection bias. There is

² The intention to end fundholding was announced shortly after the election of the Labour government in May 1997 though the policy change did not take place until April 1999. Hospital providers were instructed to use common waiting lists for urgent cases from July 1997 and for all cases from April 1998. 18. Department of Health (1997). Access to Secondary Care Services. *Executive Letter*, (97)42

no means of distinguishing them unless there is data from before, during and after fundholding.

We estimated a variety of panel data models: pooled OLS, fixed effects, random effects and population averaged. The pooled OLS, population averaged and fixed effects estimators were all estimated with robust standard errors. The pooled OLS estimates and the fixed effects estimates allow for within-group correlation of the errors over time using the ‘cluster’ command. The population averaged estimator assumes that the within group correlation in the error term is a scalar that is identical across groups and constant over time. The population averaged (PA) estimator is a general linear model for panel data [19] and is asymptotically equivalent to the random effects estimator [20]. The PA estimator yields robust standard errors which do not rely on the assumption of homoskedasticity in the RE estimator. The pooled OLS models include HA effects as a means of allowing for unobserved HA level effects which could arise either from the possibility that supply variables may be endogenous [21] or because of HA level variations in the quality of population and admission data.

4.3 Differences in differences in differences

The temporal differences in differences model assumes that there are no temporal trends affecting fundholding practices differently from non-fundholders, so that the temporal change in nonfundholder waiting times can be used to control for temporal changes in fundholder waiting times which are not directly due to the ending of fundholding status in April 1999. The assumption is untestable in the standard differences in differences model because we have only one source of information on temporal trends not associated with the ending of fundholding. However, by making use of the two types of admission we can also use the information on the temporal trends in non-chargeable admission waiting times for fundholders which ought not to be affected by fundholding status.

We write the waiting time model as:

$$y_{igt} = \mu_{gjt} + \alpha'_{2j}x_i + v_i \quad (26)$$

and so

$$\begin{aligned} y_{ijt} &= \mu_{0n1} + (\mu_{1n1} - \mu_{0n1})F_i + \alpha'_{2n}x_i + (\mu_{0nt} - \mu_{0n1})D_t \\ &\quad + [(\mu_{1nt} - \mu_{0nt}) - (\mu_{1n1} - \mu_{0n1})]F_iD_t + (\mu_{0c1} - \mu_{0n1})C_j \\ &\quad + [(\mu_{1c1} - \mu_{0c1}) - (\mu_{1n1} - \mu_{0n1})]F_iC_j + [(\mu_{0ct} - \mu_{0nt}) - (\mu_{0c1} - \mu_{0n1})]C_jD_t \\ &\quad + \{[(\mu_{1ct} - \mu_{0ct}) - (\mu_{1nt} - \mu_{0nt})] - [(\mu_{1c1} - \mu_{0c1}) - (\mu_{1n1} - \mu_{0n1})]\}F_iC_jD_t \\ &\quad + (\alpha'_{2c} - \alpha'_{2n})x_iC_j + v_i + e_{it} \\ &= \beta_0 + \beta_1F_i + \beta'_2x_{it} + \delta_{0t}D_t + \delta_{1t}F_iD_t \\ &\quad + \gamma_{0c}C_j + \gamma_{1c}F_iC_j + \gamma_{0tc}C_jD_t + \gamma_{1tc}D_tC_jF_i + \gamma'_{2c}x_{it}C_j + v_i + e_{it} \end{aligned} \quad (27)$$

The coefficient γ_{14c} is the differential trend adjusted difference in difference estimate of ATT_c . The overall difference between fundholder and nonfundholder waiting times for chargeables in 1997/8 is captured by $\beta_1 + \gamma_{1c}$ and the selection bias as $\beta_1 + \gamma_{1c} - \gamma_{14c}$.

4.4 Difference in difference results

Table 6 summarises the estimated effects of fundholding from the pooled OLS and population averaged panel models (results with the other panel data estimators were very similar). The overall effect for chargeable admissions in 1997/8 is decomposed into a part due to selection bias and a part due to the fundholding status of the practice (ATT).

The chargeable versus non-chargeable DID models suggest that there is no significant selection bias. The coefficient $\hat{\beta}_1$ in (21) was not significantly different from zero which suggests there were no spillover effects of fundholding on non-chargeable admissions. The temporal DID models show a significant negative effect, though only accounting for a relatively small proportion of the overall effect of fundholding.

The chargeable status-temporal DID models all show significant negative overall effects and negative estimates of the effect of fundholder status on fundholder waiting times. The chargeable and temporal difference in difference estimates are similar and also close to the estimates from the kitchen sink regression (-4.79 days, and -4.99 days respectively). The difference in difference in difference estimates are somewhat more negative (-6.03 days). The unweighted DID models have insignificant selection bias whereas the weighted DID models have significant positive selection bias.

Table 7 gives more detail of the DID estimates for chargeable and non-chargeable admissions. The gap between fundholder and non-fundholder waiting times falls over time for chargeable admissions. It increases for non-chargeable admissions though the increase is significant only for the weighted log model. Figure 4 graphs the estimated (DID log models) differences in mean practice waiting times between fundholder and non-fundholder practices over time for chargeable and non-chargeable procedures. It shows that for chargeable procedures, mean fundholder practice waiting times were over 6% lower than non-fundholders in the penultimate year of fundholding (1997/8). Following the abolition of fundholding in 1999/2000 the difference between fundholder and non-fundholder mean chargeable waits were still significantly different, but had reduced to less than 1% by the year 2000. The graph also highlights the fall in fundholder non-chargeable waiting times relative to non-fundholder waiting times between the years 1999/2000 and 2000/1.

The temporal DID is based on assumptions about common trends for fundholders and non-fundholders and the chargeable versus non-chargeable DID on assumptions about a common difference between chargeable and non-chargeable admissions. We estimate the magnitude of selection bias from the temporal DID estimates by comparing the difference in fundholder and non-fundholder waiting times in 2000/1 (when the financial incentives created by fundholding were removed), with the expected difference between fundholder and non-fundholder waiting times in 1997/8 (when the fundholding scheme was still in place). The fact we are using the ex-post difference in waiting times between fundholder and non-fundholder practices to estimate and control for selection bias means that any bias may be due in part to the experience of fundholding inducing permanent changes in GP practice behaviour. For example, fundholding practices may have learnt more about the availability of shorter

waiting times in the health care system. Differences due to such learning effects are a genuine effect of fundholding status in the sense that they would not have occurred if the practice had not chosen to be a fundholder. However it is impossible without data for periods before, during and after fundholding, to distinguish between learning effects and selection bias arising from previously existing unobserved differences between fundholders and non-fundholders. By removing what we have labelled as selection bias, but which might include learning effects, we have estimated the effects of fundholding on the waiting times of fundholders which were associated with the financial regime.

The use of waiting times for non-chargeable admissions to control for unobservable differences between fundholders and non-fundholders in the 1997/8 DID and in the temporal-chargeable status DIDID may not be appropriate because of data problems. As the scatter plot in Figure 2 indicates, dropping practices with a small number of admissions does relatively little to reduce the variability in practice waiting times for non-chargeable admissions. There were also (see Table 1) very large proportional changes in both practice waiting times and in the number of admissions per practice between 1997/8 and 2000/1. We suspect therefore that non-chargeable admissions may not be an appropriate control for temporal trends in chargeable admissions.

5 Conclusion

We have examined three broad groups of methods of allowing for potential selection bias in estimating the effect of fundholding on fundholding practices. The cross-section methods which rely on the assumption that only observable factors affect the decision to be a fundholder, suggest that allowing for covariates increases the estimated negative effect of fundholding from around - 3.1 days to around - 5.5 days. The cross-section methods which attempt to allow for selection on unobservables suggest that selection bias is large and positive: fundholders would have had larger waiting times than nonfundholders if they had not chosen to be fundholders. Hence, these methods estimate an effect of fundholding status that is considerably more negative (around -8.5 days) than the OLS estimates.

The temporal DID estimates find a small negative selection bias: fundholders would have had smaller waits than non-fundholders if they had not become fundholders. The temporal DID estimates of the effect of fundholding status are somewhat smaller than the OLS estimates. The chargeable status DID shows an insignificant, and sometimes positive, selection bias and the DIDID estimates using both temporal and chargeable status differences show a positive selection bias.

The different methods of estimating the effect of fundholding status on the waiting time of the fundholders' patients rest on untestable assumptions. However, the untestable assumptions differ across methods, so that the fact that all models show a significant negative effect of the financial status of fundholding practices on their waiting times suggests that the result is robust. Holding a budget enabled practices to get shorter waiting times for their patients.

References

1. Department of Health (1989). Working for patients. *HMSO, Cm 555*
2. H. Glennerster, M. Matsaganis & P. Owens (1994). *Implementing GP Fundholding: Wild Card or Winning Hand?* Buckingham: Open University Press.
3. Department of Health (1997). Changing the Internal Market. *Executive Letter*, (97)33
4. B. Dowling (2000). *GPs and Purchasing in the NHS*. Ashgate: Aldershot.
5. C. Propper, B. Croxson & A. Shearer (2002). Waiting times for hospital admissions: the impact of GP fundholding. *Journal of Health Economics* 21, 227-252.
6. M. Dusheiko, H. Gravelle, R. Jacobs & P.C. Smith (2003). The effect of budgets on doctor behaviour: evidence from a natural experiment. *Department of Economics and Related Studies Discussion Paper*, <http://www.york.ac.uk/depts/econ/dp/2003.htm>.
7. J.M. Wooldridge (2002). *Econometric Analysis of Cross Section and Panel Data*. Cambridge, Massachusetts: The MIT Press.
8. R. Blundell & M. Costa Dias (2000). Evaluation methods for non-experimental data. *Fiscal Studies* 21, 427-468.
9. J.J. Heckman, R.J. Lalonde & J.A. Smith (1999). The economics and econometrics of active labor market programs. In *Handbook of Labor Economics*, pp. 1866-2097. Edited by A. Ashenfelter & D. Card. San Diego: Elsevier Science.
10. M. Sutton, H. Gravelle, S. Morris, A. Leyland, F. Windmeijer, C. Dibbin & M. Muirhead (2002). Allocation of Resources to English Areas: Individual and Small Area Determinants of Morbidity and Use of Health Care: Report for Department of Health.
11. J.J. Heckman, J.L. Tobias & E. Vytlacil (2000). Simple estimators for treatment parameters in a latent variable framework with and application to estimating the returns to schooling. *National Bureau of Economic Research Working Paper Series*, 7950
12. S.O. Becker & A. Ichino (2002). Estimation of average treatment effects based on propensity score. *The Stata Journal* 2, 358 - 377.
13. D. Baines & D.K. Whynes (1996). Selection bias in GP fundholding. *Health Economics* 5, 129-140.
14. D.K. Whynes, C. Ennew & T. Feigham (1999). Entrepreneurial attitudes of primary health care physicians in the United Kingdom. *Journal of Economic Behavior and Organization* 38, 331-347.

15. C.F. Baum, M.E. Schaffer & S. Stillman (2003). Instrumental variables and GMM: Estimation and testing. *The Stata Journal* 3, 1 - 31.
16. G.C. Davis & S-Y. Kim (2002). Measuring instrument relevance in the single endogenous regressor-multiple instrument case: a simplifying procedure. *Economics Letters* 74, 321-325.
17. A. Aakvik, J.J. Heckman & E.J. Vytlačil (2003). Treatment effects for discrete outcomes when responses to treatment vary among observationally identical persons: An application to Norwegian vocational rehabilitation programs. *National Bureau of Economic Research Technical Working Paper*, 262
18. Department of Health (1997). Access to Secondary Care Services. *Executive Letter*, (97)42
19. K.Y. Liang & S.L. Zeger (1986). Longitudinal data analysis using generalized linear models. *Biometrika* 73, 13-22.
20. Stata (2001). *Stata Reference Manual Release 7*. College Station, Texas: Stata Press.
21. H. Gravelle, P.C. Smith & A. Xavier (2003). Waiting lists and waiting times: a model of the market for elective surgery. *Oxford Economic Papers* 55, 81-103.
22. DETR (2000). Measuring Multiple Deprivation at the Small Area Level: The Indices of Deprivation 2000. *Department of Environment, Transport and the Regions*,

Data Appendix

Waiting times

Data on elective (non-emergency) admissions at NHS Trusts (hospitals) were taken from Hospital Episode Statistics for 1997/8 to 2000/1 for consultant episodes which finished in each year (approximately 5.4 million per year). Each finished consultant episode was then classified as a chargeable admission if any procedures carried out were on the list of procedures chargeable to fundholders. (About 7000 of 8000 procedures were listed as chargeable.) Finished consultant episodes were assigned to the patient's general practice. The waiting time (the difference between the date of the elective procedure and the date the patient was placed on the elective waiting list) was available from HES for each patient admitted as an elective patient. The waiting time for each practice for each year was calculated as the mean elective wait for its patients admitted as electives in the year (mean and median waiting times were very similar).

Practice populations

Data on practice populations (total and by age and sex groups) were taken from the PCT database at the National Primary Care Research and Development Centre (<http://www.primary-care-db.org.uk/>) for each of the four years and used to calculate crude admission rates for each practice for elective and non-elective surgery. Because of delays in removing patients who die or move from lists these data suffer from list inflation. We also had list inflation corrected population data for one year (2000/1) from the AREA database [10] which deflated practice populations by applying separate age, sex and local authority specific correction factors to practice populations.

Practice characteristics

The fundholding status for each practice was derived from lookup tables from the Prescription Pricing Authority and the Organisational Codes Service of the Department of Health. We had data on practice characteristics for 1999, based on the Department of Health's General Medical Statistics, from the NPCRDC website. They included GP age, sex, country of qualification, numbers of GPs, whether GPs were approved trainers, whether the practice was in receipt of quality payments, and whether the practice offered different types of clinics.

Practice patient characteristics

In addition to the age and sex composition of the practice populations, we also had information on their socio-economic characteristics. The main sources of socio-economic data were the 1991 Census and the components of the Index of Multiple Deprivation [22] which uses information on Social Security payments in 1998 and 1999. The data are available at small area (frozen 1998 electoral ward) level. They were attributed to practices by taking weighted averages based on the proportion of practice populations resident in each ward (from the Department of Health's Attribution Data Set used to calculate the 2000/1 funding allocations to HAs). Some socio-economic data, such as the Low Income Scheme Index (the proportion of prescriptions from a practice which were dispensed without charge because the patient was exempt on grounds of low income), related directly to the practice.

Supply factors

We used data on supply factors from the AREA project [10] including distance from practice populations to NHS Trusts, private hospitals, residential and nursing homes, numbers of beds and consultants at NHS Trusts.

Table 1. Summary statistics and definitions of variables used in the analysis

Variable	Definition	Source	Mean	Std. Dev.	Max	Min
mewcel1997	Mean practice waiting time (chargeable admissions) 97/98 (days)	HES	97.446	22.060	235.050	19.542
mewcel1998	Mean practice waiting time (chargeable admissions) 98/99 (days)	HES	108.557	24.611	225.227	40.357
mewcel1999	Mean practice waiting time (chargeable admissions) 99/00 (days)	HES	99.547	21.716	215.704	23.733
mewcel2000	Mean practice waiting time (chargeable admissions) 00/01 (days)	HES	100.742	22.186	188.193	9.750
mewncel1997	Mean practice waiting time (non-chargeable admissions) 97/98 (days)	HES	60.547	44.027	637	1
mewncel1998	Mean practice waiting time (non-chargeable admissions) 98/99 (days)	HES	50.919	35.930	468	1
mewncel1999	Mean practice waiting time (non-chargeable admissions) 99/00 (days)	HES	42.490	30.437	339	1
mewncel2000	Mean practice waiting time (non-chargeable admissions) 00/01 (days)	HES	39.241	26.437	361	1
nchel1997	Number of chargeable admissions 97/98 per practice	HES	424.608	287.704	2504	14
nchel1998	Number of chargeable admissions 98/99 per practice	HES	463.526	302.516	2662	18
nchel1999	Number of chargeable admissions 99/00 per practice	HES	474.125	312.031	2631	6
nchel2000	Number of chargeable admissions 00/01 per practice	HES	465.968	315.474	2606	5
nnchel1997	Number of non-chargeable admissions 97/98 per practice	HES	52.832	48.777	499	5
nnchel1998	Number of non-chargeable admissions 98/99 per practice	HES	90.398	73.632	644	5
nnchel1999	Number of non-chargeable admissions 99/00 per practice	HES	99.088	82.771	855	5
nnchel2000	Number of non-chargeable admissions 00/01 per practice	HES	99.619	82.869	603	5
stanfund1997	Standard GP fundholder	OCS/PPA	0.434	0.496	1	0
totpop1997	List size of GP practice (1997)	GMS/NPCRDC	6342	3702	33303	1042
listgp1997	List size per GP (1997)	GMS/NPCRDC	1993.227	552.099	5319	521
ukgps	Proportion GPs qualified in UK	GMS/NPCRDC	0.730	0.393	1	0
malegps	Proportion of male GPs	GMS/NPCRDC	0.704	0.265	1	0
trainprac	Practice has approved training status	GMS/NPCRDC	0.287	0.452	1	0
childhgps	Proportion of GPs offering child health surveillance services	GMS/NPCRDC	0.925	0.245	1	0
minsurgps	Proportion of GPs performing minor surgery	GMS/NPCRDC	0.749	0.370	1	0
asthmagps	Proportion of GPs offering asthma services	GMS/NPCRDC	0.960	0.189	1	0
contragpsl	Proportion of GPs providing contraceptive services	GMS/NPCRDC	0.131	0.250	1	0
dispgps	Proportion of GPs providing dispensing services	GMS/NPCRDC	0.148	0.353	1	0
deputgps	Proportion of GPs permitted to use deputising services	GMS/NPCRDC	0.744	0.405	1	0

acc_gp2	Accessibility to general practitioners / 1000	ID/AREA	0.193	0.065	0.340	0.045
acutdistn5	Beds weighted distance to secondary care	OCS/AREA	25.638	11.481	109.095	11.757
acc_priv2	Accessibility to private beds / 1000	OCS/AREA	0.358	0.212	1.143	0.024
opwait_26	Proportion of outpatients seen within 13 weeks at providers used	OCS/AREA	0.938	0.026	0.993	0.848
hospconsults	Average number of consultants at acute providers	OCS/AREA	133	60	391	38
acutebeds	Average beds at 5 nearest acute providers	OCS/AREA	831	356	2566	255
placerate	Residential places per person over 75	OCS/AREA	0.095	0.069	1.219	0
lisi	Percentage of prescriptions with low income exemption	PSU/NPCRDC	11.006	7.526	54.650	0.380
scoreemp	DETR ward level index of employment deprivation	ID/AREA	12.180	6.207	44.315	1.589
scorehous	DETR ward level index of housing deprivation	ID/AREA	0.317	0.832	2.984	-2.199
scoreeduc	DETR ward level index of education deprivation	ID/AREA	0.205	0.749	2.792	-2.219
pcnotuni	Percentage of individuals who did not attend university	ID/AREA project	84.842	6.565	98.327	46.246
r_ibsd	Incapacity / Severe disability allowance claimants	ID/AREA	98.480	52.761	434.157	13.772
jsa_bip	Proportion eligible population claiming job seekers allowance	ID/AREA project	4.664	3.184	20.550	0.285
eldal6v1	Proportion population over 75 and living alone	Census/AREA project	0.480	0.048	0.645	0.127
pr_aadla	Proportion population over 75 and living alone	Census/AREA	5.288	2.035	16.614	1.431
migr10v2	Proportion population with a change of address	Census/AREA	0.099	0.027	0.307	0.043
ethn5v2	Proportion population from ethnic minority	Census/AREA	0.072	0.110	0.688	0
cmf	Comparative mortality factor	ONS/AREA	101.749	14.776	165.245	63.387

Financial year: April to March. Statistics based on final sample of 6171 practices.

Table 2. Cross section estimates of effect of fundholding status on fundholder mean waiting time

	OLS	Kitchen sink	Propensity score	IV estimation	Heckman selection (2-step)	Heckman selection (MLE)
_Istanfund1_1	-5.641 [13.26]**	-5.344 [11.81]**	-5.271 [11.62]**	-8.438 [6.71]**	-8.550 [6.86]**	-8.778 [6.58]**
ukgps	-1.882 [2.78]**	-1.638 [2.31]*	-1.653 [2.41]*	-1.657 [2.43]*	-1.659 [2.42]*	-1.641 [2.40]*
dispgps	-1.935 [2.34]*	-2.143 [2.59]**	-2.017 [2.44]*	-1.988 [2.41]*	-2.074 [2.51]*	-2.079 [2.52]*
deputgps	-1.568 [1.94]	-1.722 [2.13]*	-1.618 [2.00]*	-1.600 [1.99]*	-1.642 [2.03]*	-1.644 [2.04]*
listgp1997	0.001 [2.91]**	0.0011 [2.53]*	0.001 [3.28]**	0.001 [3.28]**	0.001 [3.30]**	0.001 [3.35]**
acc_gp2 × 1000	151.781 [3.63]**	145.858 [3.39]**	163.235 [3.88]**	163.453 [3.90]**	153.294 [3.62]**	154.205 [3.64]**
acc_gp22 × 1000	-405230 [3.73]**	-383925 [3.41]**	-436066 [3.99]**	-436863 [4.02]**	-413021 [3.75]**	-415505 [3.78]**
acc_priv2 × 1000	-38.119 [7.78]**	-37.824 [7.67]**	-38.736 [7.91]**	-38.619 [7.90]**	-38.385 [7.84]**	-38.425 [7.86]**
hospconsults	0.144 [6.40]**	0.143 [5.95]**	0.144 [6.38]**	0.142 [6.35]**	0.143 [6.35]**	0.143 [6.36]**
hospconsults2	-0.00033 [6.35]**	-0.00033 [6.19]**	-0.00033 [6.39]**	-0.00033 [6.37]**	-0.00033 [6.35]**	-0.00033 [6.37]**
jsa_bip	-0.849 [4.37]**	-0.838 [4.17]**	-0.861 [4.43]**	-0.858 [4.44]**	-0.815 [4.16]**	-0.815 [4.18]**
scorehous	1.726 [2.43]*	2.044 [2.73]**	1.691 [2.38]*	1.652 [2.34]*	1.874 [2.58]**	1.869 [2.59]**
pcnotuni	0.188 [3.38]**	0.168 [2.87]**	0.189 [3.40]**	0.194 [3.52]**	0.171 [2.97]**	0.171 [3.00]**
ethn5v2	13.086	11.046	13.084	13.270	12.976	12.989

	[3.02]**	[2.06]*	[3.02]**	[3.10]**	[2.99]**	[3.03]**
r_ibsda	0.045	0.042	0.046	0.045	0.044	0.044
	[3.88]**	[3.45]**	[3.91]**	[3.87]**	[3.78]**	[3.78]**
migr10v2		-23.456			-24.930	-25.026
		[1.72]			[1.84]	[1.88]
totpop1997		-0.00004				
		[0.58]				
malegps		-4.020				
		[1.18]				
malegps2		3.048				
		[1.12]				
trainprac		-0.333				
		[0.69]				
childhgps		-0.595				
		[0.62]				
minsurgps		1.000				
		[1.24]				
asthmagps		-0.068				
		[0.07]				
contragpsl		1.477				
		[1.79]				
eldal6v1		-10.156				
		[1.36]				
placerate		0.543				
		[0.15]				
scorehous2		0.062				
		[0.15]				
opwait_26		-12.773				
		[0.65]				
fundprop			-3.202			

			[2.35]*			
invmills					1.964	2.118
					[2.48]*	[2.49]*
Constant	137.334	158.353	137.334	136.873	145.612	145.921
	[1.23]	[1.41]	[1.23]	[1.24]	[1.31]	[1.33]
Observations	6171	6171	6171	6171	6171	6171
R-squared	0.510	0.510	0.510		0.510	
Hansen J-statistic				11.556		
				Chi-sq (12)		
				P-val = 0.48193		
Shea Partial R ²				0.1168		
				F(1, 6049) = 799.61		

Dependent variable: mean practice waiting time (level) for chargeable admissions. All models use unweighted observations.

Robust t statistics in brackets.

* significant at 5%; ** significant at 1%

Table 3. Fundholder status selection models (probit)

	Basic model	Including exogenous variables from cross-sectional waiting times model
ukgps	-0.227 [3.79]**	-0.226 [3.76]**
malegps	0.865 [2.86]**	0.865 [2.86]**
malegps2	-0.673 [2.80]**	-0.676 [2.81]**
trainprac	0.317 [7.15]**	0.320 [7.17]**
childhgps	0.459 [5.12]**	0.463 [5.14]**
minsurgps	0.241 [3.47]**	0.244 [3.49]**
asthmagps	0.253 [2.45]*	0.252 [2.44]*
contragpsl	-0.259 [3.40]**	-0.260 [3.42]**
totpop1997 × 1000	0.103 [14.81]**	0.103 [14.64]**
listgp1997 × 1000	0.154 [4.06]**	0.155 [4.07]**
acc_gp2 × 1000	12.216 [3.58]**	12.603 [3.49]**
acc_gp22 × 1000	-30324 [3.46]**	-31613 [3.41]**
opwait_26	4.687 [3.39]**	4.565 [3.07]**
eldal6v1	1.870 [3.07]**	1.992 [3.08]**
lisi	-0.014 [3.32]**	-0.013 [2.70]**
placerate	0.834 [2.67]**	0.846 [2.66]**
acc_priv2	-928.95 [2.35]*	-834.12 [2.01]*
migr10v2	-2.388 [2.08]*	-2.124 [1.79]
dispgps		0.023 [0.36]
deputgps		0.025 [0.38]
hospconsults		-0.001 [0.69]
hospconsults2 × 1000		0.003 [0.57]
jsa_bip		0.001 [0.04]
scorehous		-0.037 [0.59]

pcnotuni		0.006
		[1.10]
ethn5v2		0.229
		[0.58]
r_ibsda		-0.001
		[0.58]
Constant	-3.116	-3.372
	[0.33]	[0.35]
Observations	6171	6171

Robust z statistics in brackets.

* significant at 5%; ** significant at 1%

Table 4. Propensity score estimates of average effect of fundholder status on fundholding waiting times

	On mean wait		On log of mean wait	
	ATT	t-statistic	ATT	t-statistic
Nearest neighbour matching	-5.498	-5.280	-0.057	-5.518
Radius matching	-4.190	-6.860	-0.044	-7.308
Stratification matching	-6.164	-7.322	-0.062	-7.768
Kernel matching	-6.100	-8.136	-0.061	-7.694
Unweighted estimates				

Table 5. Average effects of fundholding status on fundholder waiting times: 1997/8 cross section estimates

	Mean wait (unweighted)	Log mean wait (unweighted)	Mean wait (weighted)	Log mean wait (weighted)
Unconditional means	- 3.120 [-5.52]	- 0.033 [-6.29]		
OLS	- 5.641 [-13.26]	-0.056 [-13.09]	-5.337 [-12.20]	-0.053 [-12.03]
OLS kitchen sink	-5.344 [-11.81]	-0.054 [-11.90]	-5.187 [-11.45]	-0.053 [-11.53]
OLS conditioning on propensity score	-5.271 [-11.62]	-0.053 [-11.72]	-5.124 [-11.29]	-0.052 [-11.36]
Heckman	-8.550 [-6.86]	-0.078 [-6.30]	-6.715 [-4.94]	-0.060 [-4.41]
IV	-8.438 [-6.71]	-0.078 [-6.18]	-6.862 [-4.96]	-0.061 [-4.39]
Heterogeneous effects	-7.091 [-4.00]	-0.066 [-3.80]	-6.298 [-3.76]	-0.055 [-3.39]

Table 6. Difference in difference estimates of average effect of fundholding status on fundholder practice waiting times

	Overall FH effect in 1997/98	Selection bias ³	Average effect of fundholding on FH practices
On mean wait (unweighted)			
DID cross-section - chargeable/non-chargeable ¹	-5.3999 [-11.99]	-0.6068 [-0.56]	-4.7932 [-4.20]
DID time series ²	-6.2399 [-13.80]	-1.2425 [-2.93]	-4.9974 [-8.85]
DIDID time series – chargeable/non-chargeable ¹	-6.1228 [-13.31]	-0.0857 [-0.07]	- 6.0371 [-5.01]
On log mean wait (unweighted)			
DID cross section - chargeable/non-chargeable ¹	-0.0546 [-12.08]	-0.0084 [-0.48]	-0.0462 [-2.59]
DID time series ²	-0.0621 [-13.53]	-0.0081 [-1.87]	-0.0534 [-9.31]
DIDID time series –chargeable/non-chargeable ¹	-0.0613 [-13.27]	0.0340 [1.57]	-0.0953 [-4.42]
On mean wait (weighted)			
DID chargeable/non-chargeable ¹	-5.1814 [-11.50]	-0.8684 [-0.56]	-4.3130 [-4.41]
DID time series ²	-6.5952 [-13.68]	-1.4598 [-3.28]	-5.1354 [-9.19]
DIDID time series – chargeable/non-chargeable ¹	-6.4658 [-13.41]	0.6218 [4.05]	- 7.0876 [-6.72]
On log mean wait (weighted)			
DID chargeable/non-chargeable	-0.0525 [-11.53]	-0.0038 [-0.22]	-0.0488 [-2.83]
DID time series ²	-0.0666 [-13.70]	-0.0115 [-2.58]	-0.0551 [-9.96]
DIDID time series –chargeable/non-chargeable ¹	-0.0655 [-13.48]	0.0601 [2.75]	-0.1256 [-5.73]

¹ Pooled OLS estimates. ² Population-averaged (random effects) estimates. ³ The selection effect is calculated as the difference between the coefficients on the 1997/8 FH effect and the treatment effect, and the reported t-test is a joint test on coefficients summing to zero.

Table 7. Average effect of fundholding status on fundholding practice waiting times: difference in difference estimates for chargeable and non-chargeable admissions

	Unweighted		Weighted	
	Levels	Logs	Levels	Logs
Chargeable				
stanfund1997	-6.265 [13.81]**	-0.062 [13.55]**	-6.445 [13.49]**	-0.065 [13.43]**
year_1998	10.547 [34.01]**	0.101 [34.51]**	9.501 [31.81]**	0.092 [32.34]**
year_1999	-0.041 [0.13]	0.001 [0.38]	-0.545 [1.80]	-0.005 [1.58]
year_2000	1.198 [3.29]**	0.010 [2.70]**	1.016 [2.75]**	0.008 [2.29]*
StanfundXyear_1998	1.325 [2.80]**	0.014 [3.13]**	2.371 [5.12]**	0.023 [5.33]**
StanfundXyear_1999	5.194 [10.50]**	0.052 [10.63]**	5.443 [11.21]**	0.054 [11.36]**
StanfundXyear_2000	5.002 [8.83]**	0.053 [9.29]**	5.171 [9.13]**	0.055 [9.85]**
Non-chargeable				
stanfund1997	0.120 [0.12]	0.003 [0.18]	0.318 [0.36]	0.028 [1.52]
year_1998	-9.545 [12.63]**	-0.133 [9.73]**	-7.696 [12.48]**	-0.129 [9.40]**
year_1999	-18.260 [24.51]**	-0.317 [22.55]**	-15.182 [23.31]**	-0.309 [20.71]**
year_2000	-21.019 [27.71]**	-0.368 [24.76]**	-16.881 [24.34]**	-0.333 [21.53]**
StanfundXyear_1998	-0.128 [0.11]	-0.002 [0.08]	-0.515 [0.56]	-0.019 [0.97]
StanfundXyear_1999	0.422 [0.37]	0.009 [0.44]	-0.602 [0.63]	-0.020 [0.98]
StanfundXyear_2000	-1.029 [0.89]	-0.042 [1.92]	-1.908 [1.92]	-0.069 [3.14]**

Pooled OLS estimates. Includes population, practice, provider characteristics as covariates.

Figure 1.

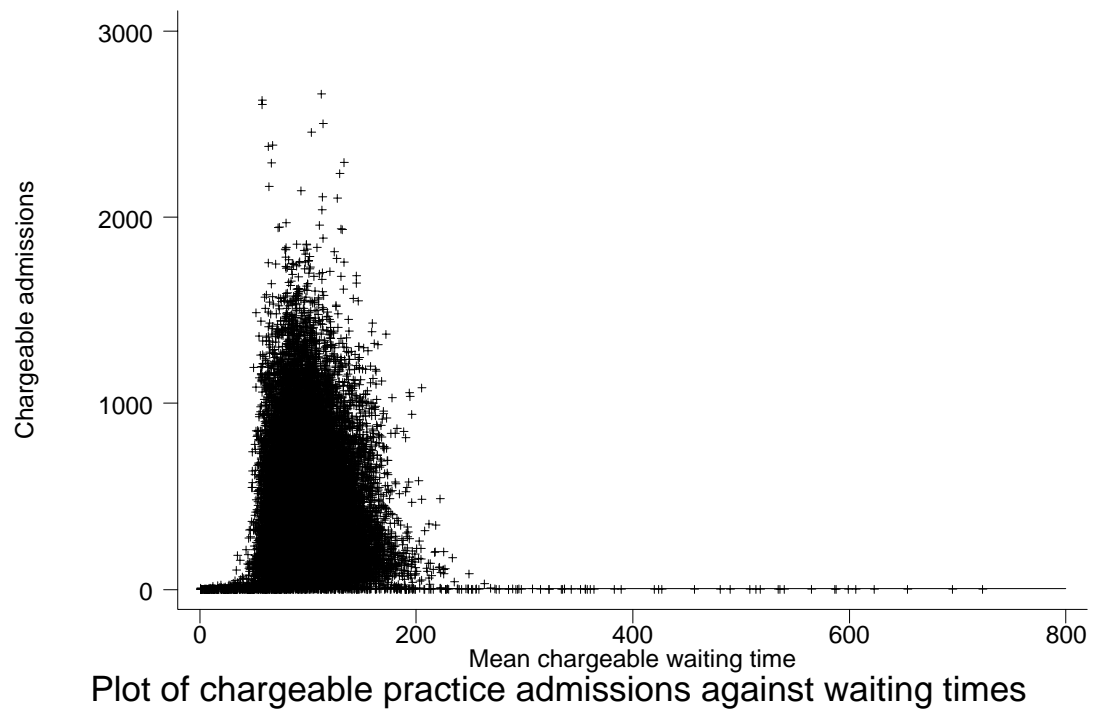


Figure 2.

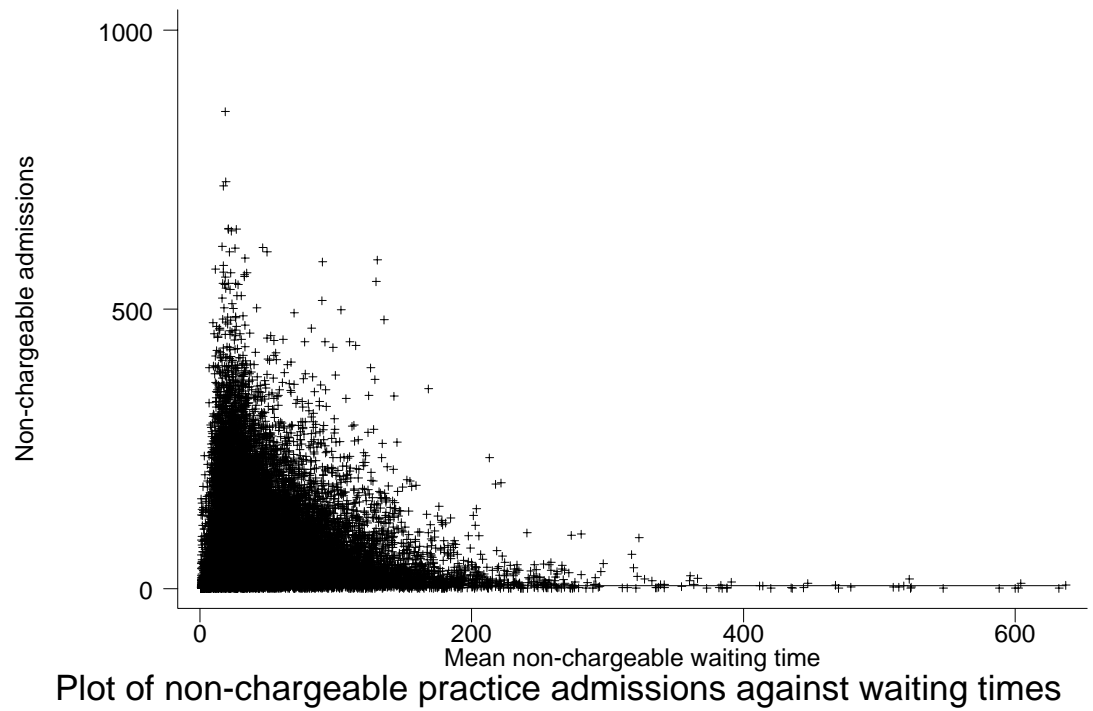


Figure 3.

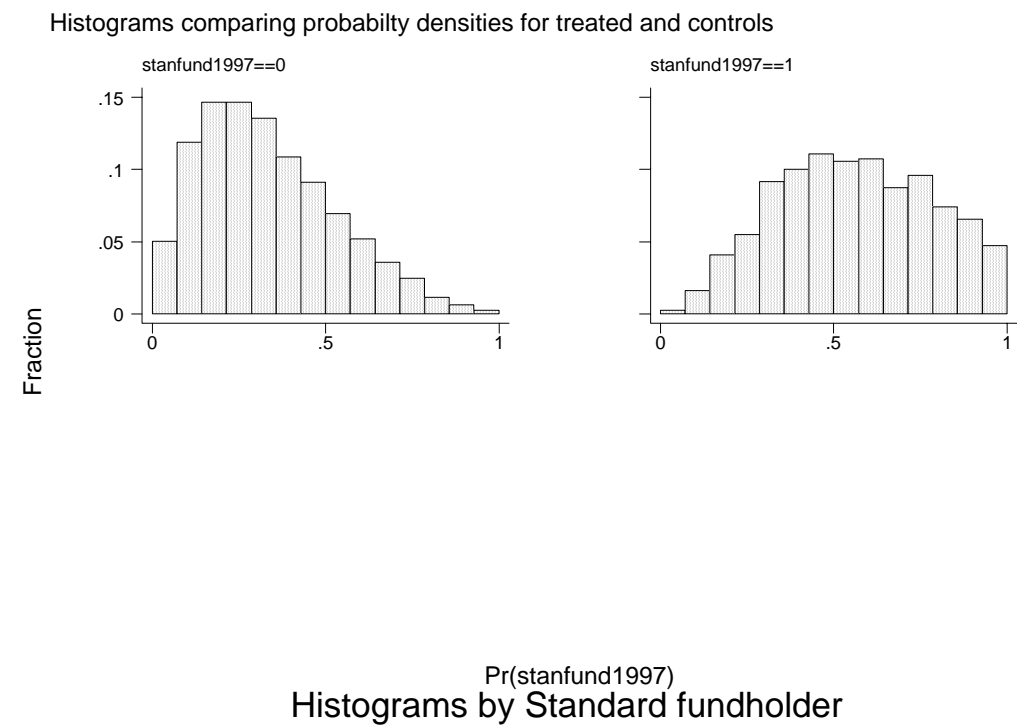


Figure 4.

