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May 2008

Working Paper No. 08/197

ISSN 1473-625X

CMPO Working Paper Series No. 08/197

How important is pro-social behaviour in the delivery of public services?

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Abstract

A number of papers have posited that there is a relationship between institutional structure and pro-social behaviour, in particular donated labour, in the delivery of public services, such as health, social care and education. However, there has been very little empirical research that attempts to measure whether such a relationship exists in practice. This is the aim of this paper. Including a robust set of individual and job-specific controls, we find that individuals in the non-profit sector are significantly more likely to donate their labour, measured by unpaid overtime, than those in the for-profit sector. We can reject that this difference is simply due to implicit contracts or social norms. We find some evidence that individuals differentially select into the non-profit and for-profit sectors according to whether they donate their labour.

Keywords: pro-social behaviour; public services; donated labour; motivation

JEL Classification: H11, J32, J45, L31, L32

Electronic version: **http://www.bris.ac.uk/Depts/CMPO/workingpapers/wp197.pdf**

Acknowledgements

We thank the ESRC for funding this research.

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CMPO is jointly funded by the Leverhulme Trust and the ESRC

1. Introduction

The idea that there is a relationship between institutional structure and pro-social behaviour has been prevalent for many years, notably in the work of Hansmann (1980) and Rose-Ackerman (1996), and has recently been re-visited by Benabou and Tirole (2006), Besley and Ghatak (2005), Glaeser and Shleifer (2001), Francois (2000, 2001, 2003, 2007), and Prendergast (2007).[1] A key prediction from this literature is that there will be a positive relationship between employment in the non-profit sector[2] and pro-social behaviour, and donated labour in particular. By donated labour is meant any additional effort beyond what is contractually necessary and excluding that motivated by career concerns (Dewatripont et al., 1999).

A simple example illustrates how this relationship may arise. Consider a small hospital where the employees care not only about their current and future remuneration but also about the quality of their patients' care. As a result, they agree not to leave their shift if, because of a random event, there is nobody else to take over. In a world of incomplete contracts for-profit employers will find it hard to pre-commit not to take advantage of this decision by hiring fewer employees than they otherwise would. For example, since they are now less likely to be sued for negligence than before (the employees have ensured that there will always be cover available) they can reduce their staff numbers. The net effect is that some, possibly all, of the proposed donated labour is expropriated to increase profit. Since ex ante the employees realise this, they will decide not to donate their labour in the first place because it will not improve the quality of patient care. Hence, incentives to donate labour will not be present or will be muted in for-profit firms. By contrast, in a not-for-profit organisation the non-distribution constraint prevents this expropriation from occurring and any donated labour will have a direct effect on patient care. In a

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[1] We define pro-social behaviour as helpful behaviour intended to benefit other people unmotivated by professional obligations, see Bierrhof (2002). We draw a standard distinction between actions that agents may take as a consequence of their other-regarding preferences and the characteristics of the preferences. We use the terms other-regarding, pro-social motivation, and public service motivation to refer to characteristics of agents' preferences (see, for example, Francois and Vlassopoulos, 2008), whereas pro-social behaviour and donated labour describe actions that agents take. Donated labour is essentially pro-social behaviour in the specific labour market context.

[2] We use "non-profit sector" to refer to any organisation that is not profit-making, which includes both not-for-profit organisations, as well as government organisations.

government organisation, the fact that budgets are set bureaucratically has a similar effect.

In this simple illustration all employees are pro-socially motivated but will only donate their labour in a non-profit organisation not in a for-profit organisation. We refer to this as the ‘organisational-form’ explanation and it is the essence of the mechanism suggested by Francois (2000). Another approach suggests that ‘mission-oriented’ individuals (those who are pro-socially motivated) will be attracted to organisations with a similar mission (Besley and Ghatak, 2003, 2005). Making the additional assumption that non-profit organisations are associated with pro-social missions, individuals who wish to donate labour are more likely to be matched with non-profit rather than for-profit organisations.

In contrast to the growing theoretical literature there has been very little empirical economic research on pro-social behaviour and none that provides very firm evidence on the relationship with institutional structure. There are a number of surveys that find evidence of differences in individuals’ self-reported motivations across sectors and a greater prevalence of intrinsic motivations in the non-profit sector.[3] However, these may reflect a halo effect as much as genuine differences. Frank and Lewis (2004) look at differences in self-reported effort by sector and find evidence of greater reported effort in the public sector. But again the measure is highly subjective. They also do not have information on individuals’ actual sector of employment, relying instead on constructed estimates based on industry.

The aim of this paper is to provide evidence on whether pro-social behaviour, i.e. donated labour, varies by sector. We use unpaid overtime as our measure of donated labour; compared to self-reported motivations or levels of effort, we would argue that hours of unpaid overtime are more directly comparable across all employees and less subject to problems of reporting bias by sector. We investigate whether employees provide more unpaid overtime in the delivery of public services if the services are provided by the non-profit sector rather than by the for-profit sector. We also begin to explore the mechanism by which any such relationship may arise.

[3] Le Grand (2003), chapter 2 provides a summary of a number of these studies. See also Marsden and French (1998).

We use data from the British Household Panel Survey (BHPS). As discussed further in section 3, the BHPS is well-suited for examining the relationship between donated labour and institutional form for a number of reasons. Unlike many other datasets, it has information on the two key variables – sector of employment (non-profit and for-profit) and hours of unpaid overtime. Also, as a panel, it enables us to follow the same individuals switching between sectors and observe any change in their pro-social behaviour.

The plan of the paper is as follows. The next section discusses the main models in the literature and our empirical strategy, while section 3 contains further details on the data and definitions of key variables. In section 4 we show that there is indeed a positive and significant correlation between sector and donated labour, controlling for a wide range of individual- and job-specific characteristics. Of course, this difference may simply be explained by implicit contracts or social norms operating within each of the sectors. In section 5 we exploit the panel nature of our data to estimate a simple fixed effects model. We show that there is no evidence that individuals change their donated labour when they switch sector and thus we reject these alternative explanations. This finding also causes us to reject a strong organisational-form explanation, suggesting that the observed relationship is more likely to be explained by a process of mission-matching or selection into different sectors. In section 6 we present evidence consistent with this explanation. Section 7 concludes.

2. Background and empirical approach

The literature identifies two related, but formally distinct, mechanisms that may give rise to a relationship between institutional form and donated labour. The first, which we call the 'organisational-form' approach is expressed most clearly by Francois (2000). In this model, individuals working in caring industries, including for example, health, education and social care, exhibit pro-social motivation in that they care directly about the quality of the output.[4] But the extent to which they will engage in

[4] Here we are sidestepping the distinction between individuals who care only about the overall value of the public service to which they contribute (pure or output-oriented altruism), individuals who receive a warm glow from their participation (impure or action-oriented altruism), or those that value both. See Francois and Vlassopoulos (2008) for a detailed discussion of this distinction.

pro-social behaviour, in this case donate their labour, depends on the organisational form. As in the hospital example above, if there is a residual claimant who can expropriate any labour that is donated, as in a for-profit organisation, then the incentive to donate labour is muted since the extra effort does not benefit the intended recipients. In the case of not-for-profit organisations there are a number of mechanisms that work to prevent this expropriation from occurring: the non-distribution constraint means that any 'profits' and income are only to be applied to the firm's objectives, dividend payments are prohibited and an asset lock-in means that, on winding-up, all assets must be transferred to another body with similar objectives. Thus in a not-for-profit organisation pro-socially motivated employees will be willing to provide extra effort because it will improve the quality of output. A somewhat related argument applies to government agencies who will not expropriate donated labour because decisions are made bureaucratically rather than to maximise profit. The organisational-form model predicts that there is likely to more donated labour in non-profit organisations than for-profit organisations. A further implication is that a change in the institutional form (between for-profit and non-profit) is likely to affect the extent to which individuals donate their labour.

An alternative mechanism, which we call the 'mission-matching' approach, has been most clearly formalised by Besley and Ghatak (2005). In this model individuals exhibit particular missions which motivate them to engage in pro-social behaviour. While the mission – and the associated behaviour – is a fixed individual characteristic, people will be attracted to organisations that share their mission, so that mission-oriented organisations that favour high quality public service provision will attract employees whose personal mission matches this. The core distinction in the model is between mission-oriented and profit-oriented organisations. However, while the theory is based on this distinction, rather than the for-profit/non-profit distinction, mission oriented organisations are typically aligned with not-for-profit organisations and public bureaucracies so the results are deemed to be informative about the differences between for-profit and non-profit organisations. As Besley and Ghatak (2003) put it, "if a nurse believes that nursing is an important social service with external benefits, then it should not matter whether he or she is employed by the public or private sector, except in so far as this affects the amount of benefit that he or she can generate." Because of the assumption that non-profit organisations are more likely to be mission-oriented, the mission-matching model also predicts that there should be more donated labour in non-profit organisations than for-profit organisations. However, the emphasis is on the process through which mission-oriented individuals are attracted to work in the non-profit sector.

Our primary aim is to test the central prediction of both these models, which is that there is a positive association between non-profit organisations and donated labour. We use unpaid overtime as our measure of donated labour. Since actual work intensity is not easily observable, we would argue that unpaid overtime is a good proxy since it captures the hours worked over and above the contractual requirement for which the individual does not receive any direct financial compensation. Of course, individuals may do unpaid overtime in the expectation of receiving compensation in the form of higher wages in the future (career concerns) and we discuss in section 3 how we control for this.

We estimate the probability that an individual does any unpaid overtime using a linear probability model. We show below that the greatest variation is in this extensive margin. We include four binary indicators representing the non-profit and for-profit "caring" sectors and the non-profit and for-profit "non-caring" sectors (defined in section 3 below). Our main interest is in the difference between the two caring sectors since that is where pro-social behaviour is likely to matter, but we include the non-caring sectors since they may reveal interesting more general differences between the caring and non-caring sectors and between the for-profit and non-profit sectors. We include controls for both individual characteristics and job characteristics, including a number of variables to control for the extent to which unpaid overtime is motivated by career concerns. Initially we treat the data simply as pooled cross-sections and do not take the panel data structure into account explicitly.

As shown in section 4, we find strong evidence of a non-profit premium. Individuals in the non-profit sector are 12 percentage points (or more than 40 per cent) more likely to do unpaid overtime than individuals in the for-profit sector. Of course, a simple difference in unpaid overtime between people working in the two sectors is not necessarily evidence of pro-social behaviour in the non-profit sector. It may simply reflect differences in implicit contracts over hours of work between non-profit and for-profit caring sectors, or that individuals abide by different social norms in the two sectors.

To rule out these alternative explanations, we exploit the panel nature of the data and look at what happens when individuals switch sectors. If the non-profit premium reflected either implicit contracts or social norms, we would expect to see individuals changing their donated labour when they switch between the non-profit and for-profit caring sectors in order to abide by the implicit contract/ social norm in their new sector. We therefore also estimate a fixed effects regression where the standard error term is decomposed into a constant individual specific effect and a pure random error term: $u_{it} = \eta_i + v_{it}$. In the fixed effects specification, the sector effects are identified only from individuals who change sector. As shown in section 5, we find no evidence that individuals change their behaviour when they switch sector, which we take as strong evidence that differences between sectors are not simply attributable to implicit contracts or social norms. This finding is also inconsistent with a strong form of the organisational form model where a change in sector is likely to be associated with a change in behaviour.

Instead, we would argue that the estimated non-profit premium is likely to reflect the selection of individuals into different sectors on the basis of their pro-social motivation. Put simply, "caring" individuals appear to select themselves into the non-profit sector and "non-caring" individuals into the for-profit sector. Formally, the selection story is that $E\left(\eta_i \mid sector_{it} = s\right) \neq 0$. In section 6, we present evidence that supports this selection story. We show that individuals who switch from the non-profit caring sector to the for-profit caring sector are less likely to do unpaid overtime (when they are in the non-profit sector) than those who stay in the non-profit caring sector. This difference is statistically significant. We also find that individuals who switch from the for-profit caring sector to the non-profit caring sector are more likely to do unpaid overtime when they are in the for-profit sector than those who stay in the for-profit sector.

3. Data

The data we use are taken from the British Household Panel Survey (BHPS). Since 1991 this survey has annually interviewed members of a representative sample of around 5,500 households, covering more than 10,000 individuals. On-going representativeness of the non-immigrant population is maintained by using a “following rule” – i.e. by following original sample members (adult and children members of households interviewed in the first wave) if they move out of the household or if their original household breaks up.[5]

A key advantage of using the BHPS is that as a panel it allows us to observe the same people working in both the for-profit and non-profit sectors. It also collects a wide range of detailed demographic and employment information. A potentially limiting factor is that the sample sizes in each wave of the BHPS are not sufficiently large to allow us to estimate standard deviations of wages by occupation with any precision. We use these to control for career concerns as discussed further below. We therefore supplement our analysis with data from the Labour Force Survey, a quarterly sample of 60,000 individuals. This limits our analysis to the period 1993 – 2000 for which we have common information across both datasets.

We select a sub-sample of individuals aged 16 – 60 who work between 30 hours and 90 hours per week. We exclude the self-employed and individuals in industries with non-standard working practices such as the armed forces, forestry and agriculture. We drop observations with missing information in key variables and also trim the top and bottom 0.5 per cent of the distributions of key variables such as hours of overtime (paid and unpaid), usual job hours and hourly pay.[6] Our final BHPS sample contains 6,061 individuals (24,135 person observations).

The BHPS does not directly ask individuals how many hours unpaid overtime they work. Instead, they are asked the following three questions about their hours of work:

- Thinking about your (main) job, how many hours excluding overtime and meal breaks are you expected to work in a normal week?
- And how many hours overtime do you usually work in a normal week?
- How much of that overtime (usually worked) is usually paid overtime?

[5] The survey incorporated booster samples from Scotland and Wales in 1999 and Northern Ireland in 2001 but we restrict our sample to original sample members.
[6] We also follow the practice used in deriving government statistics from LFS data of excluding individuals with weekly earning in excess of £3500, and £1000 for manual workers.

The answer to the first question is assumed to reflect an individual's basic, contracted hours. The second two questions are used to derive the number of hours of unpaid overtime. Although calculated as a residual, estimates of unpaid overtime using the BHPS compare well to those obtained using the LFS where individuals are asked directly how much unpaid overtime they do.[7]

The main focus of our analysis is a comparison of unpaid overtime worked by individuals in different sectors (for-profit and non-profit). We define individuals' sector on the basis of the following question:

- Which of the types of organisations on this card do you work for (in your main job)?

Individuals are prompted with a list of options. Those who respond "private firm/ company" are allocated to the for-profit sector. All other responses are allocated to the non-profit sector. These include "civil servant/central government", "local government/town hall", "NHS or higher education", "nationalised industry", "non-profit organisation".[8] Our non-profit sector therefore includes individuals working in the public sector, as well as in (traditionally defined) non-governmental not-for-profit organisations.

A potential problem with this self-reported measure is that it may be subject to non-random measurement error. Estimates of the public sector workforce based on a self-reported measure in the LFS have been shown to overestimate the size of the public sector workforce. However, this bias has been shown to be mainly attributable to (self-employed) general medical practitioners wrongly classifying themselves as public sector and to staff in higher education classifying themselves as public sector, as opposed to the not-for-profit sector.[9] Since we drop the self-employed from our sample and since we are interested in the distinction between the for-profit and (widely-defined) non-profit rather than between the public and not-for-profit sectors,

[7] We estimate that 27% of individuals supply unpaid overtime in the BHPS compared with 29% in the LFS.
[8] The two other categories – armed forces and other – are dropped from our analysis.
[9] Millard and Machin (2007).

we would argue that these measurement error issues do not pose a problem for our analysis.

Our analysis of donated labour focuses on individuals working in caring industries since this is where we would expect individuals' motivation to be manifested in extra donated labour. There is no formal definition of caring industries. To avoid imposing our own, possibly arbitrary, definition we follow Francois (2003) in identifying caring industries as those with a "…a public good component. Examples of such services are childcare, medical care, education, and care for the aged". We therefore define individuals working in health, education and social care industries as being in caring industries using the 1980 Standard Industrial Classification (SIC) two digit codes. Individuals working in these industries comprise 17 per cent of our total sample.

It could be argued that an industry-wide definition of caring is too broad; for example a hospital cleaner may not donate their labour because they work in a hospital rather than in an office, whereas hospital doctors may posses a greater level of attachment to the service they provide. For this reason, we also used a more restricted definition that cross-classifies industry with job occupation and defines caring occupations within caring industries, to include managers, natural scientists, health and teaching professionals and childcare workers. This definition restricts individuals working in caring to 14 per cent of our sample. A third possible definition of caring includes research and development, the arts and culture, corresponding to a broader set of industries where not-for-profit organisations are concentrated according to Rose-Ackerman (1996). This broadens the group of caring individuals to 20 per cent of our sample. We have assessed that our main conclusions are not sensitive to the definition of caring that we use and in the rest of the analysis presented below we focus on the first definition.

Table 1 summarises the distribution of caring services across sectors and across individual industries. Caring services are concentrated in the non-profit sector, with only 15 per cent of individuals employed in caring industries working in the for-profit sector. The breakdown is similar across the three industries (health, education and social care) although the largest sector (education) has the smallest proportion of for-profit sector employees.[10]

Table 1. Distribution by sector

	Full sample	Percentage	Health	Education	Social care
Non-profit caring	3573	14.80	1179	1617	777
For-profit caring	651	2.70	294	208	149
Non-profit non-caring	3219	13.34			
For-profit non-caring	16692	69.16			
Total	24135	100	1473	1825	926

Non-profit refers to not-for-profit organisations and public organisations; For-profit refers to private firms
Caring refers to health, education and social care; Non-caring refers to all other industries

Table 2 shows a clear distinction in the prevalence of donated labour between “for-profit caring” and “non-profit caring”. 46 per cent of people working in “non-profit caring” do some unpaid overtime, compared to only 29 per cent in “for-profit caring”. There is a similar pattern in the intensive margin with individuals who work in “non-profit caring” supplying an average 1.25 more unpaid overtime hours per week compared to “for-profit caring”. The difference does not appear to be attributable to a general non-profit effect since the proportion doing unpaid overtime in non-caring industries does not vary significantly between the for-profit and non-profit sectors, while average hours are lower in non-profit non-caring than in for-profit non-caring.

It is possible is that the additional unpaid overtime hours worked in the non-profit caring sector form part of an implicit contract and may compensate for shorter basic hours. Even if individuals are not formally contracted to work unpaid overtime, the expectation to do it may be sufficiently strong as to act as a binding constraint. Column (5) in Table 2 therefore compares the average number of hours of basic plus unpaid overtime worked by individuals in each of the sectors. Those in the non-profit caring work longer basic plus unpaid overtime hours than those in for-profit caring; the hours of unpaid overtime do not simply reflect shorter basic hours. However, when paid overtime is included in column (6), the difference between non-profit caring and for-profit caring disappears. Those in the non-profit caring sector are less

[10] Most private schools are formally not-for-profit organisations and, as such, should not be included in the for-profit sector. However, this sector includes for-profit nurseries.

likely to work paid overtime than those in all other sectors. Total hours (including unpaid and paid overtime) worked in the non-profit and for-profit caring sectors are the same, but the allocation between basic hours, unpaid overtime and paid overtime differs.[11] This may indicate an implicit contract to work overtime on an unpaid basis in the non-profit sector, and on a paid basis in the for-profit sector. However, another possibility is that, outside the non-profit caring sector, employers cannot rely on unpaid overtime to make marginal adjustments in labour supply and must use formal paid overtime. We return to this issue in section 5.

Table 2. Hours worked by sector

	Unpaid overtime		Paid overtime		Total hours	
	(1) Prop^n > 0	(2) Mean (>0)	(3) Prop^n > 0	(4) Mean (>0)	(5) Contracted hours + Unpaid OT	(6) Contracted hours + Unpaid OT + Paid OT
Non-profit caring	0.46	9.59	0.10	7.90	41.44	42.22
	(0.50)	(7.34)	(0.30)	(5.86)	(8.26)	(8.55)
For-profit caring	0.29*	8.34*	0.22*	7.21	40.53*	42.10
	(0.45)	(5.86)	(0.41)	(6.22)	(7.10)	(7.71)
Non-profit non-caring	0.22*	6.56*	0.26*	8.21	39.53*	41.66*
	(0.42)	(5.80)	(0.44)	(6.69)	(5.20)	(7.12)
For-profit noncaring	0.24*	8.49*	0.34*	8.51	41.32	44.20*
	(0.43)	(6.49)	(0.47)	(6.09)	(6.94)	(8.22)
Total	0.27	8.55	0.29	8.41	41.07	43.52
	(0.44)	(6.67)	(0.46)	(6.15)	(6.98)	(8.18)

Standard deviations in brackets
Non-profit refers to not-for-profit organisations and public organisations; For-profit refers to private firms
Caring refers to health, education and social care; Non-caring refers to all other industries
* indicates that the difference with the non-profit caring sector is significant at 5% level

4. Pooled estimation results

The preliminary descriptive statistics show a distinction in unpaid overtime between individuals in the for-profit and non-profit caring sectors. However, there are a number of other differences between the two sectors – in both the characteristics of the jobs and the individual employees – that may account for this difference. As

[11] In principle, we could look explicitly at whether individuals are remunerated for their unpaid overtime by comparing average hourly pay across sectors, including hours of unpaid overtime in the denominator. However, as shown in Postel-Vinay and Turon (2007), differences between the sectors are not fully captured by current pay. Our alternative approach is to include measures capturing pay dynamics in our regression analysis.

shown in Appendix A, individuals working in the non-profit sector are typically older, they are more likely to be female, they face different earnings profiles and risk of job loss. All of these factors may affect the likelihood of doing unpaid overtime and to control for this, we therefore estimate a model of the following form:

$$D_{it} = \sum_{s=1}^{4} \beta_s \left\{ sector_{it} = s \right\} + x_{it}'\delta + z_{it}'\gamma + u_{it} \tag{1}$$

where D_{it} is a binary indicator variable equal to one if individual *i*, *i=1,…,N*, does any unpaid overtime in time *t*, *t=1,…,T*, and zero otherwise. $\left\{ sector_{it} = s \right\}$ is a set of four binary indicators representing the non-profit and for-profit caring sectors and the non-profit and for-profit non-caring sectors. The vector x_{it} contains individual characteristics whereas z_{it} is a vector of an individual's job characteristics. Since the data show a clear distinction in whether individuals do any overtime, our main focus is on this extensive margin, although we have also run a Tobit regression on the number of hours overtime.[12] We estimate a linear probability model for ease of interpretation of the results.[13]

The estimation results in Column I in Table 3 are not adjusted for individual and job characteristics and confirm the results of the previous section that there is a significant difference between the for-profit caring sector (the omitted sector) and the non-profit caring sector, equal to 17 percentage points. Individuals working in the non-profit non-caring sector are significantly less likely to do any unpaid overtime than those in the for-profit caring sector, while the difference between the for-profit caring and for-profit non-caring sectors is not significant.

Column II introduces a number of individual characteristics (means and standard deviations for all covariates are presented in Appendix A). These include standard controls for age, gender, ethnicity, education, marital status and region. We also include controls for the presence and ages of children since they are likely to affect the opportunity cost of doing unpaid overtime. We allow the presence of children to differentially affect women. The inclusion of these individual characteristics reduces

[12] The Tobit regression confirms the results of the linear probability model. Results are available on request.
[13] The results using a probit regression were similar.

the size of the non-profit caring premium by 20 per cent, but it remains positive and significant.

Column III adds a number of characteristics relating to the individual's job. The first is a wage measure. A number of studies have drawn attention to the importance of unpaid overtime as an investment in future earnings (see Francesconi, 2001, Campbell and Green, 2002, Pannenberg, 2005). An individual's current hourly wage is therefore likely to be endogenous since it will reflect unpaid overtime worked in the past (which in turn may be correlated with current overtime) and we include, instead, the log of the median wage by occupation, year and age group (16-29, 30-45 and 46+) calculated using LFS data.[14] This wage variable may capture a number of things. First there is the potential opportunity cost – that the cost of doing unpaid overtime is greater at higher wages. In this case, however, the wage variable would be expected to attract a negative sign, rather than a positive one. The estimated positive coefficient may reflect an income effect – that at higher wages individuals can afford to do more unpaid overtime. More likely, however, it might reflect the selection of career-oriented individuals into high-paying occupations and/or the effect of high wages on unpaid overtime motivated by career concerns.

As well as including a measure of average wage by occupation, we control for career concerns by including a measure of the variance of wages within an occupation to capture the future pay-off to unpaid overtime. This follows Bell and Freeman (2001) who argue that longer hours worked in the US compared to Germany can be attributed to greater wage inequality in the US, which in turn increases the financial rewards from promotion and the motivation to work harder. They estimate labour supply equations at the occupation and individual level including the standard deviation of log hourly wages at the occupation level as a proxy for wage inequality and find this variable to be positively correlated with hours worked. We therefore include the standard deviation of log hourly wages at the occupation level (calculated using data from the LFS) as our measure of career concerns. However, we refine the measure by calculating the standard deviation across the part of the age distribution that we think will be most relevant to individuals at different stages of their career. Thus we calculate the standard deviation based on the entire age distribution for individuals

[14] We use the standard occupational classification, with 90 occupations

aged 16 – 30, the standard deviation over the age range 30 – 60 for individuals aged 30 – 45, and the standard deviation over the age range 45 – 60 for individuals of this age. The standard deviations are therefore greater for younger workers, reflecting the fact that career concerns are likely to matter more for this age group. Our preferred career concerns variable (the standard deviation of log hourly wages by occupation, age group and year) enters positively and significantly in the regression. Additionally, we include controls for an individual's tenure in their current job since they may be motivated to work harder early on to gain a good reputation to help secure future promotions.

Calculating the standard deviation of log hourly wages at the occupation level assumes that individuals consider the distribution of wages across all sectors in making decisions about unpaid overtime, and will therefore consider career moves between sectors. However, if individuals consider careers within sector,[15] only the sector-specific standard deviation will matter in practice. Since the wage distribution is typically more compressed in the non-profit sector,[16] using sector-specific career concern measures will tend to reduce the effect of career concerns on unpaid overtime in the non-profit caring sector and increase the coefficient on the sector indicator. In practice, however, the difference between the results of the two different specifications is very small.

We include two additional variables to capture career concerns. We include an indicator variable (opportunity for promotion), which takes the value one if individuals say that they have opportunities for promotion in their current job. We also include an indicator variable if the individual's pay includes a bonus since this type of performance-related pay may induce greater effort.[17] Both variables enter positively and significantly as expected. We also try to take account of the fact that people may work harder to avoid being fired, as well as to gain promotion. The BHPS asks individuals about their level of satisfaction with job security in their current job

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[15] Or, alternatively, if the future rewards to unpaid overtime operate only within sectors.

[16] The averages of the log wage standard deviation measures are 0.45 in the for-profit sector and 0.40 in the non-profit sector.

[17] Specified examples include a Christmas or quarterly bonus, profit-related pay or profit-sharing or an occasional commission.

Table 3. Results for the pooled linear probability model

Dependent variable: whether individual does unpaid overtime (0/1)

	Column I		Column II		Column III	
	Coeff	SE	Coeff	SE	Coef	SE
For-profit caring (omitted)	-	-	-	-	-	-
Non-profit caring	0.174***	0.032	0.139***	0.030	0.123***	0.027
Non-profit noncaring	-0.062**	0.031	-0.053	0.030	-0.148***	0.032
For-profit noncaring	-0.045	0.029	0.003	0.027	-0.118***	0.030
Educ: No qualifications			-	-	-	-
Educ: school level			0.108***	0.013	0.012	0.012
Educ: college level			0.284***	0.014	0.090***	0.012
Age			0.036***	0.003	0.008***	0.003
Age squared			-0.045***	0.004	-0.012***	0.004
Married			0.009	0.011	0.000	0.010
Female			0.016	0.012	0.035***	0.010
Children in household			-0.038**	0.019	-0.034**	0.016
Female*children			-0.043**	0.021	-0.022	0.018
Youngest child aged 02			0.014	0.022	-0.010	0.019
Youngest child aged 34			-0.030	0.022	-0.043**	0.019
Youngest child aged 511			-0.008	0.018	-0.014	0.015
Youngest child aged 12+			-	-	-	-
Non-white			-0.089***	0.027	-0.052**	0.023
Ln wage, occ/age/year					0.326***	0.015
SD Ln wage, occ/age/year					0.364***	0.048
Job tenure					-0.008***	0.001
Job tenure squared					0.018***	0.005
Opportunity for promotion					0.032***	0.007
Pay includes bonus					0.031***	0.007
Job is secure					-	-
Job is not secure					-0.012	0.008
Job neither secure/insecure					-0.012	0.009
Individual is a manager					0.149***	0.009
Small firm (<50)					0.032***	0.012
Medium firm (50-499)					0.032***	0.010
Large firm (500+)					-	-
Trade Union at workplace					-0.071***	0.011
Indiv is member of union					-0.028**	0.011
Firm has pension scheme					0.010	0.011
Indiv is member of pension					0.055	0.011
Usual hours<35					0.026	0.015
Usual hours 35-40					0.037***	0.008
Usual hours 40+					-	-
Health industry					-0.190***	0.026
Social care industry					-0.117***	0.030
Observations	24135		24135		24135	
Number of Individuals	6016		6016		6016	
Adjusted R-squared	0.031		0.117		0.263	

Regressions include region and year dummies
Robust standard errors are clustered at the individual level
*** indicates significant at 1% level, ** at 5% level

and we include indicator variables for whether individuals are not satisfied that their job is secure, or are neither satisfied nor dissatisfied. The results show that, compared to being satisfied with job security, increasing insecurity is negatively correlated with doing unpaid overtime, suggesting that individuals put in effort when they think there is a chance of promotion, rather than to avoid being fired.

Managers typically do more unpaid overtime because of the more complex and nebulous nature of their tasks (Hart, 2004). Employees who underestimate task times must work unpaid overtime to fulfil contractual obligations. Also, managers are more likely to work unpaid overtime where their performance is judged by the performance of their team (see Bell and Hart, 1999). We therefore include an indicator for whether individuals report having managerial/supervisory duties at work. This is positive and significant.

Finally, we include a number of controls for institutional settings that may affect unpaid overtime, including the presence of trade unions, employer pension schemes and the size of the firm. We also control for the basic number of hours an individual is expected to work since this may act as a constraint on their ability to do any unpaid overtime.[18]

Including these additional job characteristic variables reduces the size of the non-profit caring unpaid overtime premium further, but it remains positive and significant. After allowing for a robust set of controls for career concerns and for other individual and job characteristics, we find that individuals in the non-profit caring sector are more than 12 percentage points (or more than 40 per cent) more likely to do unpaid overtime than individuals working in the for-profit caring sector. Of course, this analysis does not enable us to explain why the difference arises, which is the focus of the analysis in the next section.

In Table 4 we report the results of two further regressions where the dependent variable is total hours worked in a normal week. These confirm the unadjusted findings from the previous section. Individuals in the non-profit caring sector work

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[18] We have also included a control for time spent travelling to work. This information is not available for all observations and we therefore exclude it from our main specification, but it does not affect the overall results in the subsample.

significantly longer hours when total hours are defined as basic hours plus unpaid overtime. Thus, we can rule out the possibility that longer unpaid overtime hours are simply an adjustment for shorter basic hours. However, when paid overtime hours are included in the regression, there is no significant difference between the for-profit and non-profit caring sectors in total hours. What differs is the allocation of these total hours across basic hours, unpaid overtime and paid overtime. As already discussed, this different allocation may be attributable to institutional practices that vary across sectors. Or it may arise as a response to different levels of donated labour across the sectors. We explore these alternative explanations further in the next section.

Table 4. Results for pooled OLS model

Dependent variable: number of hours worked in a normal week

	Column I Basic hours + unpaid OT		Column II Basic hours + unpaid OT + paid OT	
	Coeff	SE	Coeff	SE
Non-profit caring	0.0231**	0.0105	0.0003	0.0110
Non-profit noncaring	-0.0633***	0.0123	-0.0632***	0.0132
For-profit noncaring	-0.0451***	0.0117	-0.0235	0.0122
Observations	24135		24135	
Adjusted R-squared	0.202		0.168	

Regressions include the full set of control variables
Robust standard errors are clustered at the individual level
*** indicates significant at the 1% level, ** at the 5% level

5. Fixed effects estimation results

Our pooled regression results identify a significant difference in the probability of doing unpaid overtime between individuals in the non-profit and for-profit caring sectors. However, this is not necessarily evidence of pro-social behaviour. It may instead reflect sector norms in the allocation of hours between basic hours and paid and unpaid overtime, or implicit contracts operating in the different sectors. If so, however, we would expect individuals who switch sector to comply with the prevailing behaviour in their new sector, and therefore change behaviour when they switch. To investigate this, we estimate the following fixed effects regression where the sector effects are identified only from individuals who change sector:

$$D_{it} = \sum_{s=1}^{4} \beta_s \{sector_{it} = s\} + x'_{it}\delta + z'_{it}\gamma + \eta_i + v_{it} \qquad (2)$$

The error term in equation (1) has been decomposed into a constant individual specific effect and a pure random effect: $u_{it} = \eta_i + v_{it}$.

Information on our sample is summarized in Table 5, showing destination and origin sectors for individuals observed in consecutive periods. In all, nearly 6 per cent of observations involve a change in sector. Switches from the for-profit caring sector to the non-profit caring sector are relatively more common (as a proportion of all people working in the for-profit caring sector) than switches going the other way.

Table 5. Switches across sectors

	Sector, time t			
Sector, time t – 1	Non-profit caring	For-profit caring	Non-profit noncaring	For-profit Noncaring
N-P caring	2404	83	135	50
F-P caring	80	288	5	88
N-P noncaring	129	9	2224	184
F-P noncaring	88	85	133	12099

Of course, switches are likely to be a non-random sample of all our observations and we discuss below how this is likely to affect our results. It might be thought that the ideal dataset for this analysis would capture an exogenous change in institution, e.g. a voluntary sector nursing home being taken over by the for-profit sector. However, even this case is likely to suffer from selection issues since the employees who remain working for the same institution after such a change are likely to be a selected group. Looking at the behaviour of switchers, while not ideal, is not obviously a lot worse than this kind of natural experiment.

The results of our fixed effects regression are reported in Table 6. Many of the control variables – particularly the set of variables to capture career concerns – that were significant in the pooled regression enter significantly in the fixed effects specification, but the magnitude of the estimated effects is smaller. This suggests that individuals who are motivated by career concerns are likely to select themselves into jobs with opportunities for promotion, as well as promotion opportunities having an additional effect on unpaid overtime.

We find that the non-profit caring sector effect is insignificant in the fixed effects regression. Of course, it might be that we have insufficient numbers of switchers to identify an effect. However, the fact that the estimated coefficient is very close to zero, rather than positive but imprecisely estimated is consistent with this being a genuine result.

A zero finding could also be due to measurement error (misreporting or misrecording of sector status) leading to spurious sector switches. This is explored further in Appendix B where we show that our findings could be due to measurement error only with a very high proportion of misrecording. We believe that the levels of measurement error required to generate our findings are unlikely to occur in practice. To explore this, we have looked at how long individuals stay in their new sector following a switch. If observed "switches" were actually one-off measurement errors then it is likely that individuals would revert back to their sector of origin the following period. In fact, 75 per cent of switchers stay in their new sector for at least two periods. Also if a very high proportion of observed switches were actually measurement error then we would expect all the coefficients on the sector dummies to be close to zero, while we find that the estimated coefficient on non-profit non-caring is quite large.

The fact that the estimated non-profit caring sector effect is close to zero and insignificant in the fixed effects regression is a strong finding. It means, for example, that we can rule out the possibility that the difference in donated labour across sectors is simply due to a difference in allocation of total hours between basic hours, unpaid overtime and paid overtime across the sectors. If the difference in donated labour reflected this kind of sector norm then we would expect individuals to adopt that norm when they changed sector but this is not the case. This makes it more likely that the observed difference in paid overtime across the sectors is a response to the difference in donated labour rather than vice versa.

Table 6. Estimation results for fixed effects linear probability model

Dependent variable: whether individual does unpaid overtime (0/1)

	Column I		Column II		Column III	
	Coeff	SE	Coeff	SE	Coef	SE
For-profit caring (omitted)	-	-	-	-	-	-
Non-profit caring	0.000	0.029	-0.001	0.028	0.002	0.028
Non-profit noncaring	-0.042	0.030	-0.039	0.030	-0.061	0.042
For-profit noncaring	-0.015	0.027	-0.015	0.027	-0.037	0.041
Age			0.011	0.011	0.001	0.011
Age squared			-0.038***	0.006	-0.026***	0.006
Married			0.002	0.012	0.002	0.012
Children in household			-0.007	0.017	-0.009	0.017
Female*children			-0.042*	0.024	-0.035	0.023
Youngest child aged 02			-0.005	0.018	-0.005	0.017
Youngest child aged 34			-0.021	0.018	-0.022	0.018
Youngest child aged 511			-0.001	0.014	0.001	0.014
Youngest child aged 12+			-	-	-	-
Ln wage, occ/age/year					0.092***	0.017
SD Ln wage, occ/age/year					0.110***	0.040
Job tenure					-0.004***	0.001
Job tenure squared					0.015***	0.005
Opportunity for promotion					0.015**	0.006
Pay includes bonus					0.012**	0.006
Job is secure					-	-
Job is not secure					-0.010	0.007
Job neither secure/insecure					-0.006	0.008
Individual is a manager					0.070***	0.008
Small firm (<50)					0.009	0.012
Medium firm (50-499)					0.016*	0.009
Large firm (500+)					-0.021*	0.011
Trade Union at workplace					-	-
Indiv is member of union					0.001	0.011
Firm has pension scheme					0.000	0.012
Indiv is member of pension					0.025**	0.011
Usual hours<35					0.003	0.017
Usual hours 35-40					0.054***	0.009
Usual hours 40+					-	-
Health industry					-0.050	0.041
Social care industry					-0.028	0.041
Observations	22703		22703		22703	
Number of Individuals	4619		4619		4619	

Regressions include region and year dummies
Robust standard errors are clustered at the individual level
*** indicates significant at 1% level, ** at 5% level

These fixed effects results also rule out a strong version of the organisational form model, i.e. a common institutional effect working on homogeneous agents, which would also imply individuals changing their behaviour when they switched sector. Instead, the results are consistent with the selection of individuals into different sectors and in the next section we present some further evidence to support this.

6. Evidence on selection

In this section we look in more detail at the behaviour of people who switch sector (and compare it to that of the stayers) to find any evidence of selection into different sectors on the basis of propensity to donate labour. By directly comparing levels of unpaid overtime among the people who switch out of the sector with levels of unpaid overtime among the stayers, we confirm that there are some differences between switchers and the other individuals in the sector they switch from. However, these differences are only significant for people switching from public to private, although this may reflect the sample sizes.

We estimate the following models – one for people working in the non-profit caring (NPC) sector (model 3a) and the other for people working in the for-profit caring (FPC) sector (model 3b):

$$D_{it}^{NPC} = \varphi_{11} Switch_i^{FPC} + \varphi_{12} Switch_i^{NC} + x'_{it}\,\delta + z'_{it}\,\gamma + u_{it} \qquad \text{(3a)}$$

$$D_{it}^{FPC} = \varphi_{21} Switch_i^{NPC} + \varphi_{22} Switch_i^{NC} + x'_{it}\,\delta + z'_{it}\,\gamma + u_{it} \qquad \text{(3b)}$$

The aim is to see whether people who switch out of the sector at some point in the future are systematically different to people who stay in the sector since this would indicate a sorting of individuals across sectors. As before D_{it}^{s} is an indicator variable equal to one if the individual does unpaid overtime when they are working in the non-profit caring sector or in the for-profit caring sector. $Switch_i^{s}$ is an indicator variable equal to one if the individual switches out of the sector at any point in the future – into the for-profit sector for people working in the non-profit sector, or into the non-profit sector for those in the for-profit sector, or into (either the non-profit or for-profit) non-caring sector for either sample. The coefficients on the switching indicators therefore pick up systematic differences in the propensity to donate labour between those who stay in a sector and those who switch out of the sector at some future point. Our prior is that people switching from the non-profit to the for-profit sector will be less likely to do unpaid overtime than the stayers ($\varphi_{11} < 0$) and that people switching from the for-profit sector to the non-profit sector will be more likely to do unpaid overtime than the stayers ($\varphi_{21} > 0$). We would expect switchers from the non-profit caring sector to the non-caring sectors to look more like people in the non-caring sector than like people in the non-profit caring sector ($\varphi_{12} < 0$). We have no prior belief about how switchers from the for-profit caring sector to the non-caring sector might differ from the stayers.

As before, we include a wide set of control variables for individual and job characteristics. The results are presented in Table 7. Note that we use a slightly modified sample. In practice, some individuals are observed to switch more than once. To simplify the analysis, we truncate each individual's observations after their first observed switch.

Table 7. Estimation results for linear probability model

Dependent variable : whether individual does unpaid overtime (0/1)

	Employees in the non-profit caring sector		Employees in the for-profit caring sector	
Switch to for-profit caring	-0.132*	-0.114**		
	(0.075)	(0.058)		
Switch to non-profit caring			0.078	0.039
			(0.089)	(0.069)
Switch to non-caring	-0.141***	-0.064	-0.053	0.025
	(0.052)	(0.044)	(0.076)	(0.068)
Control variables	No	Yes	No	Yes
N	3134		517	

Robust standard errors are clustered at the individual level

*** indicates significant at 1% level, ** at 5% level, * at 10% level

These results provide some evidence of differential selection. All the coefficients have the expected sign. However, the only differences that are statistically significant are between people who stay in the non-profit sector and those who switch out, who are less likely to do unpaid overtime than the stayers. While the coefficient on the for-profit caring dummy in the non-profit caring sector regression is positive, it is insignificant and the magnitude is reduced when the control variables are included. However, there is a much smaller sample of people working in the for-profit caring sector.

7. Discussion and conclusions

Our results provide the first clear evidence of a strong link between institution and pro-social behaviour in the form of donated labour in the provision of caring services. Consistent with a number of theories, we have shown that individuals in the non-profit sector are significantly more likely to donate their labour than those in the for-profit sector, and we have ruled out that this result is simply attributable to sector norms or implicit contracts. Our results also rule out a strong version of the organisational form model with homogeneous agents, since this would imply that all individuals who switched sector would change their behaviour and there is no evidence to support this.

We have provided some evidence that individuals differentially select into the two sectors on the basis of their propensity to donate labour. An extreme version of the selection story would imply that all the difference in donated labour between the two sectors is attributable to selection, with no role for the kind of organisational incentives described by Francois (2000). Our results do not prove this strong selection story. An alternative explanation that we cannot rule out (since it is observationally equivalent to the pure selection story) is that organisational incentives matter to some people who are not among the switchers. This can be represented by including an additional sector-specific effect ψ_i^s in the individual error term, i.e. $u_{it} = \eta_i + \psi_i^s + v_{it}$

While we find some evidence to support a selection story, we cannot rule out that a change in sector might affect behaviour for some people. Also, while our evidence supports a story of selection or mission-matching, organisational incentives may play an important role in creating and supporting missions. These remain important areas for further work.

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Appendix A: Summary statistics

	Full sample	Non-profit caring	For-profit caring	Non-profit non-caring	For-profit Non-caring
Educ: school level	.356	.158	.291	.369	.399
	(.478)	(.364)	(.454)	(.483)	(.489)
Educ: college level	.549	.803	.662	.573	.486
	(.497)	(.398)	(.473)	(.494)	(.499)
Age	36.44	39.15	36.13	37.98	35.59
	(10.90)	(10.18)	(10.90)	(10.10)	(11.07)
Married	.707	.697	.651	.728	.707
	(.455)	(.459)	(.477)	(.444)	(.456)
Female	.407	.714	.794	.378	.332
	(.491)	(.491)	(.404)	(.484)	(.471)
Children in household	.307	.286	.270	.350	.306
	(.461)	(.452)	(.444)	(.477)	(.461)
Youngest child aged 02	.066	.040	.029	.073	.071
	(.248)	(.197)	(.168)	(.260)	(.257)
Youngest child aged 34	.049	.032	.029	.056	.053
	(.216)	(.175)	(.168)	(.231)	(.222)
Youngest child aged 511	.129	.125	.139	.152	.124
	(.334)	(.330)	(.347)	(.359)	(.330)
Non-white	.034	.043	.030	.033	.032
	(.180)	(.204)	(.173)	(.180)	(.175)
Median ln wage, occ/age/year	2.15	2.29	2.14	2.23	2.09
	(.349)	(.356)	(.403)	(.317)	(.339)
SD Ln wage, occ/age/year	.419	.401	.408	.413	.424
	(.078)	(.083)	(.078)	(.079)	(.075)
Job tenure	4.26	4.51	3.23	5.26	4.05
	(5.59)	(5.24)	(4.13)	(6.19)	(5.57)
Opportunity for promotion	.545	.479	.445	.663	.523
	(.497)	(1.077)	(.497)	(.473)	(.500)
Pay includes bonus	.349	.056	.197	.199	.448
	(.477)	(.229)	(.398)	(.298)	(.492)
Job is not secure	.164	.161	.094	.217	.158
	(.371)	(.368)	(.292)	(.412)	(.364)
Job neither secure/insecure	.098	.066	.083	.096	.106
	(.297)	(.248)	(.276)	(.295)	(.308)
Individual is a manager	.426	.510	.496	.426	.404
	(.494)	(.500)	(.500)	(.494)	(.491)
Small firm	.278	.253	.393	.172	.300
	(.448)	(.434)	(.489)	(.378)	(.458)
Medium firm	.529	.464	.534	.574	.534
	(.499)	(.498)	(.499)	(.494)	(.499)
Trade Union at workplace	.512	.892	.290	.929	.359
	(.499)	(.310)	(.454)	(.256)	(.479)
Individual member of union	.343	.662	.197	.648	.222
	(.474)	(.473)	(.398)	(.478)	(.416)
Firm has pension scheme	.731	.945	.427	.968	.651
	(.444)	(.229)	(.495)	(.175)	(.478)
Indiv is member of pension	.601	.841	.325	.900	.503
	(.489)	(.366)	(.468)	(.298)	(.500)
Usual hours<35	.062	.178	.133	.039	.039
	(.242)	(.383)	(.340)	(.195)	(.196)
Usual hours 35-40	.611	.661	.514	.702	.587
	(.487)	(.473)	(.500)	(.458)	(.492)
Sample size	24135	3573	651	3219	16692

Standard deviations in brackets
Non-profit refers to not-for-profit organisations and public organisations; For-profit refers to private firms
Caring refers to health, education and social care; Non-caring refers to all other industries

Appendix B: Measurement error, misclassification of for-profit and non-profit sectors

As the for-profit and non-profit sector allocations come from self-reported answers to the question as outlined in section 3, there could be misreporting or misrecording error. If this is the case then we could potentially observe a reported but not real switch in sector, which will especially affect the fixed effects panel data estimates, as these are identified solely from people that switch sector.

If we consider a simple 2-period 2-sector model, then the fixed effects estimate for the non-profit premium in unpaid overtime in a model without other covariates is given by

$$\hat{\beta} = \lambda\left(\bar{y}_1^{01} - \bar{y}_0^{01}\right) + (1-\lambda)\left(\bar{y}_1^{10} - \bar{y}_0^{10}\right)$$

where the 0-sector is the for-profit sector and the 1-sector the non-profit sector. $\bar{y}_a^{01}$ is the proportion of people working unpaid overtime while employed in sector $a = \{0,1\}$ for those that in the first period worked in the for-profit sector and in the second period in the non-profit sector. Similarly for $\bar{y}_a^{10}$, for those who started in the non-profit sector and moved to the for-profit sector. λ denotes the proportion $\lambda = n^{01} / \left(n^{01} + n^{10}\right)$.

Different misclassification processes will lead to different biases. If we take the results from the pooled regressions as an estimate of the true effect (although these estimates will also be downward biased through misrecording error) then we could observe the fixed effects results of no differences between sectors due to reporting error in the following circumstances.

Misrecording error in one period only

In this example, the sector in one period is misrecorded and the observed switches entirely spurious. We assume that unpaid overtime behaviour itself is not affected by the misrecording.[19] For ease of exposition we further assume that misrecording error only occurs in the first period. Individuals will on average do less unpaid overtime in the reporting period than the sector average if they misreport to be in the non-profit sector and vice versa. Let δ_0 denote the fraction that misreport to be in the for-profit sector in the first period and δ_1 the fraction that misreport to be in the non-profit sector in the first period. The effect estimate is then

$$\begin{aligned}\hat{\beta} &= \lambda\left(\delta_0\left(\overline{y}_{11}^{01}-\overline{y}_{01}^{01}\right)+\left(1-\delta_0\right)\left(\overline{y}_{11}^{01}-\overline{y}_{00}^{01}\right)\right) \\ &\quad +\left(1-\lambda\right)\left(\delta_1\left(\overline{y}_{11}^{10}-\overline{y}_{01}^{10}\right)+\left(1-\delta_1\right)\left(\overline{y}_{11}^{10}-\overline{y}_{00}^{10}\right)\right)\end{aligned}$$

where now e.g. $\overline{y}_{ab}$ is the proportion of people working unpaid overtime when reporting to be in sector *a* and working in sector *b*. In this case $\hat{\beta}$ will be downward biased with the bias larger with increasing proportions of misrecording. If, $\delta_0=\delta_1=\delta$, $E\left(\overline{y}_{11}^{01}\right)=E\left(\overline{y}_{11}^{10}\right)=E\left(\overline{y}_{01}^{10}\right)=E\left(\overline{y}_{01}^{01}\right)=E\left(\overline{y}_{1}\right)=\mu_1$ and $E\left(\overline{y}_{00}^{01}\right)=E\left(\overline{y}_{00}^{10}\right)=E\left(\overline{y}_{10}^{10}\right)=E\left(\overline{y}_{10}^{01}\right)=E\left(\overline{y}_{0}\right)=\mu_0$, then $E\left(\hat{\beta}\right)=\left(1-\delta\right)\left(\mu_1-\mu_0\right)$. As an indication of the amount of misrecording error needed to obtain our results through measurement error alone, consider the estimates of the pooled model without covariates as reported in Table 3, 0.174 (se 0.032) and those of that of the fixed effects model, 0.000 (se 0.029). Using the 95% confidence intervals, we get for the smallest possible effect size $\left(\mu_1-\mu_0\right)$ as estimated in the pooled model the value of 0.111. The largest estimate for $\left(1-\delta\right)\left(\mu_1-\mu_0\right)$ in the fixed effects model is equal to 0.057. These values could therefore occur, with small probability, due to measurement error if $\delta > 0.49$. We ignored in this calculation the downward bias of the pooled estimator itself due to the measurement error. Clearly, the zero effect obtained in the fixed effects model is therefore very unlikely to result solely due to measurement error.

[19] If people misreport because they truly belief that they work e.g. in the for-profit sector whereas they do work in a not-for-profit organisation, but learn the true status of their sector over time, then this should not affect the results as this would in effect be a genuine switch.

Misrecording in both periods

Misrecording in both periods refers to a respondent reporting to move for example from the non-profit sector to the for-profit sector whereas the opposite was the case. The estimator is then

$$\hat{\beta} = \lambda\left(\gamma_0\left(\overline{y}_{10}^{01} - \overline{y}_{01}^{01}\right) + \left(1-\gamma_0\right)\left(\overline{y}_{11}^{01} - \overline{y}_{00}^{01}\right)\right)$$
$$+\left(1-\lambda\right)\left(\gamma_1\left(\overline{y}_{10}^{10} - \overline{y}_{01}^{10}\right) + \left(1-\gamma_1\right)\left(\overline{y}_{11}^{10} - \overline{y}_{00}^{10}\right)\right)$$

where γ_0 is the proportion misrecording for-profit in the first period and non-profit in the second and γ_1 the proportion misrecording non-profit in the first period and for-profit in the second. Clearly, the estimate for the treatment effect will again be biased downward. If $\gamma_0 = \gamma_1 = \gamma$, $E\left(\overline{y}_{11}^{01}\right) = E\left(\overline{y}_{11}^{10}\right) = E\left(\overline{y}_{01}^{01}\right) = E\left(\overline{y}_{01}^{10}\right) = \mu_1$ and $E\left(\overline{y}_{00}^{01}\right) = E\left(\overline{y}_{00}^{10}\right) = E\left(\overline{y}_{10}^{01}\right) = E\left(\overline{y}_{10}^{10}\right) = \mu_0$ then $E\left(\hat{\beta}\right) = \left(1-2\gamma\right)\left(\mu_1 - \mu_0\right)$. Repeating the calculations above we would need $\gamma > 0.25$ for the estimates found to have a small probability to be due to measurement error only.

Multiple Periods

Of course, in the full panel various other (spurious) switches are possible. However, the main results obtained above remain. For example if the only switches observed in a three-year panel where of the sequence 0-1-0, then the fixed effect estimate would be equal to $\hat{\beta} = \overline{y}_{1,t=2} - \frac{1}{2}\left(\overline{y}_{0,t=1} + \overline{y}_{0,t=3}\right)$. If a proportion δ of sector 1 in period 2 is reported with error, then, again,

$$E\left(\hat{\beta}\right) = E\left(\delta\overline{y}_{0,t=2} + \left(1-\delta\right)\overline{y}_{1,t=2} - \frac{1}{2}\left(\overline{y}_{0,t=1} + \overline{y}_{0,t=3}\right)\right) = \left(1-\delta\right)\left(\mu_1 - \mu_0\right).$$

As mentioned in the text in section 5, the pattern of switches found in the data does not indicate this type of misrecording error, as most individuals stay in the new sector after switching.