Cyclicality in work absenteeism across employment sector: an exploratory study of the role of vocation in public health sector using UK HLS

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Abstract

This paper empirically tests the hypothesis of cyclicality in work absenteeism across several employment sectors. The paper applies random effect logit and ordinal regression models to a British panel data – Understanding Society – using waves 1992 to 2012. Whilst business cycle is measured by the regional quarterly unemployment rate, work absence is measured by (i) sickness absence, (ii) 'other' absence (proxy for voluntary absenteeism) and (iii) number of yearly GP visits, respectively. In addition of analysing the associations between business cycle and work absenteeism amongst traditional employment sectors, such as private, public, self-employed and non-profit sector; the public sector was divided into two: vocational (health and education) and non-vocational (administration and local Government) sectors. Thusly, the paper explored the potential role of vocation in the decision of work absence, delving further in the theory of job attachment and economics of vocation. Whilst we find no evidence of a pro-cyclicality between sickness absence and business cycle, we found an inverse and significant association between 'other' work absence and business cycle. Furthermore, there was no evidence of pro-cyclicality between yearly GP visit and unemployment. Interaction term between unemployment and public vocational was positive and significant however.

1. Introduction

Work absenteeism is costly for employers and for the society as a whole. In 2013, 131 million days were lost due to sickness absence (ONS 2014). There is also evidence that employment sectors are affected differently by sickness absence rates; such that private and self-employed sectors experience lower sickness absence rates than the public sector (ONS 2014, Wooden 1990, Barmby, Ercolani & Treble 2002, Whittaker et al. 2012). This may be attributed to the employment protection system that varies by employment sector and tends to be more protective in the public sector than its other counterparts. In the UK, employees are entitled to be paid a weekly statutory sick pay (SSP) (Department of Work and Pensions 2015). SSP is usually lower than the employees' wages, but this may vary as many employers pay out more than the statutory minimum.

Sickness absence also seems to vary by season (days of the week, month or year/business cycle); suggesting sickness absence may experience seasonality (i.e. cycle), and the rationales of sickness absence may in certain case be disputed (e.g. 'taking a sickie'). Previous findings assert cyclicality

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in absenteeism is inversely related with unemployment rates (Leigh 1985, Riphahn, Wambach & Million 2003, Riphahn 2004, Heyes 2005, Askildsen, Bratberg & Nilsen 2005, Hesselius 2007, Pichler 2015). High unemployment rates may deter employees to take sick leave by fear of losing their job (Leigh 1985, Heyes 2005, Arai, Thoursie 2005). Alternatively, higher level of sickness absence in period of high unemployment may be attributed to poor health rather than behavioural changes (Virtanen et al. 2005). The sensitivity of sickness absence in time of economic downturn could also be attributed to the changes in the workforce composition (i.e. more sickness-prone workers entering the labour force in upturns). However, cyclicality in sickness absence has been attributed to established workers rather than the composition of the labour force (Askildsen, Bratberg & Nilsen 2005). The so-called 'shirking' theory also provides explanation for the inverted relationship between work absenteeism and unemployment rates. According to this theory, shirking behaviour could be alleviated by monitoring employees, promotions and credible threats ("fire shirkers") (Shapiro, Stiglitz 1984, Barmby, Sessions & Treble 1994).

This study advances the literature by exploring cyclicality in work absenteeism. More broadly, the paper examined the relationship between unemployment rates and work absenteeism propensity across different sectors (private, public, self-employed and non-profit sector), using UK longitudinal data. A particular interest was placed on the public sector, which was divided into vocational (i.e. health and education) (Heyes 2005) and non-vocational sector (local administration, nationalised industries). We asserted that there exists intrinsic differences within the overall public sector omitted in previous studies. Exploring the potential role of vocation, it is assumed that vocation may bring a greater attachment to the job, potentially altering the sick leave decision process. Thusly, cyclical absenteeism in the vocational sector would be expected to be less prominent than absenteeism in the public non-vocational sector.

It is important to understand the cyclical pattern of sickness absence among employees for policy making, with regards to health insurance and related labour market institutions. More specifically, it is important to disentangle whether work absenteeism is attributed to the individuals' health and/or working condition or depends more on the individual's economic incentives (Johansson, Palme 1996). Pfeifer (2013) asserted that absenteeism could be considered as a proxy for work effort to analyse the effects of employment and monetary rewards. Besides, moral hazard behaviour could make an insurance policy inefficient for workers fully insured against loss during sickness and for workers whose demand for medical certificate is met by physicians (Askildsen, Bratberg & Nilsen 2005). The context in which medical certificates are distributed and whether they involve objectives discoveries is important. Whether medical certificates are dispensed as a request from patients, rather than carefully recommended by the GP is an important issue to consider.

2. Modelling cyclicality in work absenteeism

A model for work absenteeism cyclicality (Leigh 1985, Allen 1981) is considered. It accounts for non-pecuniary element of an individuals' work and unemployment. We also add a component accounting for the 'vocational' feature of employees, measured by the level of commitment *c*. The model involves the labour-leisure choice. For simplicity, the assumptions introduced in the model are also assumed to hold for self-employed individuals.

Individuals' full expected income is Y, and it includes non-pecuniary aspects of their work, as well as the level of commitment c. The non-pecuniary premium is all the more relevant for public vocational workers and known as a vocational premium (Heyes 2005). These workers are assumed to have a "feeling that the purpose of [their] life is to do a particular work, especially because it allows [them] to help other people, or [they] do a particular type of work [they] feel is right for [them] (Longman dictionary of contemporary English). This also means that individuals with a vocation over-perform when they are given the opportunity to do so and enjoy behaving as such (Heyes 2005). The level of commitment of employees, c, is unobservable to employers and it is assumed that $c_v > c_{nv}$. This simply suggests that employees in the vocational sector have a larger commitment level (c_v) than employees from the non-vocational sector (c_{nv}).

Individuals' total number of hours is T. H represents the actual hours of works, a is the hours of absence and h is the contracted hours of work; such that $H = h - a$. Individuals' leisure time and contracted hours away from work are L and l respectively, so that $L = l + a$. The unearned income is I, while pecuniary and non-pecuniary wages are w^p and w^{np} respectively. It is assumed that w^{np} varies with the working conditions and the vocational feature of employees (if the sector concerned is the public vocational sector). P is the probability of keeping the job and u the level of unemployment, which is exogenous. Thus, the full expected income of individual i at time t can be expressed as follows:

$$Y_{it} = \left(w_{it}^p + w_{it}^{np} + c_{it}\right)(h_{it} - a_{it})P(a_{it}, u_t) + I_{it} \quad (1)$$

$$s.t.\ H_{it} = T_{it} - L_{it} \quad (2)$$

Whilst equation (2) describes the hour constraint, equation (1) simply shows that the individuals' full expected income is function of the pecuniary and non-pecuniary wages, and the commitment level; which are factors of the number of hours worked and the probability of not being dismissed from work. This latter is function of the number of absences and the level of unemployment. The model further assumes that absenteeism and unemployment are inversely related, have increasing effect and no cross-effect, such that:

$$\frac{\partial P}{\partial a} < 0;\ \frac{\partial P}{\partial u} < 0; \frac{\partial^2 P}{\partial^2 a} < 0;\ \frac{\partial^2 P}{\partial^2 u} < 0;\ \frac{\partial^2 P}{\partial a \partial u} = 0$$

The probability of being fired is more likely (i) when unemployment rises $[1 - P(a, u)]$ and (ii) for worker with poor attendance compared to those with perfect record, *ceteris paribus*. The worker's maximisation problem is as follows:

$$Max\ U(Y, L) \quad (3)$$

Substituting for Y and L yields:

$$Max\ U[\left(w_{it}^p + w_{it}^{np} + c_{it}\right)(h_{it} - a_{it})P(a_{it}, u) + I_{it},\ T_{it} - h_{it} + a_{it}\ ] \quad (4)$$

Differentiating equation (4) with respect to absence a, yields:

$$-U_y[\left(w_{it}^p + w_{it}^{np} + c_{it}\right)P - \left(w_{it}^p + w_{it}^{np} + c_{it}\right)(h_{it} - a_{it})P_a] + U_L = 0 \quad (5)$$

Where the subscript on U and P indicate partial derivatives respectively. After rearranging the terms in equation (5), it yields:

$$U_L/_{U_Y} = \left(w_{it}^p + w_{it}^{np} + c_{it}\right)[(P - ((h_{it} - a_{it})P_a))] \quad (6)$$

According to equation (6), the marginal rate of substitution of leisure for income is function of the sum of both pecuniary and non-pecuniary wages, and the job commitment level; which is factor of the probability of keeping the job minus the product of the slope of the probability function. More broadly, the worker's labour-leisure choice depends on (i) the value she attributes to her expected wages, and (ii) a factor representing an adjustment to the probability of job retention as a result of the increased absence. Making a few reasonable assumptions about the relative size of second and cross partials derivatives, it can be shown that the first order conditions (FOC) of equation (6) is:

$$\frac{\partial a}{\partial w_{it}^{p}} \lesseqgtr 0;\ \frac{\partial P}{\partial w_{it}^{np}} \lesseqgtr 0; \frac{\partial a}{\partial c} < 0; \frac{\partial a}{\partial I} > 0;\ \frac{\partial a}{\partial u} < 0$$

It is assumed that the effect of a change in wage rate on absence is theoretically unknown, since income and substitution effects oppose each other. Other theories assert that wages could be used as a method to regulate absence and could be beneficial since raising wages (and promotion) would in principle discourage shirking (Barmby, Sessions & Treble 1994, Hassink, Koning 2009, Ose 2005). Nevertheless, raising wages could also reduce the proportion of employees who have a vocation, and attract the wrong sort of people (Heyes 2005). Sickness absence could also be monitored by provision of a medical justification.

The initial model of work absenteeism cyclicality (Leigh 1985) assumed that a change in w_{it}^{np} does not yield income effect; since working conditions are exogenous to the worker's wealth. It was further asserted that good (poor) working conditions would discourage (encourage) absence (Leigh 1985, Ose 2005). This hypothesis is all the more relevant for self-employed workers, considering they have more autonomy to 'influence' their work environment. Thusly, the decision to go to work on a given day and (in)voluntary absenteeism are assumed to be influenced by both physical and psychological aspects of the work (Ose 2005). Leigh's (1985) model also assumed that non-pecuniary wages do not permit to buy tangible goods. Nevertheless, we assumed that vocational workers are driven by their passion/vocation, and not only by the wages and working conditions. It is expected that the 'vocational' feature 'correct' for the moral hazard behaviour of such workers. Furthermore, the level of job commitment is assumed to be inversely linked with absenteeism, such that larger level of c induces lower shirking behaviour ($s=0$). Alternatively if $c=0$, then shirking behaviour amounts to one ($s=1$). Alternatively, the initial model of work absenteeism cyclicality (Leigh 1985) asserts that employees would increase their demand for normal goods (including absence), as unearned income rises.

Thus far, nothing has been said on the nature of absence (sick leave or other absence). The literature suggests that most absences are the results of illness, which to some extent is exogenous to the employees (Leigh 1985). It can be assumed that the determination to work despite illness varies with the individuals and the risks associated with the illness (risk of spreading to other co-workers, recovery time, reduced labour productivity). Yet, health behaviour can be considered as an investment (e.g. diet and physical activity); such that minor illnesses could be prevented. In such case, absenteeism could be considered as endogenous. Hence, it is important to account for exogenous factors when estimating worker absence model; such as the worker's mental and/or physical illness or the household composition (young children, etc.).

3. Empirical strategies

Firstly, we estimate a model of work absenteeism cyclicality across different sectors, using the reason employees were off-work the week preceding the interview as the dependent variable. Ideally, the number of absent working days in a given year would have been a better measure of work absence cyclicality. This information is not available in the UK household longitudinal study (UK HLS), however. We apply a random-effect logit model to estimate a model of work absenteeism cyclicality, amongst public (vocational and non-vocational), private, self-employed and non-profit (non-profit organisations and other) sectors. The model is specified as follows (Cameron, Trivedi 2010):

$$y_{1i} = \begin{cases} 1 \; with \; probability \; p \\ 0 \; with \; probability \; 1-p \end{cases}$$

where y is the probability of work absence for individual *i* and takes only two values. Sickness and 'other reason' of absence are the 2 dependent variables of interest in the model. The latter is all the more interesting because every other absences seem justified or expected (holiday, maternity leave, on strike, made redundant, family/personal reasons), except this one. This latter could provide more insight to the notion of 'voluntary' work absences. Then, *p* is parameterized to depend on an index function $\boldsymbol{x}'\boldsymbol{\beta}$, where x is a $K \times 1$ regressor vector and $\boldsymbol{\beta}$ is a vector of unknown parameters. Hence, the conditional probability function has the form:

$$p_i \equiv \Pr(y_i = 1|\boldsymbol{x}) = F(\boldsymbol{x}_{1i}'\boldsymbol{\beta}) \tag{7}$$

where $F(\cdot)$ is a cumulative distribution function $\boldsymbol{x}'\boldsymbol{\beta}$ defined on $(-\infty, \infty)$ to ensure $0 \leq p \leq 1$.

Secondly, we apply an ordinal regression model (ORM) to estimate the determinants of the number of GP visits by employees during the year of the interview. The dependent variable is somehow limited since the number of visits accounts for such a large period of time. It is another measure of work absence, however. Whilst nothing is said about the day of the visitation, it is assumed the visit is done during working hours since most GP clinics are closed during the weekends (Saturday and Sunday) in the UK. The structural model of the ORM is as follows (Cameron, Trivedi 2013):

$$y_{2i}^* = \boldsymbol{x}_{2i}\boldsymbol{\beta} + \boldsymbol{\varepsilon_i} \tag{8}$$

The measurement model consists in dividing y_{2i}^* into J ordinal categories, such that:

$$y_{2i} = m \; if \; \tau_{m-1} \leq y_{2i}^* \leq \tau_m \qquad for \; m = 1 \; to \; J \tag{9}$$

where the thresholds $\tau_{1,..,J-1}$ are estimated.

We expect unemployment rate to be inversely related with the probability of absence because employees may fear losing their job in period of recession. Alternatively, increasing level of absenteeism may occur during economic expansion, suggesting that established workers may have an (economic) incentive for work absenteeism. Interaction terms between unemployment rates and employment sectors were added to test the hypothesis of job attachment and sensitivity to cyclical absenteeism; with vocational workers expected to be less procyclical in work absenteeism than non-vocational workers. More broadly:

$$work \; absence \; (WA) = f\begin{pmatrix} u, & se, & p, & p_v, & p_{nv}, & n, & u_{se}, & u_p & u_{p_v}, & u_{p_{nv}}, & u_n, & \boldsymbol{X} \\ - & - & - & + & + & ? & - & - & + & + & ? & +/\_ \end{pmatrix} \tag{10}$$

where work absence (WA) : sickness, other absence or number of GP visit; u: unemployment rate; se: self-employed sector; p: private, p_v: public vocational; p_{nv}: public non-vocational; n: non-profit sector; u_{se}: unemployment rate*self-employed; u_p: unemployment rate*private; u_{p_v}: unemployment rate*public vocational; $u_{p_{nv}}$:unemployment rate*public non-vocational; u_n: unemployment rate*non-profit sector; $\boldsymbol{X}$: vector of demographic, employment and health-related variables. Ultimately, we expect that $u_{p_v} < u_{p_{nv}}$.

4. Data and the variables

The UK household longitudinal study (UK HLS) is an annual survey of a nationally representative sample of 40,000 households. It is the successor of the British Household Panel Survey (BHPS). Both datasets were collected by the Institute of Social and Economic Research (ISER) and provide social, economic and health-related information. Whilst BHPS stopped in 2008, it was incorporated into the second wave of UK HLS (2010) onwards. Matching of BHPS and UK HLS respondents was made possible by using the respondents' unique identifier (i.e. personal identifier, pid). Whilst each wave of the BHPS lasted a year, every wave of the UK HLS was collected over 24 months; such that the first wave was collected between January 2009 and January 2011, the second wave between January 2010 and January 2012 and so forth. We used 17 waves of the BHPS (1992-2008) and 3 waves of the UK HLS (2010-2012). Wave 2009 of UK HLS is not used since there is no matching of BHPS respondents in this wave.

To estimate a model of cyclicality in work absenteeism, we used two binary variables, indicating whether respondents were off-work the week preceding the interview. Respondents were asked whether they had a job and whether they attended their job the week prior the interview. If not, they gave the reason why they did not attend. The reasons for being absent were paternity/maternity leave, other leave/holiday, on strike, training course, laid off/short time or personal/family reasons. We were interested in those who were absent for 'sickness/injuries' and for 'other reasons'. Sickness absences spell is assumed to be more than a week but less than 6 months (since in the UK, statutory sick pay SSP is paid to an individual who has been off work sick for 4 or more days in a row, non-working days inclusive. Beyond 28 weeks, the SSP is no longer paid by an employer (Gov.uk 2015). The variable 'other reasons' was used since it could capture sickness absence for less than a week, or simply absences which do not require justification to the employers. In such case, this variable could be considered as a proxy for voluntary absenteeism. In our model, absenteeism was interpreted as a measure of worker effort as suggested in previous studies (Toharia, Serrano 1996, Treble 2001, Riphahn 2004, Ichino, Riphahn 2005). Secondly, we were interested in the number of GP visits by respondents during the year. Number of visits were ranked as follows: none, 1 or 2, 3 to 5, 6 to 10, more than ten. This ranking primarily justifies the use of an ordered regression model. The number of doctor visits was more likely to be a health-related problem, rather than shirking behaviour. Yet, it is still an indicator of work absence (Pfeifer 2013). The frequency of visit to the GP and the intensity of therapy are endogenous to the employees however, and more likely to influence their future health and working absence days.

Regional unemployment rates were assigned to UK HLS respondents according to their region and the survey year (1992-2012). Cyclicality was accounted for via the unemployment rates. Whilst the process was relatively straightforward for the BHPS sample, we used the starting date for the UK HLS sample since each wave was collected over a 24 months period. Since waves of UK HLS were available from 1992 to 2012, we also ran a model with a dummy variable capturing the period pre and post Global-recession (pre 2008 and post 2008), to provide more insight to cyclical absenteeism and its potential link with time of great unemployment rates/recession.

There were 5 employment sectors: private (reference), self-employed, public vocational (health and education), public non-vocational (civil service, local government and nationalised industries), and non-profit sector (non-profit and other). To have a more robust vocational variable, we accounted for both the sector and the standard occupational classification (SOC) of the respondents. This ensures only those working in the public sector and having a vocational feature were included in the vocational variable. The full list of professions included in the public vocational sector is provided in the appendix.

The model also controlled for household demographics, such as marital status, age of the respondents and household composition. Employment, financial and health-related information were also accounted for (part/full-time status, job tenure, labour income, physical and mental health status). The sample was restricted to working age population (18-65 years old) and employees to have a more homogenous sample. The regression sample size was 141,532. Table 1 and 2 show the list of variables used for the analysis and a basic descriptive statistics, respectively.

Table 1: List of variables used for the analysis on cyclicality in work absenteeism across various employment sectors

Dependent variables	Description
Work absence 1: Sickness absence	Dummy variable equals 1 if respondent was off-work due to sickness or injury the week prior the interview; 0 otherwise (absence spell is more than a week but less than 6 month).
Work absence 2: Other absence	Dummy variable equals 1 if respondent was off-work due to other reasons the week prior the interview; 0 otherwise (proxy indirectly capturing absence spell due to sickness/injury for less than a week and voluntary absenteeism).
Work absence 3: Number of GP visit	Number of visit to the GP during the year. Ordinal ranking: none, 1 to 2, 3 to 5, 6 to 10, more than 10.
Independent variables	**Description**
Measure of business cycle	
Unemployment rate	Regional quarterly unemployment rate (source: ONS).
Unemployment*private (reference)	Interaction term between regional unemployment rate and private sector.
Unemployment*public vocational	Interaction term between regional unemployment rate and public vocational sector.
Unemployment*public non-vocational	Interaction term between regional unemployment rate and public non-vocational sector.
Unemployment*self-employed	Interaction term between regional unemployment rate and self-employed sector.
Unemployment*non-profit	Interaction term between regional unemployment rate and non-profit sector.
Employment and education variables	
	Dummy variable equal 1 if:
Private sector (reference)	Respondent works in the private sector; 0 otherwise.
Public vocational	Respondent works in the public vocational sector (health and education); 0 otherwise.
Public non-vocational	Respondent works in the public non-vocational sector (civil service, local government and nationalised industries); 0 otherwise.
Self-employed	Respondent is self-employed; 0 otherwise.
Non-profit	Respondent works in the non-profit employment sectors (non-profit and other); 0 otherwise.
Professional and managerial (reference)	Respondent works in the professional and managerial occupation; 0 otherwise
Intermediate occupation	Respondent works in the intermediate occupation; 0 otherwise.
Routine and manual occupation	Respondent works in the manual and routine occupation, 0 otherwise.

Education	Dummy variable indicating whether the respondent has a degree, other higher degree, A level, GCSE, other qualification or no qualification (reference) respectively; 0 otherwise.
Labour income	Log of gross income of the respondent.
Job status	Variable indicating whether the respondent is working full-time (reference) or part-time.
Job tenure (squared)	Job tenure of the respondent (and its square, respectively).
Demographic variables	
Marital status	Variable indicating the marital status of the respondent: married/living as couple (reference); divorced/separated; widowed; single.
Age (squared)	Age of the respondent (and its square, respectively).
Ethnicity	Dummy variable equals 1 if respondent is White, 0 otherwise.
Number of children	Dummy variable if respondent has none (reference), 1, 2, 3 or more children, respectively; 0 otherwise.
Health-related information	
Health status	Dummy variable indicating the health status of the respondent: good (reference), fair and poor respectively; 0 otherwise.
Caseness	Variable indicating whether the respondent has mental illness. It take the value 1 if GHQ12≥4 (=caseness/mental illness); 0 if GHQ12<4 (no caseness/mental illness).

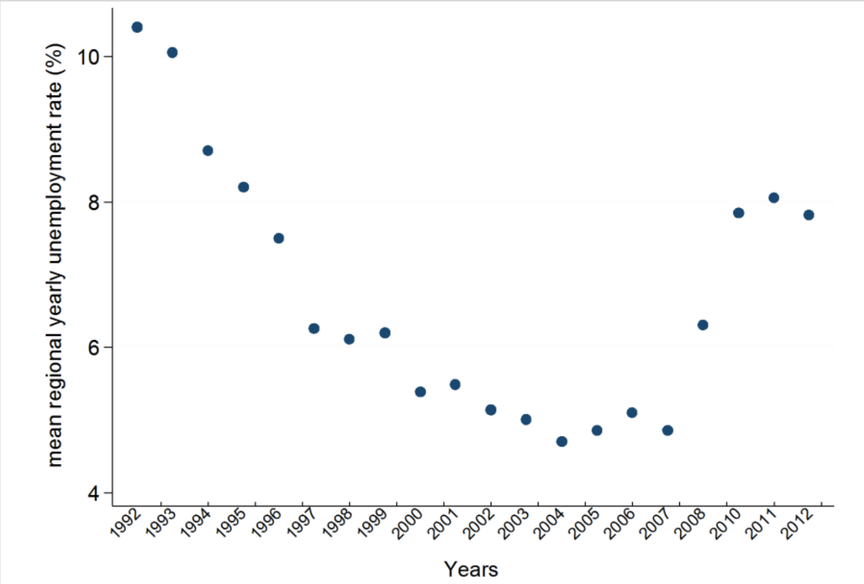
Table 2: Descriptive statistics of variables of interest

Variables	Mean/%	SD
Sick/injury leave (*n= 146,016)*	1.47%	0.12
Other reason	0.23%	0.05
Regional unemployment (*n= 146,016)*	6.14%	2.35
Private*unemployment *(n= 141,532)*	3.47%	3.41
Self-employed*unemployment	0.79%	2.23
Public vocational *unemployment	0.37%	1.53
Public non-vocational*unemployment	1.20%	2.67
Non-profit*unemployment	0.20%	1.14
Private *(n=141,532)*	58.06%	0.49
Self-employed	12.98%	0.34
Public vocational	5.69%	0.23
Public non-vocational	19.69%	0.40
Non-profit	3.58%	0.19
Full-time *(n=141,040)*	80.63%	0.40
Part-time	19.37%	0.40
Job tenure *(n=111,386)*	4.80	6.26
Professional and managerial occupation *(n=143,911)*	39.30%	0.49
Intermediate occupation	53.49%	0.50
Routine and manual occupation	7.21%	0.26
Degree *(n=136,302)*	18.01%	0.38
Other higher degree	27.89%	0.45
A level	15.69%	0.36
GCSE	20.16%	0.40
Other qualification	6.75%	0.25
No qualification	11.50%	0.32
Caseness *(n=134,054)*	17.24%	0.38
No Caseness	82.76%	0.38
Health: good *(n=137,681)*	80.47%	0.40
Health: fair	15.50%	0.36
Health: poor	4.04%	0.20
Age *(n=145,478)*	39.85	11.7
No children *(n=146,014)*	59.47%	0.49
1 child	18.37%	0.39
2 children	16.46%	0.37
3 children	5.70%	0.23
White *(n=143,565)*	97.15%	0.17
Non-White	2.8%	0.17
Male *(n=146,005)*	51.96%	0.50
Female	48.04%	0.50
Married/Living as couple *(n=145,990)*	73.28%	0.44
Widowed	1.07%	0.10
Divorced	6.94%	0.25
Single	18.71%	0.39

5. Results

Figure 1 shows the variation of UK regional unemployment rate using the UK HLS (1992-2012). There is a clear downward trend from 1992 to 2004. Unemployment rates slightly increased from 2005 to 2007, then sharply rose from 2007 onwards and reduce much later in 2012.

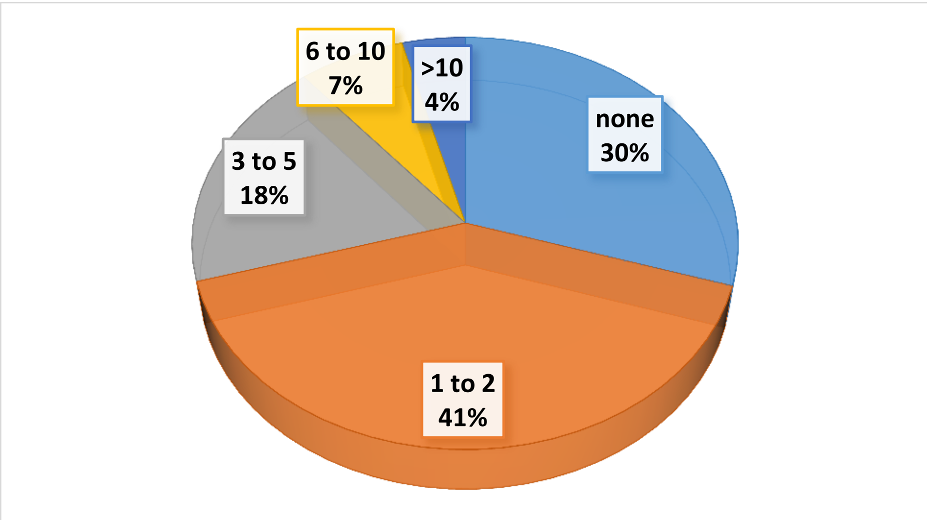
Figure 1: *Trends in UK regional unemployment rates over time in the UK HLS*



Source: based on ONS data (1992-2012) – Computed by the authors

The frequency of visits to the GP by respondents is displayed in Figure 2. 41% of GP visits was classified as low (1 to 2), 18% of GP visits were considered moderate (3 to 5), 7% of GP visit were deemed high (6 to 10) and only 4% were very high (more than 10). 30% of GP visit were classified as null (i.e. no visit).

Figure 2: Frequency (%) of the number of visits to the GP by UK HLS respondents



Source: Computed by the authors using UK HLS (1991-2012)

Work absence cyclicality

Results from the random-effect (RE) logit regression for work absenteeism cyclicality are displayed in Table 3. Odd ratios (OR) greater (lower) than one indicate a greater (lower) likelihood for work absenteeism due to sickness (or injury) or "other" reason respectively, compared to the base category. For each type of model of absence (sickness, other reason and GP visit), 2 specifications are presented: (i) work absenteeism cyclicality with unemployment only (basic model) and (ii) cyclicality with interaction terms (full model).

We found no evidence of pro-cyclicality between sickness absence and business cycle (unemployment) in both specifications. There is also no association between the interaction terms and sickness absence. Nevertheless, the coefficients have the expected sign and magnitude. Although surprising, the lack of significance of unemployment rate and interaction terms, respectively, were also found in previous studies (Pfeifer 2013 and Pichler 2015). The time dummy variable indicating the post 2008 period is significant and suggest that sickness absenteeism was lees likely to occur after that period.

We found evidence of pro-cyclicality between "other" absence and business cycle. Since other absence did not correspond to any other legitimate reason for absence (i.e. maternity leave, on strike, training, family reason) it was considered as a proxy for voluntary absenteeism. The positive and significant coefficient of business cycle indicate that absence for "other" reason is less likely in period of high unemployment; aligning with results from the literature. Interactions terms were not significant, to the exception of self-employed individuals (as found in Pfeifer 2013); suggesting that in period of high unemployment they are more likely to be absent.

Results from the ordered logit regression for the number of GP visit during the year are displayed in Table 4. Two models were run: a basic model of work absence cyclicality and the complete models with interactions respectively. The sign of the regression parameters β can be interpreted as determining whether the latent variable y^* (number of GP visit) increases with the regressor. If β_j is positive (negative), then an increase (decrease) in x_{ij} necessarily decreases (increases) the probability of being in the lowest category (y_i=1 or 2) and increases (decreases) the probability of being in the highest category (y_i= more than 10). For simplicity of interpretation, odds ratios (OR) are reported.

We found no evidence of pro-cyclicality between the business cycle and number of GP visit. Although the coefficient is not significant, the width of the confidence interval [0.995; 1.020] suggests the likelihood of vising a GP during the year could also be pro-cyclical. Interaction terms were not significant, except for public vocational sector; suggesting that in period of high unemployment, being in the vocational sector increases the likelihood to visit the GP during the year.

Table 3: Results of the RE logit for work absenteeism cyclicality, odds ratios (OR) reported

	Sickness absenteeism				Other work absence			
	Work absenteeism cyclicality (basic model)		**Work absenteeism cyclicality (full model)**		**Work absenteeism cyclicality (basic model)**		**Work absenteeism cyclicality (full model)**	
	OR (SE)	***CI***	***OR***	***CI***	***OR***	***CI***	***OR***	***CI***
Unemployment	1.005 (0.014)	0.978; 1.033	0.997 (0.019)	0.961; 1.035	0.813**(0.057)	0.708;0.933	0.775**(0.087)	0.362; 0.965
Unemployment*Public vocational			1.029 (0.048)	0.940; 1.126			1.080 (0.274)	0.657; 1.775
Unemployment*Public non-vocational			1.016 (0.034)	0.953; 1.084			0.882 (0.194)	0.573; 1.359
Unemployment*Self employed			1.092 (0.247)	0.702; 1.700			1.316* (0.214)	0.957; 1.809
Unemployment*Non-profit			0.977 (0.074)	0.702; 1.700			0.879 (0.232)	0.525; 1.473
Public vocational			1.281 (0.286)	0.827; 1.983			0.929 (1.367)	0.052; 16.63
Public non-vocational			1.543 (0.491)	0.827; 2.879			2.533 (3.056)	0.238; 26.95
Self-employed			0.161 (0.352)	0.002; 11.56			0.696 (0.892)	0.057; 8.573
Non-profit			1.114 (0.564)	0.413; 3.003			2.098 (3.037)	0.123; 35.81
Post 2008			0.625*** (0.088)	0.474;0.823			1.115 (0.436)	0.518;2.399
Socio demographic and health characteristics	Yes		Yes		Yes		Yes	
Observation	90,023		87,227		90,023		87,227	

*, **, *** significant at the 1, 5 and 10% level respectively
Standard errors in brackets

Table 4: Ordered logit model for the number of GP visit during the year, odds ratios (OR) reported

	Work absenteeism cyclicality (basic model)		**Work absenteeism cyclicality (complete model)**	
	OR	**CI**	**OR**	**CI**
Unemployment	1.007 (0.005)	0.997; 1.016	1.008 (0.006)	0.995; 1.020
Unemployment*Public vocational			1.031**(0.017)	0.998; 1.066
Unemployment*Public non-vocational			1.017 (0.012)	0.994; 1.040
Unemployment*Self employed			0.947 (0.041)	0.870; 1.032
Unemployment* Non-profit			1.011 (0.020)	0.972; 1.052
Public vocational			0.881 (0.102)	0.703; 1.104
Public non-vocational			0.960 (0.075)	0.824; 1.118
Self-employed			1.303 (0.527)	0.590; 2.878
Non-profit			1.074 (0.141)	0.830; 1.389
Post 2008			1.038 (0.030)	0.981; 1.098
Socio demographic and health characteristics	Yes		Yes	
/cut1	-3.908***(0.210)	-4.320; -3.497	-3.931***(0.215)	-4.351; -3.510
/cut2	-1.308***(0.209)	-1.718; -0.897	-1.327***(0.214)	-1.746; -0.907
/cut3	0.576** (0.209)	0.166; 0.986	0.561** (0.214)	0.141; 0.980
/cut4	2.108***(0.210)	1.696; 2.521	2.095***(0.215)	1.673; 2.517
/sigma2 u	1.809 (0.041)	1.730; 1.892	1.826 (0.042)	1.745; 1.911
Observations	*89,931*		*87,137*	

*, **, *** significant at the 1, 5 and 10% level respectively
Standard errors in brackets

6. Concluding remarks

The paper investigated the pro-cyclical nature of absenteeism across different employment sectors, with a particular interest for public vocational sector. The paper was interested in the potential role of vocation in the relationship between absenteeism and business cycle. We found no evidence of pro-cyclical association with business cycle and sickness absenteeism. Although the coefficient were not significant, their signs and magnitudes were as expected, aligning with the theory of cyclicality in work absenteeism. The time variable indicating the post 2008 crisis period was significant; suggesting that sickness absenteeism was less likely to occur after that period. Pro-cyclical absenteeism was found with the proxy measuring voluntary absenteeism: "other" reason. Whilst reasons for absence were clearly stated in the survey, this category did not permit a clear identification of the reason (and legitimacy?) of the absence. Fear of dismissal or disciplinary actions may explain the pro-cyclical nature of absenteeism in that case.

We found no evidence of a pro-cyclical relationship between number of GP visit during the year and business cycle. Interestingly the coefficient was above zero. Had it been significant, this would suggest that the likelihood to visit his/her GP rises in period of high unemployment. This is an interesting result in itself as some may attribute it to the potential adverse effect of the economic conjuncture on employees' well-being for instance and their contingent likelihood of being absent from work. Of all the interaction terms, only employees of vocational-intensive sector was positive and significant, such that in period of high unemployment such workers are more likely to visit their GP during the year. Workers of this sector are usually less exposed to redundancy than their counterparts in the private sector. As such, the fear of job dismissal may represent a small threat for such workers. This result imply that vocation seems not to alter sickness decision.

Overall, results of this study partially align with the theory of business cycle in absenteeism. Although some of the coefficients of interest were not significant, they had the expected signs and magnitudes. The exploratory analysis of the potential role of vocation in the absenteeism and business cycle analysis could be reinforced by an external validity measure of vocation since the measure of vocation in this study was defined by the researchers. The pro-cyclical relationship with "other" absence and the business cycle is interesting in itself and could benefit from further research measuring "voluntary" absenteeism and the business cycle.

7. References

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Appendix

List of professions included in the public vocational variables, based on the standard occupation classification (SOC)

SOC	Description of professions
233	Secondary (& middle school deemed secondary) education teaching professionals
234	Primary (& middle school deemed primary) & nursery education teaching professionals
235	Special education teaching professionals
293	Social workers, probation officers
340	Nurses
341	Midwives
343	Physiotherapists
344	Chiropodists
347	Occupational & speech therapists, psychotherapists, therapists
640	Assistant nurses, nursing auxiliaries
641	Hospital ward assistants
644	Care assistants & attendants