Do the Flexible Employment Arrangements Increase Job Satisfaction and the Loyalty of the Employees? An Evidence from Great Britain.

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Abstract

This study explores the relationship between job satisfaction, employee loyalty and various types of flexible employment arrangements using the Workplace Employee Relations Survey (WERS) in 2004 and 2011. A propensity score matching and fixed effects regressions are applied. Finally, Bayesian Networks (BN) and Directed Acyclic Graphs (DAGs) are employed in order to confirm the causality between employment types explored and the outcomes of interest. Furthermore, an instrumental variables (IV) approach based on BN framework is proposed and applied in this study. The results support that there is a positive causal effect from these employment arrangements on job satisfaction and employee loyalty.

Keywords: Bayesian Networks; Directed Acyclic Graphs; Employee Loyalty; Employment Arrangements; Job Satisfaction; Teleworking; Workplace Employment Relations Survey

JEL codes: C11, J28, J53, J63, J81

1. Introduction

Work especially the last years with the fast enhancement of technology and networks has been disconnected from a particular place and time and information technologies have made it possible for organizational workers to become untethered from their traditional office setting (Golden et al., 2006). While the traditional place of work used to be the employer's premises, nowadays it is carried out in other locations, such as the employee's home or while traveling. Advances in technology reshape the relationship between work and home, where in some cases the traditional flow of employees from home to office is reversed (Bailyn, 1988). The virtualization and this shock of the contemporary organisation has evolved as a vital necessity for the firms to be able to compete for workers globally and advances in information technology provide the means (WorldatWork, 2011). By 2016 it is estimated that around 90 million of self-employed and employed U.S. workers will work from home or from a remote location at least 2 to 3 days a week (Lister and Harnish, 2011). This study examines the relationship of teleworking or homebased working with job satisfaction and the employee loyalty in a sample of firms in Great Britain using the Workplace Employee Relations Survey (WERS) and two waves in 2004 and 2011. Then additional employment arrangements are explored, such as flexible time, implying that there is no fixed or set up time of starting and ending the job, the option of reducing or increasing the working hours and others and they will be compared with those of teleworking.

Teleworking is a term used to describe an alternative work arrangement that enables employees to work from anywhere other than the traditional work setting or employer's premises. Teleworking or telecommuting as it's sometimes called has gained increasing popularity and acceptance throughout the United States and the world (Gajendran and Harrison, 2007). According to the research study by Crandell and Gao (2005) telework has become an international phenomenon. Thus, teleworkers spend some portion of their time away from the

conventional workplace, working from home, and communicate by way of computer-based technology (Nilles, 1994).

The concept of teleworking and flexible employment arrangements in general, are reflected in the principles of more and better jobs and better working conditions implemented by European Employment Strategy, Europe 2020 strategy and Guidelines for national employment policies. Employment Strategy was formally initiated at the Luxembourg European Council in 1997, reflected almost exclusive focus on job creation, with very little emphasis on job quality issues. But as job creation took off in the late 1990s, the European consensus shifted towards to a more balanced view of employment growth. After the Lisbon Council in 2000, the European Employment Strategy placed the same emphasis on the quantitative and qualitative elements of job creation. In 2002, the Barcelona Council adopted "more and better jobs" as the motto for the European Employment Strategy (Eurofond, 2008). In European Union level there are no legislative acts issued on teleworking and other flexible working arrangements. Implementation of teleworking is regulated by the European Framework Agreement on Teleworking signed by European social partners on 16 July 2002 and although it is not incorporated into directive, it creates a contractual obligation for the affiliated organisations of the signatory parties. In the context of Article 139(2) of the EC Treaty, agreements between European Union level social partners are voluntary and autonomous and they are not foreseen to be implemented by Council decision.

Previous studies have outlined the reasons for the growth of teleworking or other kinds of flexible type of employment, which are owned mainly to its perceived benefits. In particular, these benefits refer on both telework and employer including job satisfaction, increasing productivity, organizational loyalty, improved employee morale and employer retention and saving in space office among others (Bélanger, 1999; Potter, 2003). Secondly the relationship between teleworking and job satisfaction, as well as, the relationship between teleworking and

employee loyalty is examined. Since well-being and better quality of jobs are implemented and considered as the main objectives of the European Employment Strategy, job satisfaction and turnover intention or employee loyalty can be two alternative measures of examining the quality of job by the perspective of employees. This study adds to the previous literature by examining the above-mentioned linkages using panel data regressions, while the majority of the previous studies examined only one of the two above-mentioned relationships using mainly cross-sectional data. Moreover, various types of employment arrangements are explored. Fixed effects models base on propensity score matching, accounting for intercept heterogeneity and selection and heterogeneous bias are estimated. In addition, a Bayesian Network framework and Directed Acyclic Graphs (DAGs) representation are applied in order to examine and confirm the causal effect of flexible working employment arrangements on job satisfaction and employee's loyalty on organisation. Moreover, in order to limit the endogeneity issue which might be coming from firm or employees' relocation, only the firms who are located in the same area during the period examined are included into the sample as well as, the employees who have not changed travel to work area (TTWA). Regarding the job stayers, the panel structure of the data is such that only individuals who are employed in the same firm are followed. Nevertheless, the conclusions remain similar when the total sample is considered, since also the non-movers and job-stayers from the matched sample derived by the propensity score procedure constitute roughly the 85 per cent of the total sample, while the respective percentage for the unmatched sample is approximately 88 per cent. The findings support a positive effect from the employment arrangements examined on both job satisfaction and employee loyalty. This can have possible policy implications not only to employees and firms, but to society overall, which are discussed later.

The paper is organised as follows: Section 2 is devoted to the literature review on teleworking, job satisfaction and performance. Sections 3 presents the methodology, while in

section 4 the datasets are discussed. Section 5 considers the results and section 6 presents the concluding remarks and areas for future research.

2. Literature Review

In this section previous research studies on the association between teleworking and job satisfaction are briefly discussed. Organisation theorists have long recognized that any kind of interaction on the working environment can be an important determinant of job satisfaction. Sims et al. (1976) suggest that jobs, offering opportunities feedback, friendship and interacting with other people can improve employee's job satisfaction. Previous studies note that face-to-face interaction is associated with positive outcomes (Olson et al., 2002). Social interaction at work can facilitate social presence, foster mutuality and common ground and improve communication quality (Short et al., 1976; Burgoon et al., 2002). On the other hand, employees who face a small social presence at work and increased reliance on technology based job activities may experience lower levels of proper communication and less communication richness and quality (Lowry et al., 2006). Therefore, based on the previous researches teleworkers may report lower levels of job satisfaction owned to reduced frequency and quality of interaction with other people. Since this relationship is still unknown on a large scale study, this paper aims to examine the relationship between teleworking, job satisfaction and turnover intentions or employee loyalty.

On the other hand, recent research studies confirm a positive relationship between teleworking and job satisfaction (Gajendran and Harrison, 2007), while other studies have found a curvilinear association, where increases of the teleworking hours increase the employee's job satisfaction up to a point, after which the effects slightly fade out (Golden and Veiga, 2005). Thus, the traditionally belief that the face-to-face interactions at work have positive effects on job satisfaction may be overestimated and overgeneralised. Fonner and Roloff (2015) using a sample of 89 teleworkers and 103 office-based employees applied a path

analysis in order to test the adequacy of their mediation model and to examine the relationship between teleworking and job satisfaction. Additionally, they examined the indirect paths from telework to job satisfaction through work-life conflict, information stress exchange frequency and quality, stress from meetings and interruptions, general politics, and get ahead politics. Their results support that teleworking directly affects job satisfaction positively.

This study adds to the previous research by examining the relationship between teleworking and job satisfaction and it is compared with other flexible working arrangements. In this study this relationship, incorporated into a BN framework and DAG representation and using panel datasets, is explored. Moreover, various econometric techniques for robustness checks are followed, including fixed effects, two stage and three stage least squares.

3. Methodology

3.1 Theoretical Framework

In this section a conceptual framework of the relationship between job satisfaction, employee loyalty and various types of working arrangements is presented. Initially, the theoretical framework is presented in figure 1.

In figure 1 it is assumed that telework affects the employee loyalty (EL) and job satisfaction (JS), while Z is a vector of individual, employee and firm and other job characteristics, which can affect, the employee loyalty and satisfaction, as well as, the decision and the propensity to choose this type of working arrangements, defined as the arrow headed from the characteristics Z to these arrangements. Finally, the arrows heading from job satisfaction to employee loyalty and vice versa indicate that a reverse causality might exist, as higher levels of job satisfaction can lead to higher levels of employee loyalty, while the vice versa can hold as well.

On the other hand, it may be possible to find an effect from job satisfaction to flexible working arrangements, as for instance those who are less satisfied, they may decide to choose

these options in order to increase their job satisfaction. This effect may be much less plausible regarding the employee loyalty. In order to examine the causal effects of these flexible working arrangements on job satisfaction and employee loyalty a propensity score matching and a Bayesian Network framework is applied.

(Insert Figure 1)

3.2 Panel Regressions and Three Stage Least Squares

The following job satisfaction function for individual *i*, in firm *k*, area-region *j* at time *t*.

$$JS_{i,j,k,t} = a_0 + a_1 WA_{i,j,k.t} + \alpha' z_{i,j,k,t} + \mu_i + \delta_\kappa + \theta_t + l_j + l_j T + \varepsilon_{i,j,k,t} \quad (1)$$

$JS_{i,j,k,t}$ denotes the job satisfaction and the vector $WA_{i,j,k,t}$ is a dummy indicating whether or not the respondent is involved in the current type of working arrangement or not in firm *k,* in region *j* and in time *t*. and *z* is a vector of individual and firm characteristics, including age, education level, marital status, whether there are dependent children 0-2 years old in the household or no dependent children, ethnicity, skills matching the job, the quality of relations between the managers and employees, whether the employees receive profit-related payments, whether the employees' payment is linked to the outcome of the performance evaluation, whether there are formal job evaluation schemes in the workplace, whether there are more than one establishments of this workplace in the UK, trade union membership, total employment, the firm type, such as public, private, charity and local government among others, whether the workplace has a written policy on discrimination and equal opportunities, whether the respondent-employee supervise other employees, whether the place-location of the product or service of the workplace is local, regional, national or international, and whether this workplace faces competition from other over-seas companies. In addition, the market share could have been included, but it is highly correlated. Finally, the regression controls for standard travel tow

work areas (TTWA). Set μ_i denotes the individual-fixed effects, δ_κ is the firm fixed effect, l_j is the area fixed effects, which is expressed by the TTWA, θ_t is a time-specific vector, while l_jT is a set of the area-specific linear time trends which controls for unobservable, time-varying characteristics in the TTWA. Finally, $\varepsilon_{i,j,k,,t,}$ express the error terms which it is assumed to be *iid*. Standard errors are clustered at the wave specific TTWA level and job satisfaction function (1) is estimated using WERS and the panel survey which was conducted in 2004 and 2011 and has information about employee, employer and firm characteristics.

The working arrangements explored in this study are the following: *flexi time* which means that there is no fixed or specific start or end of the job, *reducing working hours*, implying that the employee has the option to transit from full-time to part-time, while *increasing working hours* imply the opposite, switching from part-time to full-time. The fourth employment type refers to employees who are home-based workers or teleworkers and work some days of the week at home. The next type is the option of *changing shift*s, while the last employment arrangements is *compress hours*, which is the option of working standard hours in less number of days, i.e. 35 hours in 4 days, instead of 5-6 days.

Then relation (1) is estimated by replacing the dependent variable with the ordered variable expressing the employee loyalty. In its current form, the model (1) cannot be estimated by ordered Probit or Logit using fixed effects. With cross-sectional data, it is very easy to use and to estimate by maximum likelihood these parametric models. However, in panel data no simple transformation -such as first-differencing or within-transformation- is available that would purge the ordered response models from the individual-specific fixed effects. Therefore there are two options, either estimating the model considering the dependent variable as continuous or converting the dependent ordinal variable in continuous variable assigning z-scores. This study follows the first approach, while the second method, proposed by van Praag and Ferrer-i-Carbonell (2004) and the "Blow-Up and Cluster" (BUC) estimator developed by

Baetschmann et al. (2011) have been applied; however, the results are similar and are not presented here. In addition, the population of interest is limited to non-movers, which sample in this study is defined, as it has been mentioned, by the employees who have not relocated, based on TTWAs and the firms that have not moved to another location during the period examined. As it has been already mentioned, the WERS follows the same employees which are employed in the same firm-organisation. On the other hand, the movers sample assumes the opposite; employees and firms that have been relocated. Thus, the endogeneity issues refer to unobserved employee and firm characteristics. Similar to Manning (2003a, 2003b) the non-movers, the job-stayers and the firms that do not relocate are considered in the sample. A similar approach has been followed by Mulalic et al. (2014), however they examine the wage differentials for commuting for workers belonging on the same firm and not teleworking. Concluding, the "sorting" issue can be associated to the choice of employees changing location which may affect their propensity to telework or to choose any other employment arrangement mode, as well as, to switch from one firm to another. In this case the fixed effects estimates will eliminate the firm-area (TTWA) fixed effects for non-movers and the job –stayers, while for movers the error term will contain the difference in the area and firm fixed effects of the two locations and two employers-firms, which may be correlated with the propensity to choose a specific employment arrangement affecting job satisfaction and vice versa. Next the following structural equation for job satisfaction and employee loyalty is estimated with 3SLS:

$$JS_{i,j,k,t} = a_0 + a_1 WA_{i,j,k.t} + a_2 EL_{i,j,k,t} + \alpha' z_{i,j,k,t} + \mu_i + \delta_\kappa + \theta_t + l_j + l_j T + \varepsilon_{i,j,k,t} \quad (2)$$

$$EL_{i,j,k,t} = \beta_0 + \beta_1 WA_{i,j,k.t} + \beta_2 JS_{i,j,k,} + \beta' z_{i,j,k,t} + \mu_i + \delta_\kappa + \theta_t + l_j + l_j T + \varepsilon_{i,j,k,t} \quad (3)$$

3.3 Bayesian Networks and Instrumental Variables

This section discusses the directed acyclic graphs (DAGs) and describes the Bayesian Network (BN) used in this study for causal inference. Even if this study is based on panel data

and fixed effects are considered, still a strong evidence of reverse causality remains. The graphical structure G= (**V, E**) of a BN is a directed acyclic graph DAG where $\boldsymbol{V}$ denotes the vertex or node set and **E** represents the edge set as $\boldsymbol{V_i \rightarrow V_j}$ The notation $\mathbf{P_i^G}$ is used to denote the parent set of V_i in G. $\mathbf{p_i^j}$ is used to denote the *j-th* configuration of the parents of $\boldsymbol{V_i}$: $\mathbf{P_i} \in \{\mathbf{p_i^1} \ldots, \mathbf{p_i^{qi}}\}$. Based on that the definition of BN is:

Definition 1 (Bayesian network) (Pearl, 2000; Neapolitan, 2003): A Bayesian network model M over a set of variables $\mathbf{V} = \{X_1, \ldots, X_N\}$ is a pair $(\Gamma, \boldsymbol{\theta})$, where $G(\mathbf{V})$ is a DAG over **V** and $\boldsymbol{\theta}$ is a set of conditional probabilities: $\theta = \{\theta_{ijk}: \forall (ijk)\}$ such that $(\theta_{ijk} = X_i = x_i^k \,|P_i = p_i^j)$.

A BN is a graphical structural model that encodes probabilistic relationships among the variables of interest (Heckerman, 1997)[1]. A graph $G(V,E)$ can be referred to as a directed acyclic graph (DAG), when the edges E linking nodes-set of variables V are directed and acyclic. *Directed* means that edges E represent direct causal effects, while *acyclic* means that the directed edges do not form circles. (Spirtes et al., 2000; Pearl, 2000; 2009). Following Heckerman's (1997) notation, a generic graph is presented in Figure 2. The arrow between T and F in figure 2 means that T may have a direct causal effect on F. Similarly, for the arrow between B and T or A and C or B and C. In the case where there are *missing arrows*, it is implied that the strong assumption of no direct causal effect between two variables is rejected, which is so-called "strong null" hypothesis of no effect. All variables directly or indirectly caused by a given variable are called its *descendants*. The descendants of T are F and Y, while the *descendants* of B are *C, D, T* (B's children), *E* (D's and T's child), *F* (T's child) and *Y* (child of *A, C, D, E, F*) and similarly for the remained nodes-variables. On the other hand, *parents* are the variables that direct cause another variable. In figure 2 the only parent of F is T, while the only parent of T is B. A similar definition to *descendants*, working on the opposite way, is the variables that directly and indirectly cause of another variable and are called *ancestors.* For

[1] Major advances have been made in inferring causal relationships from observational data (Pearl 1998, Spirtes et al. 2000).

example the *ancestors* of *F* are *T* and *B*, while the *ancestors* of *E* are *B*, *D*, and *T*. *Paths* are sequences of adjacent arrows that traverse any given variable at most once. The arrows along a path may point in any direction. For example if *B* is the treatment and *F* is the outcome *then* $B \rightarrow T \rightarrow F$ is the only causal path.

(Insert Figure 2)

The DAG defines a factorization of the joint probability distribution of V = $\{X_1, \ldots, X_N\}$, often called the global probability distribution, into a set of local probability distributions, one for each variable. The form of the factorization is given by the Markov property of Bayesian networks which states that every random variable X_i directly depends only on its parents:

$$p(x) = \prod_{i=1}^{m} p(x_i \mid par_i) \tag{4}$$

Applying the chain rule of probability, we have:

$$p(x) = \prod_{i=1}^{m} p(x_i \mid x_1, \ldots, x_{i-1}) \tag{5}$$

The causal Markov assumption is that each node is independent of its non-descendants in the graph conditional on its parents in the graph.

Definition 2 (One-step ahead conditional independence non-causality). *X* does not strongly cause *Y* one-step ahead given a set of covariates *Z* and *Y* does not cause *X* given a set of covariates *K* if (6)-(7) hold.

$$Y_{i,t} \perp X_{i,t-1} \mid Z_{i,t} \tag{6}$$

$$X_{i,t} \perp Y_{i,t-1} \mid K_{i,t} \tag{7}$$

$Y_{i,t} \subseteq Z_{i,t} \subseteq \Omega_{i,t}$ and $X_{i,t} \subseteq K_{i,t} \subseteq \Omega_{i,t.}$ and Ω is the set of all covariates included in sets *K* and *Z*, for individual *i* and time *t*. The symbol $\perp$ is used to express independence.

Definition 3 (Conditional independence non-causality). The conditional independence *X* is conditional independent from *Y* in the edge set *E* iff $Y_{i,t} \perp X_{i,t} \mid \Omega_{i,t}$

The independence assumptions discussed above and are represented by the graph imply that parameters need to be estimated because the probability distribution for each variable depends only on the node's parents as it is shown in relations (4)-(5). Using the factorisation equation (5) it allows the network factorisation in such a way that it considers each node and its parents in isolation from the rest of the model variables. Otherwise, without employing this factorisation, far more parameters would be required to be estimated and therefore to specify the causal-effect relationships by a fully connected network and "unfactorable" model. Thus, employing factorisation model (5) the very complex models can be estimated avoiding the combinatorial explosion problem. In Figure 2 the Markov condition for F to B entails the following conditional independence relation:

$$F \perp B \mid T \tag{8}$$

More specifically, (8) implies that nodes F and B are independent as there is no direct edge connecting them and given T. A similar interpretation can be derived for the remained nodes. Next one very important definition for the DAG and BN, which is the *d-separation* is discussed.

Definition 4. (d-separation) (Pearl, 1988; Spirtes et al., 2000; Neapolitan, 2003): Let $G=(V,E)$ be a DAG, $A \subseteq V$, X and Y be distinct nodes in $V—A$, and h be a chain between X and Y. Then h is blocked if one of the following cases holds:
There is a node $S \in A$ on the chain h and the edges incident to S on h meet head-to-tail at S.
There is a node $S \in A$ on the chain h and the edges incident to S on h meet tail-to-tail at S.
There is a node S such that S and all of S's descendants are not in A on the chain h and the edges incident to A on h met head-to-head at S.

The *d*-separation condition is especially important and useful in constructing a BN because it controls for possible confounds as in the form of S described here. In other words, a set of variables S *d*-separate variable X from Y, if and only if S blocks every path from X to Y. Graphically, *d*-separation usually exhibits two main cases: firstly $X \rightarrow S \rightarrow Y$ and secondly $X \leftarrow S \rightarrow Y$. The intuition behind this graphical representation is that X and Y are independent from each other conditioned on S. In the first case X causes Y through S, while in the second

case X and Y have a common cause S. To ascertain whether a particular conditional independence statement $X \perp Y|S$ is implied the possible paths from any node in X to any node in Y are considered. Any such path is blocked if it includes a node such that either the arrows on the path meet either head-to-tail or tail-to-tail at the node, and the node is in S, such as the relations $X \rightarrow S \rightarrow Y$ and $X \leftarrow S \rightarrow Y$ or the arrows meet head-to-head at the node, and neither the node, nor any of its descendants, is in S. If all paths are blocked, X is d-separated from Y given S, and the joint distribution over all of the variables in the graph will then satisfy $X \perp Y|S$.

Lemma 1: Suppose Γ is a Bayesian network, and Y is a leaf node, where a leaf node is defined as the node that has no children. Let Γ' be the Bayesian network obtained from Γ by removing Y. Let $\mathbf{\Omega}$ be the set of all nodes in Γ. Then it will be:

$$P_{\Gamma}(\mathbf{\Omega}) = P_{\Gamma'}(\mathbf{\Omega}) \tag{9}$$

Proof:

$$P_{\Gamma}(\mathbf{\Omega}) = \sum_{Y} P_{\Gamma}(\mathbf{\Omega}, Y) = \sum_{Y} [\prod_{W \in \Omega} P(W \mid par(W))] P(Y \mid par(Y)) =$$

$$\prod_{W \in \Omega} P(W \mid par(W)) \sum_{Y} P(Y \mid par(Y)) = \prod_{W \in \Omega} P(W \mid par(W)) = P_{\Gamma'}(\mathbf{\Omega})$$

The third equality holds because is a leaf node; thus Y is not in X and cannot be in any $par(W)$ for any $W \in \Omega$. Also the fourth equality holds because probability sums to one.

Proposition 1. Let **X** be a set of nodes in a Bayesian network Γ and suppose **X** is ancestral. Let Γ' be the Bayesian network obtained from Γ' by removing all nodes outside **X**. Then

$$P_{\Gamma}(\mathbf{X}) = P_{\Gamma'}(\mathbf{X}) \tag{10}$$

Proof:

First step is to find a leaf node and then remove it. Next we get Γ'. According to *Lemma* 1 the probability distribution of **X** remains unchanged throughout the procedure.

Proposition 2. Let **X**, **Y**, and **S** be three disjoint sets of nodes in a Bayesian network such that their union is the set of all nodes. If **S** d-separates **X** and **Y** as above then $\mathbf{X} \perp \mathbf{Y} | \mathbf{S}$.

Proof:

Let $\mathbf{S_1}$ be the set of nodes in **S** that have parent in **X** and let assume that $\mathbf{S_2}=\mathbf{S}\setminus\mathbf{S_1}$. The latter shows that $\mathbf{S_2}$ is member of **S**, but not member of $\mathbf{S_1}$ defined by \. Because **S** d-separates **X** and **Y** then:

For any $W\in\mathbf{X}\cup\mathbf{S_1}$, $par(W)\subseteq\mathbf{X}\cup\mathbf{S}$ and

For any $W\in\mathbf{Y}\cup\mathbf{S_2}$, $par(W)\subseteq\mathbf{Y}\cup\mathbf{S}$

Then let us consider:

$$P(\mathbf{X},\mathbf{S},\mathbf{Y}) = \prod_{W\in\mathbf{X}\cup\mathbf{S}\cup\mathbf{Y}} P(W \mid par(W)) = [\prod_{W\in\mathbf{X}\cup\mathbf{S_1}} P(W \mid par(W))][\prod_{W\in\mathbf{S_2}\cup\mathbf{Y}} P(W \mid par(W))]$$

And

$\prod_{W\in\mathbf{X}\cup\mathbf{S_1}} P(W \mid par(W))]$ is a function of **X** and **S**, while $\prod_{W\in\mathbf{Y}\cup\mathbf{S_2}} P(W \mid par(W))$ is a function of **Y** and **S**.

Theorem 1. (Global Markov property) (Pearl, 2000; Neapolitan, 2003): Given a Bayesian network, let X and Y be two variables and **S** be a set of variables that does not contain X or Y. If **S** d-separates X and Y, then

$$X \perp Y \mid \mathbf{S} \tag{11}$$

Proof:

Based on the proposition 1 it can be assumed that $an(\{X,Y\}\cup\mathbf{S})$ equals the set of nodes. Thus, $X\perp Y|\mathbf{S}$ in original network iff it is true in the restriction onto the ancestral set and **S** d-separates X and Y in original network iff it is true in the restriction onto the ancestral set. Next let **X** be the set of all nodes that are NOT d-separated from X by **S** and let Y be the set of all nodes that are neither in **X** or **Z**. Because of proposition 2 it is $\mathbf{X}\perp\mathbf{Y}\mid\mathbf{S}$

There must exist functions $f(\mathbf{X},\mathbf{S})$ and $g(\mathbf{S},\mathbf{Y})$, such that $P(\mathbf{X},\mathbf{S},\mathbf{Y})=f(\mathbf{X},\mathbf{S})g(\mathbf{S},\mathbf{Y})$. Also it should be noticed that $X\in\mathbf{X}$ and $Y\in\mathbf{Y}$.

Then let be $\mathbf{X}'=\mathbf{X}\setminus\{X\}$ and be $\mathbf{Y}'=\mathbf{Y}\setminus\{Y\}$. Then we have $P(X,\mathbf{X}',\mathbf{S},Y,\mathbf{Y}) = f(X,\mathbf{X},\mathbf{S})g(\mathbf{S},Y,\mathbf{Y})$.

Consequently it will be:

$$\mathbf{P}(X,Y,\mathbf{S}) = \sum_{\mathbf{X}'\mathbf{Y}'} P(X,\mathbf{X}',\mathbf{S},Y,\mathbf{Y}') = \sum_{\mathbf{X}'\mathbf{Y}'} f(X,\mathbf{X}',\mathbf{S},Y)g(\mathbf{S},Y,\mathbf{Y}') =$$
$$[\sum_{\mathbf{X}'} f(X,\mathbf{X}',\mathbf{S},Y)][\sum_{\mathbf{Y}'} g(\mathbf{S},Y,\mathbf{Y}')] = f'(X,\mathbf{S})g'(\mathbf{S},Y)$$

And that is (11) or $X \perp Y|\mathbf{S}$

Definition 5. (Partial Correlation): For $i \neq j \in 1, \ldots, p$, $k \in X_r$, let $\rho_{i,j|k}$ be the partial correlation between X_i and X_j given X_r and X_r denotes the rest of the variables.

Based on this definition we have that $X_i \perp\!\!\!\perp X_j | X_r \Leftrightarrow \rho_{i,j|k}$. Next the Fisher's Z test for the conditional independence is presented (Spirtes et al., 2000; Kalisch and Buhlmann, 2007):

$$\rho_{XY|C} = 0 \tag{12}$$

$$z(\rho_{XY|C}{}^{,n}) = \frac{1}{2}\sqrt{n-|C|-3}\log\frac{(|1+\rho_{XY|C}|)}{(|1-\rho_{XY|C}|)} \tag{13}$$

|C| is the number of variables in C and n is the length of the sample. If X,Y,C~N under the null hypothesis of zero partial correlation:

$$z(\hat{\rho}_{XY|C}{}^{,n}) \sim N(0,1) \tag{14}$$

The test for independence is based on the PC algorithm (Spirtes et al., 2000) at significance level α. Kalisch and Buhlmann (2007) show that the choice of α is not too important. However, a significance level α=0.01 is used. The pseudo-code of the PC algorithm is presented in figure 3. The PC algorithm takes as input raw data and the degree of a vertex is the number of vertices adjacent to it. In the large sample limit in the worst case the number of conditional independence tests required by the algorithm is bounded above by n^{k+2} where k is the maximum degree of any vertex in the true DAG. More specifically, the PC algorithm consists from four steps.

In the first step the PC algorithm estimates the skeleton of the DAG starting by a complete undirected graph, where every node is connected to each other. For instance the edge between two variables X and Y is tested whether there is a conditioning set S such that X and Y are

independent given *S,* which is denoted as previously $X \perp Y|S$. In the case that such a set, called as separation set, is found then the edge between *X* and *Y* is deleted. This indicates that there is not any direct causal relationship between them and thus, there will be no edge between them in the true causal structure.

In the second step the information on separation sets is used to orient unshielded colliders. As an example the following theoretical skeleton *X*—*Z*—*Y* is considered, where *X* and *Y* are not connected. In that case, the true causal structure might be one of the following: $X \rightarrow Z \rightarrow Y$, $X \leftarrow Z \leftarrow Y$, $X \rightarrow Z \leftarrow Y$ and $X \leftarrow Z \rightarrow Y$. By applying *d-separation*, it becomes $X \rightarrow Z \rightarrow Y$, $X \leftarrow Z \leftarrow Y$ and $X \leftarrow Z \rightarrow Y$ implying that *X* is dependent on *Y* given *Z* and thus, if *Z* is not in the separation set of *X* and Y*,* the only causal structure is $X \rightarrow Z \leftarrow Y$, which is an unshielded collider. This example is generalised to the rule that in the case that *Z* is not in the separation set of *X* and *Y* in an unshielded triple *X*—*Z*—*Y* then the unshielded triple must be directed into an unshielded collider.

In the last step all the edges that are still undirected are checked such a way that two possible directions would lead to a new unshielded collider or a cycle. In the case that this will happen the undirected edge is directed into the other direction to rule out a new unshielded collider which were already found in step 2 or a cycle (for more details on PC algorithm see also Spirtes et al., 2000).

Overall, various approaches deriving causality have been developed. The first approach is the propensity score method, originally proposed by Rosenbaum and Rubin (1983), which has been developed in order to assess the causal effects of interventions. This approach however, allows only for one treatment and one effect. In the case examined here this is applicable to examine only one effect, while with BN the exploration of multiple treatment effects is possible,

Thus, the main purpose is to examine the causal effects, not only of the various employment arrangements job satisfaction and employee loyalty, but also the causal effects between the last two main outcomes of interest.

To summarise and briefly explain in plain word the BN implemented by relation (5) and the back-door and front-door criteria accounting for over control bias, in addition to X and Y, there will generally be some covariates Z which we know, and it is assumed that the DAG is known. The first condition is the back-door condition, where it is possible to condition on a chosen set of Z covariates which block all the indirect paths from X to Y, but leave the direct paths open and there should not be a variable or a set of variables blocking the path from X to Y. This can be done with regression analysis, but it should be done right and carefully. The second criterion is the front-door criterion, where a set of variables S which mediate the causal effect from X to Y and all the effects pass from X to Y through S. If the effect of M on Y can be identified, and of X on M then these effects can be combined to get the effect of X on Y. Finally, the last identification method, is the instrumental variables approach where a variable W which affect X and which only affects Y by influencing X.

Regarding the back-door criterion, when estimating the effect of X on Y a back-door path is an undirected path between X and Y with an arrow into X and these paths create confounding, by providing an indirect non causal channel along which information can flow. Thus, a set of conditioning variables or controls Z satisfies the backdoor-criterion when Z blocks every back-door between X and Y and also no node in Z is a descendant of X or both descendent of X and ancestor of Y because it will block the causal path between X and Y. Thus, if set Z satisfies the back-door criterion then it will be:

$$\Pr(Y \mid do(X = x)) = \sum_{z} \Pr(Y \mid X = x, Z = z) \Pr(Z = z) \tag{15}$$

All the items on the right hand of (15) are observational conditional probabilities and not counterfactuals. The condition that Z blocks every back-door between X and Y is met. However,

regarding the second condition, it is not desirable to include descendants of *X* which are also ancestors of *Y* because this will block off some or all of the causal paths from *X* to *Y*. Thus, this shows that Y⊥Pa(X)|X,Z, which in other words it tells us that *Y* is independent from the parents of *X* given *X* and *Z*. Nevertheless, in this study we explore whether the back-door criterion or an instrumental variable from BN is more appropriate based on the data and the causal relationships that will be derived by the BN and presented as DAG.

Next a DAG representation where an instrumental variable *I* can meet the conditions and be used into the analysis is presented in figure 4, where the instrumental variable *I* is related to the cause of interest *X* and influences *Y* only through its impact on *X* and at least one control variable blocks the other path, such the variable-node *S*, which can be also a set of variables **S**. In the case of figure 4 in order to use variable *I* as an instrument, we should condition on *S* but not on *W* because it is descendant of *Y* and the common cause of *W* coming from *I* and *Y* will lead to selection bias as it has been described in the methodology part and the *d-separation* condition. More specifically, a variable *I* qualifies as an IV for *X* (factor of interest) and *Y* (outcome of interest if the following three conditions are met: a) *I* is statistically independent of all joint common causes of *X* and *Y*; b) *I* is not independent of *X*; and c) the effect of *Z* on *Y* is mediated solely by *X*.

Lemma 2. *Given a path diagram G and which contains the direct edge X→Y, then a variable W can be an instrumental variable for X given Z, which is a set of variables that does not contain any variable from W, X,Y, or Desc(Y) if the following conditions are met:*

- In the path diagram G, X and W are connected given Z
- In the path diagram $G_{\backslash X\to Y}$ which is formed by removing X→Y from G, W and Y are d-separated given Z.

Then the direct causal effect τ_{yx} is given by:

$$\tau_{yx} = \frac{\sigma_{wy\cdot z}}{\sigma_{wx\cdot z}} \tag{16}$$

Lemma 2 can be extended into a set of instrumental variables W_i for i=1,….,k. In that case the direct causal effects $\tau_{yx_1},.....,\tau_{yx_k}$ can be solved by a system of k equations as:

$$\sigma_{w_i y \cdot z} = \sum_{j=1}^{k} \sigma_{w_i x_j \cdot z} \tau_{yx_j} \quad , for \ \ i=1,...k \tag{17}$$

For instance when $X \perp Y$ then it is cov(X,Y)=0. In relation (13), $\sigma_{wy.z}$ is the conditional covariance between W and Y given Z=z, while similarly $\sigma_{wx.z}$ is defined as the conditional covariance between W and X given Z=z. Considering the Cov(W,Y,|Z) =E[W,Y |Z] − E[W|Z]E[Y |Z]. This will be E[(W,Y − E[W|Z]Y − WE[Y |Z] + E[W|Z]E[W |Z])|Z] = E[W,Y |Z] − E[W|Z]E[Y |Z] − E[W|Z][Y |Z] + E[W|Z]E[Y |Z] = E[W,Y |Z] − E[W|Z]E[Y |Z. In a similar fashion the Cov(W,X|Z) will be E[W,X |Z] − E[W|Z]E[X |Z].

Thus, this test can be applied in other studies using IV approach and to define whether the IV is proper or not, especially regarding the selection bias.

4 Data

The Workplace Employment Relations Study (WERS) series commenced in 1980 and took place six times until 2011. The 2004 and 2011 Panel Survey was conducted in a random sub-sample of workplaces and the surveys are conducted to managers and employees. This is useful for the analysis, since the regression control not only for employee characteristics, but also for firm characteristics, such as competition, market area, status of the institution.

The first outcome of interest is the job satisfaction, which is an ordered variable measured in a Likert scale from 1 (very dissatisfied) to 5 (very satisfied). Similarly, employee loyalty is an ordered variable answering to the question “To what extent do you agree or disagree with the statement that you are loyal to your firm-organisation” measured in a scale from 1 (strongly disagree) to 5 (strongly agree). In table 1 the summary statistics for the outcomes of interest-job satisfaction and employee retention- and the factors of interest which are the employment arrangements explored in this study are presented. The average job satisfaction and employee loyalty levels are relatively high to our sample with average very close to 4. Regarding the

employment arrangements explored in this study, the lowest percentage of participation belongs to teleworking followed by compressing hours mode by 16 and 20.5 per cent respectively.

More specifically, teleworking in our sample refers to people who mainly work at home. Reducing hours it means the option that the employee can switch from full-time employment or part-time, while increasing working hours implies the opposite. Change shifts as the name declares, it obviously indicates the case where employees can change working shifts, while compressing hours employment mode is the option where the employee can be occupied the same working hours per week distributed in a smaller number of days. For instance working 35 hours per week in 4 days instead of 5 or 6 days. Additional, variables are not presented, as the descriptive statistics do not give any additional insights, for this reason a correlation matrix among the outcomes of interest and the employment arrangements is presented in table 2. In all cases there is a positive relationship among the various types of employment, as well as, a positive association between employee loyalty, job satisfaction and employment types. Additional factors are not explored as they are used as controls in to the regressions; however, some correlation statistics show for instance that wage and higher education degree are positive associated with flexi time and teleworking and negatively related to changing shifts.

(Insert tables 1-2)

5 Empirical Results

In table 3 the fixed effects estimates for job satisfaction and the various working arrangements before the propensity score matching takes place, are reported. In this case only the coefficients of these arrangements are presented, while the full estimates for the control variables are presented later in this section after the matching is conducted. In all cases there is a positive relation between the implementation of these employment arrangements and the levels of job satisfaction. The higher association is presented in the mode of flexible time

followed by change shifts and teleworking. In column (7) the results including all the employment modes are presented. However, as it can been seen the options of either reducing or increasing the working hours are insignificant, while also the magnitude of the remained coefficients is reduced. Since, these employment types may be highly correlated and it could be difficult to disentangle their effects, separate regressions for each type of working mode are taking place.

In table 4 the conditional. Logit estimates for the various employment arrangements are presented, where the dependent variable is a dummy taking value 1 whether there is the choice of the employment type examined and 0 if there is not. There is a monotonic decrease on age of the propensity to implementation of these employment types, where those aged older than 17 years old and up to 64 years old are less likely to choose one of these employment types. Regarding teleworking there is no difference on age. Married or couples seems to not be a significant factor, while those who are divorced and widowed are less likely to choose the mode of "compress hours", while the last group is more likely to choose teleworking, as well as, the probability occurrence of switching from part-time to full-time is reduced. Education level has overall mixed results and in many cases the coefficients are insignificant. Nevertheless, the exception is teleworking, where the more educated people have more chance to choose this employment type. This may be related to the fact that higher educated people are more likely to be managers or supervisors and to assign workload to other people, while they can spend more time at home. Also, teleworking can be related with information technology usage, where more educated people usually have these skills. This is also confirmed by the coefficient of the variable on whether the respondent supervises or manages other people. In the case where they do not supervise are less likely to be employed at home or to telework, while are more likely to reduce the working hours. The results additionally show that there is heterogeneity regarding

the ethnicity, such as other white, Indians, Pakistanis, other Asians, Africans and those from Caribbean are more likely to choose the various types of employment examined.

Regarding the weekly hours worked per week a negative relationship between these and reducing hours, teleworking and changing shifts is observed, while a positive relationship between weekly hours and compress hours is observed. The remained coefficients are insignificant. However, this does not necessarily implies less hours of work per week, since for example those who switch from full-time to part-time it is obviously expected a reduction of weekly hours and thus leading to a negative relationship. The weekly wage presents also mixed results, while in lower wage levels it is more likely that the respondents will choose the transition from full-time to part time and vice versa, as well as, changing shifts, while in higher levels of wage are less likely to implement these types of employment. It should be noticed that there additional scales of wages; however, are not reported here as the concluding remarks remain similar. The same applies for the table 5, where the fixed estimates of the job satisfaction function are presented. The remained employment arrangements are insignificant, while teleworking is significant in higher wage levels. However, this may imply that those who are teleworkers may earn more, based on their skills and computing information technology knowledge and the job position. It should be noticed that also whether the respondents use computer in their job or not has been also examined. The results showed that those who use mainly computer in their work are more likely to implement flexi time and teleworking employment types, while the relationship with the remained employment modes is insignificant.

Finally, regarding the product-service coverage area of the firm-organisation regional, national and international firms are less likely to implement those types of employment modes than the local ones are. On the other hand, teleworking is more plausible to be implemented in

the regional and national firms, while there is no difference between local and international organizations.

(Insert tables 3-4)

The fixed effects estimates after the propensity score matching are presented in table 5. The results show that the relationship between job satisfaction and the employment arrangements explored is positive and significant. The highest magnitudes are presented in the case of the teleworkers, followed by those who choose the option of changing shifts and those who implement flexi time. The remained coefficients show that elder workers are more satisfied with their job, while the married or couples and divorced are more likely to report higher levels of job satisfaction than the singles. Regarding education and the level of skills to job matching, those with first degree in some cases report lower levels of job satisfaction, which is consistent with other studies, arguing that more educated people have higher expectations about their pecuniary and non-pecuniary returns form their job and thus are more easily disappointed and dissatisfied (Clark and Oswald, 1996; Hamermesh, 2000). The same applies with the matching skills to job. More precisely, those who stated that their skills match the job almost the same or bit lower report higher levels of job satisfaction than those who stated that are over-qualified.

The ethnicity group is significant and more specifically, those who belong to the other white, Caribbean and African groups are less likely to report higher job satisfaction levels than British. The competition, the profit-related payments, the status of company, whether public or private, the weekly number of working hours and the proportion of non-managerial undergone performance appraisal are insignificant factors. On the other hand, performance related payments schemes and supervising other employees increase the job satisfaction levels, as well as those who state that the quality of relations between employees and managers is either good or very good, relatively to those who reported low levels of manager-employee relations. Wage presents mixed results among the employment arrangements examined. More specifically, the

wage is significant in all scales regarding flexi time and either increasing or decreasing working hours, while for the remained employment types, the wage is significant only in the lower and highest scales.

(Insert table 5)

In table 6 the propensity score matching test is presented. More specifically, the test examines the null hypothesis whether the matched samples-treated and untreated- share similar characteristics. In this case the propensity score matching passes the test for all the variables examined, with the exception of the formal written policies for equal opportunities, where the null hypothesis is rejected at 10 per cent significance level. The same conclusions are derived for the job satisfaction index and the employee loyalty; therefore are not presented.

Next a job satisfaction index based on six indices is constructed. It is argued that this index can be more complete and precise, as well as, it can be used as robustness checks to the main overall job satisfaction variable. Principal component analysis is applied, while a factor analysis can be applied as well. The six job satisfaction indices answer to the following question, and the scale is the same with the job satisfaction and it has been described in the data section, ranging between 1 and 5. *Satisfaction about using your own initiative*, *Satisfaction about the amount of influence, Satisfaction about the training you receive*, *Satisfaction about the payment amount*, *Satisfaction about the job security*, *Satisfaction about the development of job skill*.

In table 7 and panel A the results when the dependent variable is the job satisfaction factor index, which has been derived with principal component analysis are presented. In this case again all the employment arrangements are significant, with higher magnitudes on teleworking followed by flexi time and changing shifts. In addition, a confirmatory factor analysis (CFA) took place in order to test the new job satisfaction index and the tests show a good fit. More specifically, aaccording to the comparative fit index (CFI) developed by Bentler (1990) and the

Tucker-Lewis index (TLI) proposed by Tucker and Lewis (1973), values higher than 0.8 indicate a good fit of the data. In the case examined CFI and TLI were found equal at 0.958 and 0.920 respectively. In addition, if the root mean square error of approximation (RMSEA) is lower than 0.5 as a rule of thumb the CFA analysis implies a very good fit of the data. In our case RMSEA is 0.0024.

Finally, in panel B of table 7 the fixed effects estimates for the employee loyalty are reported showing again that teleworkers and home-based workers are more likely to be loyal to their firm-organization presenting the highest coefficient magnitude, followed by those who implement flexi time and changing shifts. However, the coefficient of reducing hours or switching from full-time to part-time is insignificant. The remained coefficients are not reported, as the concluding remarks derived are similar with those found in the job satisfaction regressions, as well as, these factors are not the main interest of this study.

In table 8 the job satisfaction estimates for the total and mover sample, after the propensity score matching are reported. To remind the reader, in this case the movers sample is defined as the firms that have relocated, as well as, the employees who have changed location. Since the panel is based on employee and firm, the data structure also follows the same employees in the same firms. In panel A the estimates for the total sample are very similar with those found in the table 5 considering the non-movers sample. It is observed that changing shifts presents the higher coefficient magnitude flowed by flexi time and teleworking. In panel B the estimates for the movers sample and job satisfaction are reported. All the coefficients are insignificant, with the exception of teleworking and changing shifts, where the effects of teleworking are very close with those found using the total and non-movers sample. On the other hand, the employment type of changing shifts presents lower effects on job satisfaction. Thus, this may indicate that limiting the sample to non-,movers may not lead to biased estimates regarding teleworking, since it may not be affected by the firm relocation or whether the employee moved

to another location, expressed by the TTWA. Similar conclusions are derived for the employee loyalty; however are not presented.

(Insert tables 6-8)

The 3SLS for the system of equations (2)-(3) and job satisfaction, employee loyalty and employment arrangements relationships are reported in table 9. It becomes obvious that job satisfaction causes employee loyalty and vice versa, where a higher level of job satisfaction is associated with a higher level of employee loyalty and the opposite as well. In all cases the employment types are positive and significantly associated with job satisfaction, while in the case of the employee loyalty, reducing hours and changing shifts are not significant. Moreover, based on the Hansen-Sargan statistic the null hypothesis that the variables are exogenous is rejected. For this reason in the next part of this section the BN framework is applied.

(Insert table 9)

In figure 5 the estimated DAG for teleworking is presented while the BN estimates considering all the employment arrangements explored in the study, are reported in table 10. A similar representation is observed for the remained of the employment types, but their associated DAGs are not presented here. Also separate estimates for each employment arrangements is taking place since it is difficult to disentangle their effects, when they are included into the same regression. Including all the working types into the same DAG, the estimates confirm the results of table 3 and column (7), where some of these types become insignificant. The reason is that regression presents over-control bias where some variables block the causal effect from the variable of interest to the outcome. For instance coming back to figure 2, *F* blocks off the causal effect from *T* to *Y* since there is no direct effect (arrow) from the former to the latter. Similarly, in this case teleworking may block –off the causal effect from increasing hours or changing shifts to job satisfaction. Thus, one solution is to not include them

in to the same DAG, while the second solution is to incorporate them into the same DAG and BN and applying the back-door and front-door criteria wherever necessarily.

Before we proceed to the findings conclusion, the abbreviations of the variables in the DAG figure 5 are described. Variables *ethnic*, *mastat*, *superv_other*, *num_hours* and *age* indicate respectively ethnicity, marital status, supervising other employees, number of weekly hours worked and age. The other variables have as following: dependent children 0-2 years old (dep_chil_0_2), years worked (years_exp), education level (education), status of company (status_com), number of firm establishments (single_ind), whether the skills match to employee's work (skill_job), area market of the firm (market_ope), TTWA (area), quality of relations between managers and employees (rel_mang_emp), wage (wage), percentage of employees in the firm using computer (computer_use), whether the employee is member of union trade or staff association (union_memb), formal written policies for equal opportunities in the institution (policy_dis), performance pay schemes (perf_pay), related profit schemes (related_prof), proportion of non-managerial staff under performance evaluation (prop_non_man_eval) home-teleworkers (home_tele_work), job satisfaction (job_sat) employee loyalty (loyal).

Applying the factorization model (5) and the back-door and front-door criteria and the d-separation the causal effect of the teleworking on job satisfaction is a regression of itself and its parents-*computer_use*, *wage*, education, *union_memb*, *rel_mang_emp*, *skill_job* and *superv_other.* The causal effect of teleworking is very similar to those found in table 5. Similar DAGs are estimated for the remained employment arrangements; however are not presented here, but their causal effects are reported in table, which are very close to those found in table 5. It should be noticed that the estimates differ from panel A of table 8, since in the last table the job satisfaction factor index is taken, while in tables 5 and 10 the overall job satisfaction is considered.

Various other conclusions can be derived from DAG in figure 5. For instance the regression should not condition on employee loyalty since it is caused by both job satisfaction and teleworking, leading to selection bias. Similarly, if we would like to derive the causal effect of wage on job satisfaction, a regression including the wage and its parents will take place. Another example is computer use, where its causal effect is blocked-off by teleworking. In this case also the regression should include the computer use and its parents, in order to estimate the causal effect of computer percentage use on job satisfaction. However, two things are concluded. Firstly, conditioning on teleworking, the causal effect of computer use is blocked-off from teleworking leading to over-control bias, as it has been discussed in the methodology section and since there is no direct effect-arrow to job satisfaction. Thus, in this case the front-door and back-door criteria are applied. Secondly, coming back to the figure 4 computer use can be used as an instrumental variable because is directly related to teleworking, and is conditioned on *related_prof* which the latter affects the job satisfaction. Thus, the IV should be conditioned on at least one other variable which causes job satisfaction. In this case the causal effect of teleworking on job satisfaction using the percentage of employees using computer in the institution-firm is 0.1251 (sd. error 0.0329), the weak instrument test is 84.868 rejecting the hypothesis that the instrument is weak, while the endogeneity Sargan statistic is 8.958 (p-value 0.2315). Thus, BN can be a very useful tool or empirical research allowing us to find proper instrumental variable wherever possible. However, the results confirm that IVs are not always necessarily into BN framework for causality. A similar application for the remained employment types can be considered.

Overall, the study shows that employees are likely to assess elements of job satisfaction related with their personal characteristics and beliefs, such as their skill matching, wages and age and with firm characteristics. More specifically, one type of firm characteristics is the rewarding system, such as whether there are performance to pay or profit related payments. The

second type refers to traditional economic characteristics, like area market, competition, company status and others. The last type which is of main importance to the job satisfaction and employee loyalty, is the culture of the company, represented by the quality of relations between managers and employees.

(Insert table 10)

Since the job satisfaction and employee retention have a central role to firm's organization and policy, but also are topics of the policy makers' agenda for the improvement of the society's well-being, Bayesian networks can have important policy implications, as causal inference has a central role in well-being and policy making. These implications can be extended and applied in many other domains of well-being and public policy, including life satisfaction, leisure and public health and policy generally, such as public goods and "bads" including air, noise and water pollution among others. Since the natural experiments are very difficult to be found and many times may not be under the researcher's control and instrumental variables are very difficult to be found and be convincible, Bayesian Networks is an alternative tool which can be useful, when the former cases are absent. BN can be applied not only to observation data, which data are very useful for controlling for various characteristics, which in the majority of the natural experiments are missed. Moreover, BN can be applied to randomized experiments as well (Pearl, 2000, 2009; Spirtes eat al., 2000).

Therefore, the determination that an association is causal indicates the possibility for intervention and thus for policy making and it can have profound consequences on labour productivity and firm performance through job satisfaction and employment arrangements. However, BN as any other statistical and econometric model, including natural and randomized field experiments and instrumental variables approach is the unobserved confounders which may not be under the control of the researcher and are not fixed. In addition, in the randomised experiments are fixed by the study design and thus it is usually known, while in the

observational data, as is the WERS used in this study, the true propensity score is not known and it has to be estimated from the data. Overall, the propensity score tests and results show that the treated and control groups share similar characteristics in this study.

6 Conclusions

The findings of this study suggest that there is a positive effect for a range of employment arrangements on job satisfaction and employee loyalty. The strongest effects have been found to be for teleworkers and those who have flexible working schedule. This may indicate further that these types of employment can allow the employees to use them as means of relief from stressful condition, coming mainly from commuting at work and the traffic congestion. Moreover, these types of working arrangements, may give to employees more autonomy and control of the working schedule and to allow them to adjust it on their needs, including family demands and obligations and leisure activities. Furthermore, future research might take place on how these employment arrangements improve the labour productivity and the firm performance, through job satisfaction, as well as, how much costs are saved in terms of office, equipment and other labour related costs. For example, employees spending more time at home, employers can afford to lease or purchase smaller, less expensive facilities, pay less for energy and electricity and purchase fewer supplies. In addition, this study showed that in the case of the implementation of this type of employment arrangements and especially the employees who are involved in teleworking, are more likely to report higher levels of loyalty than those who do not implement them. Overall, managing turnover intention is a challenge for many organizations that incur very high costs as a result of voluntary turnover and retaining good workers is critical to any organization, public or private and especially for valuable and high skilled employees, while the costs associated with the new employees recruitment is also high and this usually takes time. Thus, flexible employment arrangements, including

teleworking can be a solution to turnover intention reduction, increasing the job satisfaction and improving the well-being of employees and saving costs for organizations. However, most of these issues have not been examined here but are proposed for future research and application. Moreover, the type of work, such as creative or dull duties have not been explored in this study, but it is suggested for future application. For instance, those who are teleworkers may be more satisfied with their jobs if they are involved in creative duties than dull ones, while also creative jobs may increase the propensity to telework. Finally, BN and DAG, as it has been discussed, offer an alternative way of deriving causality using observational data and surveys, with various policy implications and implementations to workplaces, employees, employers and to the society overall.

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Figure 1. Conceptual Framework of Flexible Employment Arrangements, Job Satisfaction and Employee Loyalty

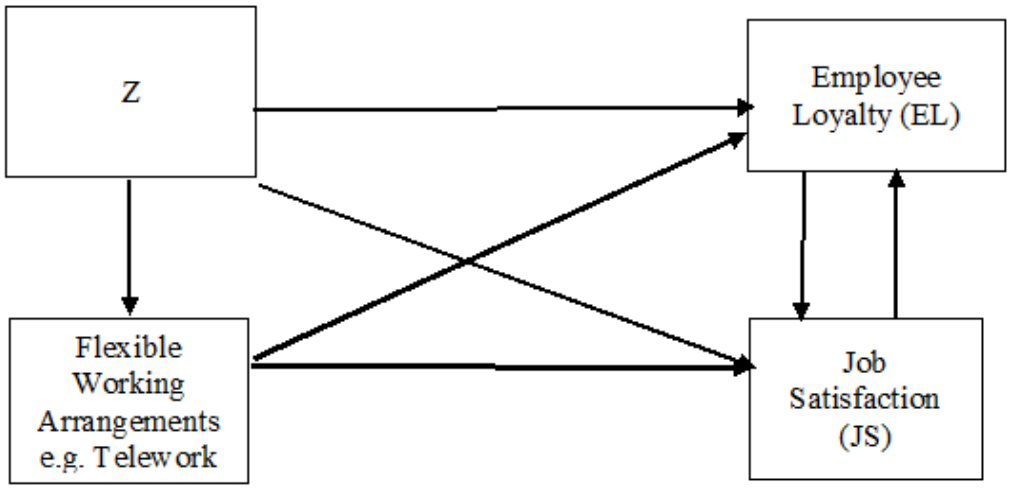

Figure 2. An example of a Directed Acyclic Graph (DAG)

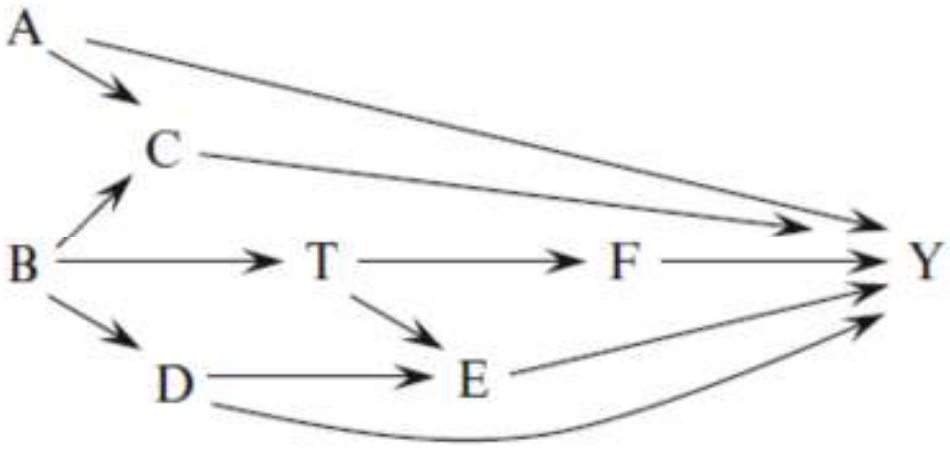

Figure 3. PC algorithm pseudo-code for the estimated DAG

Step 1:
Start with the complete undirected graph, $C^{\sim}$ with vertices $V = X_1, \ldots, X_p$. Then:
Step 2:
Set $l = -1$ and $C = C^{\sim}$
Step 3:
Increase l by one. For all pairs of adjacent nodes:

- Check for conditional independence
- Remove edge (X_i, X_j) if $X_i \perp\!\!\!\perp X_j | rest$

Step 4:
Repeat step 2 until $l = m$ or until each node has fewer than $l - 1$ neighbours
And let mr each $\in$ max l, m denote the stopping level of the algorithm and q be the maximum number of neighbours

In plain words the above pseuso-code of the PC algorithm works on the following simple steps.

- For each X and Y, see if X ⊥Y; if so, remove their edge.
- For each X and Y which are still connected, and each third variable Z1, see if X ⊥ Y|Z; if so, remove the edge between X and Y.
- For each X and Y which are still connected, and each third and fourth variables
- Z1 and Z2, see if X ⊥ Y|Z1,Z2; if so, remove their edge.

For each X and Y which are still connected, see if X ⊥ Y| all the p − 2 other variables; if so, remove, their edge

Figure 4. Illustration of IV conditions

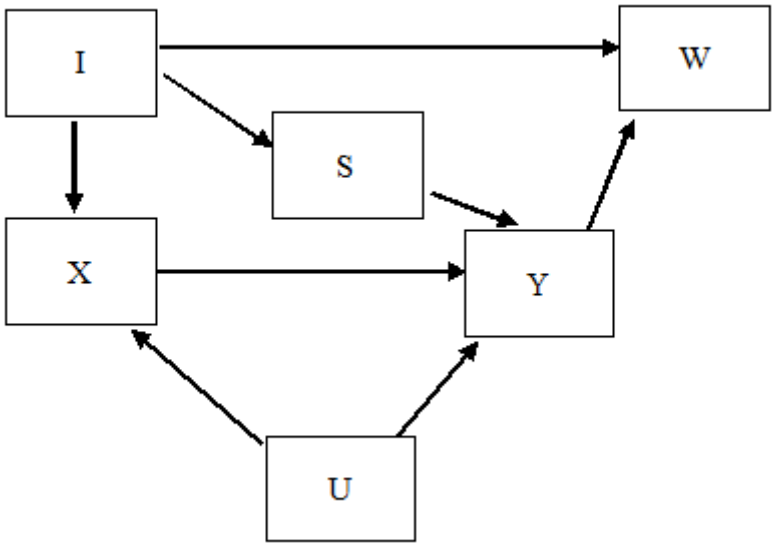

Figure 5. DAG for Teleworking

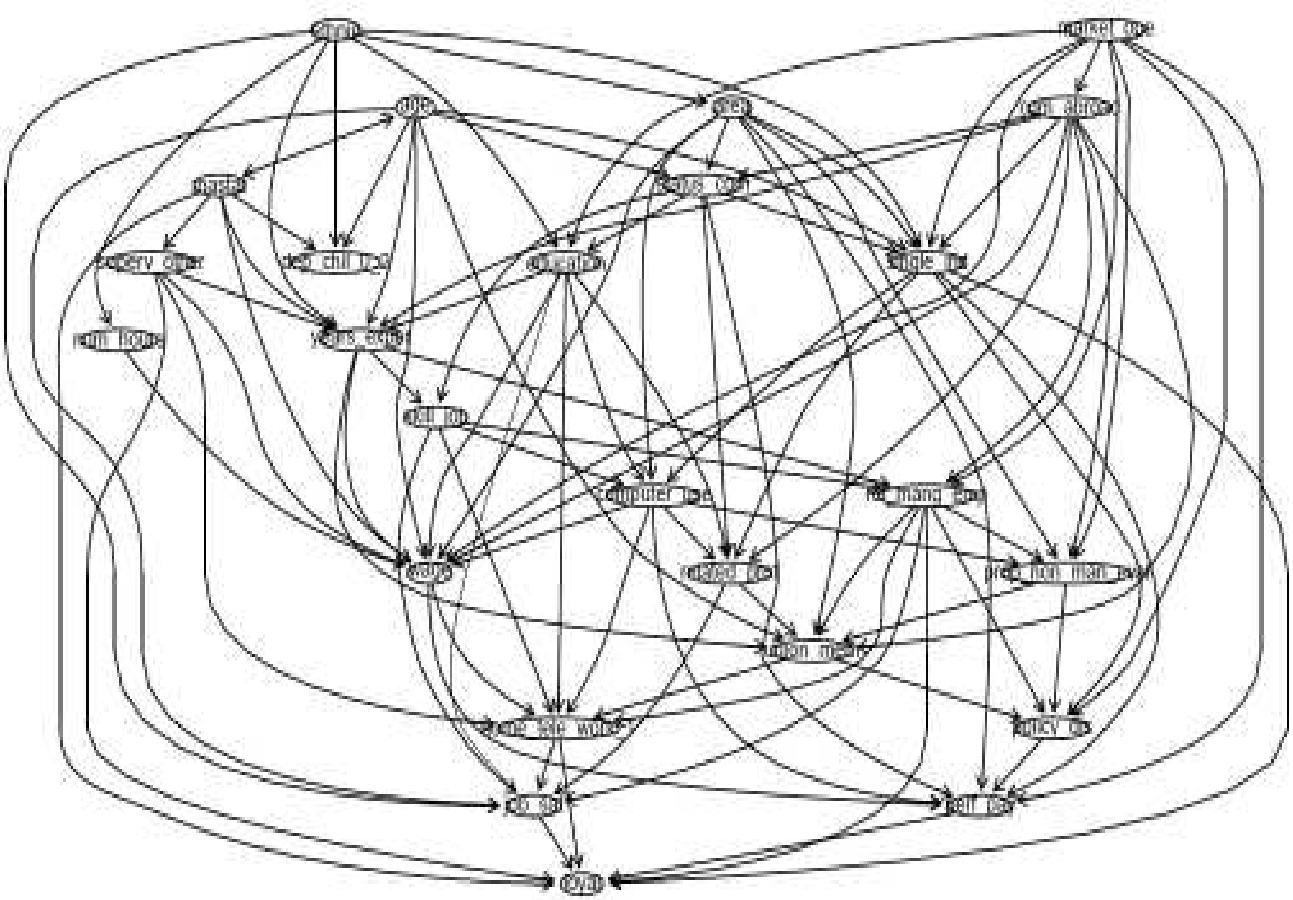

Table 1. Summary Statistics

	Mean	Standard deviation	Minimum	Maximum	
Panel A: Dependent Variables					
Job Satisfaction	3.8134	0.8939	1	5	
Employee Loyalty	3.8423	0.9264	1	5	
Panel B: Employment Arrangements					
Flexible Time (Yes)	39.08	Reduce Hours (Yes)	26.27	Increase Hours (Yes)	24.74
Flexible Time (No)	60.92	Reduce Hours (No)	73.73	Increase Hours (No)	75.26
Teleworking (Yes)	15.87	Change shifts (Yes)	21.78	Compress hours (Yes)	20.42
Teleworking (No)	84.13	Change shifts (No)	78.22	Compress hours (No)	79.58

Table 2. Correlation Matrix

	Job satisfaction	Loyalty	Flexi time	Reduce hours	Increase hours	Teleworking	Change shifts
Loyalty	0.4637*** (0.0000)						
Flexi time	0.1322*** (0.0000)	0.1473*** (0.0000)					
Reduce hours	0.0718*** (0.0000)	0.0501*** (0.0000)	0.3392*** (0.0000)				
Increase hours	0.0521*** (0.0000)	0.0418*** (0.000)	0.2712*** (0.0000)	0.5689*** (0.0000)			
Teleworking	0.1187*** (0.0000)	0.1368*** (0.0000)	0.2763*** (0.0000)	0.0757*** (0.0000)	0.0421*** (0.0009)		
Change shifts	0.0751*** (0.0000)	0.0506*** (0.0000)	0.2977*** (0.0000)	0.4144*** (0.0000)	0.3907*** (0.0000)	0.1040*** (0.0000)	
Compress hours	0.1001*** (0.0000)	0.0806*** (0.0004)	0.3336*** (0.0000)	0.4308*** (0.0000)	0.3349*** (0.0000)	0.2105*** (0.0000)	0.4432*** (0.0000)

P-values in parentheses, *** $p<0.01$

Table 3. Fixed Effects Estimates for Job Satisfaction and Flexible Working Types

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Flexible Time (Yes)	0.1383***						
	(0.0184)						
Reduce Hours (Yes)		0.0633***					
		(0.0222)					
Increase Hours (Yes)			0.0782***				
			(0.0213)				
Teleworking (Yes)				0.1335***			
				(0.0245)			
Change shifts (Yes)					0.1351***		
					(0.0208)		
Compressing Hours (Yes)						0.1220***	
						(0.0217)	
Flexible Time (Yes)							0.0983***
							(0.0283)
Reduce Hours (Yes)							0.0027
							(0.0351)
Increase Hours (Yes)							0.0402
							(0.0323)
Teleworking (Yes)							0.0968***
							(0.0355)
Change shifts (Yes)							0.0519*
							(0.0267)
Compressing Hours (Yes)							0.0498
							(0.0355)
Observations	8,204	7,419	7,263	8,923	8,145	7,261	6,102
R-squared	0.2653	0.2739	0.2740	0.2675	0.2696	0.2770	0.3097

Wave-area specific clustered standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.01

Table 4. Determinants of Employment Arrangements

VARIABLES	Flexible (1)	Reduce Hours (2)	Increase Hours (3)	Teleworking (4)	Change Shifts (5)	Compress hours (6)
Age (reference category 16-17)						
Age (18-19)	0.2235	-0.3277	-0.0787	-0.3913	-0.1421	-0.2508
	(0.2969)	(0.3293)	(0.2857)	(0.6694)	(0.2637)	(0.3246)
Age (20-21)	-0.1865	-0.4053	-0.0723	-0.2541	-0.1230	-0.2943
	(0.2932)	(0.3309)	(0.2859)	(0.6275)	(0.2631)	(0.3250)
Age (22-29)	-0.6584**	-0.8527***	-0.6122**	-0.2655	-0.7369***	-0.7591**
	(0.2639)	(0.2968)	(0.2530)	(0.5565)	(0.2352)	(0.2977)
Age (30-39)	-0.8200***	-0.7691**	-0.6935***	0.3448	-0.6911***	-0.7108**
	(0.2667)	(0.2996)	(0.2560)	(0.5538)	(0.2390)	(0.3002)
Age (40-49)	-0.8261***	-1.2338***	-0.9549***	0.1409	-0.9007***	-1.0147***
	(0.2698)	(0.3027)	(0.2609)	(0.5572)	(0.2440)	(0.3051)
Age (50-59)	-0.6775**	-1.1738***	-1.1045***	0.1161	-0.9124***	-0.9284***
	(0.2721)	(0.3075)	(0.2653)	(0.5597)	(0.2475)	(0.3078)
Age (60-64)	-0.3056	-0.4735	-1.0297***	0.2015	-0.5481*	-0.4251
	(0.3056)	(0.3462)	(0.3114)	(0.6164)	(0.2907)	(0.3476)
Age (65 and above)	0.4099	-0.1678	-0.2819	0.9058	-0.2110	-0.3500
	(0.3983)	(0.4942)	(0.4190)	(0.6223)	(0.3982)	(0.4688)
Marital status (reference category single)						
Marital status-Married or couple	0.0739	0.2752	-0.0159	0.1444	-0.1557	0.1966
	(0.1431)	(0.1973)	(0.1770)	(0.2005)	(0.1806)	(0.1691)
Marital status-Divorced	-0.0874	-0.0841	-0.1558	0.1565	-0.1563	-0.2722**
	(0.1126)	(0.1320)	(0.1270)	(0.1664)	(0.1218)	(0.1339)
Marital status-Widowed	-0.0793	-0.1092	-0.1854**	0.1961*	-0.1154	-0.1735*
	(0.0767)	(0.0890)	(0.0849)	(0.1126)	(0.0802)	(0.0886)
Education level (reference category primary school)						
Education level- GCSE D-E levels	-0.0105	-0.0942	-0.0623	0.1014	-0.0414	-0.1810***
	(0.0553)	(0.0665)	(0.0638)	(0.0816)	(0.0619)	(0.0655)
Education level- GCSE B-S levels	-0.0463	-0.0298	-0.0126	-0.1461	-0.0493	0.1086
	(0.0745)	(0.0898)	(0.0871)	(0.1042)	(0.0853)	(0.0889)
Education level- GCSE A-AS levels	0.0233	0.2087***	0.0294	0.3855***	0.1566**	0.0865
	(0.0648)	(0.0784)	(0.0761)	(0.0822)	(0.0752)	(0.0776)
Education level-First degree	0.1994***	0.0499	-0.0072	0.5650***	0.0036	-0.0709
	(0.0660)	(0.0827)	(0.0811)	(0.0819)	(0.0779)	(0.0807)
Education level-Higher degree	0.1498	-0.0742	0.0310	0.5860***	0.0562	0.1760
	(0.1059)	(0.1340)	(0.1321)	(0.1232)	(0.1356)	(0.1330)
Dependent children aged 0-2 (Yes)	0.1110	0.5655***	-0.0037	-0.1579	-0.0987	0.1334
	(0.0750)	(0.0919)	(0.0927)	(0.1059)	(0.0980)	(0.0949)
Dependent children any age (No)	-0.3817***	0.0168	-0.3980***	-0.1751*	-0.3658***	-0.3602***
	(0.0675)	(0.0803)	(0.0769)	(0.0960)	(0.0729)	(0.0808)
Skills matching with the job (reference category much higher)						
Skills matching with the -bit higher	0.6947**	-0.4633	0.1192	0.1251*	-0.3094	-0.0917
	(0.3152)	(0.4319)	(0.3611)	(0.0653)	(0.3562)	(0.3476)
Skills matching with the job-the same	0.7138**	-0.2098	0.2713	-0.0083	-0.3007	0.0447
	(0.2945)	(0.4060)	(0.3322)	(0.4702)	(0.3337)	(0.3193)
Skills matching with the -bit lower	0.6213**	-0.2288	0.2004	-0.1767	-0.3439	-0.0504
	(0.2952)	(0.4067)	(0.3322)	(0.4705)	(0.3340)	(0.3203)
Skills matching with the -much lower	0.4271	-0.3028	0.2518	-0.5089	-0.2773	-0.1808
	(0.2966)	(0.4078)	(0.3334)	(0.4767)	(0.3345)	(0.3213)
Years of experience	-0.0168	0.1031***	-0.0474**	-0.0216	-0.0032	0.0307
	(0.0203)	(0.0254)	(0.0236)	(0.0286)	(0.0232)	(0.0250)
Ethnicity (reference British)						
Ethnicity-Irish	-0.0002	-0.0921	0.2684	0.4266	-0.1464	-0.3136
	(0.2678)	(0.3290)	(0.3255)	(0.3033)	(0.3366)	(0.3437)

Table 4 (cont.) Determinants of Employment Arrangements

VARIABLES	Flexible (1)	Reduce Hours (2)	Increase Hours (3)	Teleworking (4)	Change Shifts (5)	Compress hours (6)
Ethnicity-Other White	0.3515**	-0.5615***	-0.0889	0.2143	0.0656	-0.0409
	(0.1372)	(0.1743)	(0.1646)	(0.1704)	(0.1623)	(0.1655)
Ethnicity-White and Black Caribbean	-0.1562	0.1375	-0.0105	-0.0860	0.8750	-0.2547
	(0.4618)	(0.6789)	(0.4753)	(0.5383)	(0.5581)	(0.6651)
Ethnicity-White and Black African	0.8136	-1.3955**	-0.5754	-0.2409	-0.4960	0.2602
	(0.5610)	(0.6861)	(0.7171)	(1.3114)	(0.5672)	(0.5626)
Ethnicity-White and Asian	0.5501	0.2224	-0.7352	0.9713	0.2244	0.6664
	(0.6074)	(1.0437)	(0.6368)	(0.6814)	(0.6615)	(0.6653)
Ethnicity-Indian	0.4917***	0.0099	-0.0025	-0.3487	-0.0428	0.2335
	(0.1782)	(0.2250)	(0.2193)	(0.3237)	(0.2005)	(0.1955)
Ethnicity-Pakistani	0.6464**	0.2621	0.5680	0.5176	0.5386	-0.0693
	(0.3269)	(0.3917)	(0.3580)	(0.6042)	(0.3413)	(0.3599)
Ethnicity-Bangladeshi	0.9415	0.4558	0.6827	-0.8342	-0.4420	1.4326***
	(0.6477)	(0.4940)	(0.5642)	(1.3464)	(0.6627)	(0.5326)
Ethnicity-Other Asian	0.8760***	-0.9688***	-0.3672	1.2091**	0.2492	0.6857**
	(0.3213)	(0.3659)	(0.3679)	(0.5502)	(0.2976)	(0.3082)
Ethnicity-Caribbean	0.9999***	0.2919	1.1033***	0.9584**	0.5331	0.6290*
	(0.3027)	(0.3923)	(0.3696)	(0.4579)	(0.3493)	(0.3301)
Ethnicity-African	0.6044**	0.5174	0.2862	0.7235*	0.0837	1.2009***
	(0.3014)	(0.3260)	(0.3242)	(0.4172)	(0.3181)	(0.3366)
Ethnicity-Other black	0.3621	-0.0489	1.4128***	-0.5072	0.0351	0.6599*
	(0.3901)	(0.5066)	(0.3739)	(0.5777)	(0.4772)	(0.3955)
Ethnicity-Chinese	0.5533	-0.6069	-0.3586	-0.9581	0.2324	0.2179
	(0.5955)	(0.6057)	(0.5878)	(0.7426)	(0.5215)	(0.5235)
Ethnicity-Other group	0.1593	-0.7294	0.7227	1.0734	0.6259	-0.6188
	(0.6369)	(1.1641)	(0.7645)	(1.4685)	(1.0666)	(1.0695)
Member of trade union or staff association (reference Yes)						
Member of union (No, but in the past)	-0.0558	0.1388	0.1797**	0.3565***	0.0789	0.0371
	(0.0766)	(0.0959)	(0.0911)	(0.1157)	(0.0870)	(0.0950)
Member of union (No never)	-0.0209	0.1111	0.2884***	0.3836***	0.0151	0.0409
	(0.0658)	(0.0810)	(0.0781)	(0.1020)	(0.0757)	(0.0811)
Profit related payments (Yes)	0.0003	-0.1845***	-0.1616**	0.0517	-0.0538	-0.0841
	(0.0539)	(0.0668)	(0.0632)	(0.0777)	(0.0611)	(0.0662)
Performance Payments (Yes)	-0.0950*	-0.0944	-0.0666	-0.2191	-0.0573	-0.0050
	(0.0544)	(0.0673)	(0.0634)	(0.1775)	(0.0620)	(0.0661)
Total number of employees	0.0002***	0.0001***	0.0001**	-0.00001	0.0002***	0.0002***
	(0.00003)	(0.00002)	(0.00004)	(0.00001)	(0.0000)	(0.0000)
Number of establishments (reference-one of various numbers)						
Number of establ. (single)	0.1537**	-0.0964	0.0555	0.2222**	-0.0788	0.0712
	(0.0697)	(0.0854)	(0.0829)	(0.0925)	(0.0835)	(0.0854)
Number of establ. (sole in UK-foreign)	0.1626	-0.1311	-0.3896**	0.0663	-0.0381	-0.2894
	(0.1356)	(0.1812)	(0.1891)	(0.1877)	(0.1715)	(0.1927)
Company Status (reference Public Limited Company)						
Company- Private Limited Company	-0.0574	-0.0609	-0.0470	0.2287**	-0.1673**	-0.1109
	(0.0631)	(0.0776)	(0.0730)	(0.0952)	(0.0697)	(0.0763)
Company- Limited by guarantee	0.2101	-0.1007	-0.4200**	0.5233***	-0.1776	0.0615
	(0.1372)	(0.1725)	(0.1726)	(0.1883)	(0.1763)	(0.1737)
Company- Partnership	-0.1181	0.1989	0.2163	0.2490	-0.1374	-0.0932
	(0.1320)	(0.1558)	(0.1487)	(0.1868)	(0.1502)	(0.1606)
Company-Trust/charity	0.2466**	0.1399	-0.0394	0.5559***	0.1661	0.2762**
	(0.1103)	(0.1276)	(0.1278)	(0.1566)	(0.1317)	(0.1283)

Table 4 (cont.) Determinants of Employment Arrangements

VARIABLES	Flexible (1)	Reduce Hours (2)	Increase Hours (3)	Teleworking (4)	Change Shifts (5)	Compress hours (6)
Company-Royal charter	0.3455*	0.2652	-0.0582	0.6379***	-0.4398**	-0.4579**
	(0.1781)	(0.2208)	(0.2324)	(0.2375)	(0.2133)	(0.2300)
Company- Co-operative	0.0786	-0.0661	0.2305	-0.0713	-0.4020**	0.0060
	(0.1724)	(0.2129)	(0.2020)	(0.2844)	(0.1959)	(0.2125)
Government-owned limited	0.7723***	0.3939*	-0.0853	-0.1100	-0.1895	0.5781***
	(0.1767)	(0.2142)	(0.2115)	(0.2618)	(0.2171)	(0.2157)
Formal policy equal opportunities (No)	-0.0366*	0.1741	0.1254	0.0638	0.0145	0.0983
	(0.0183)	(0.1244)	(0.1159)	(0.1433)	(0.1125)	(0.1222)
Supervise other employees (No)	-0.0108	0.1718**	-0.0305	-0.3860***	0.0278	0.1890***
	(0.0566)	(0.0694)	(0.0681)	(0.0807)	(0.0654)	(0.0712)
Quality of relations between managers and employees (reference						
Number of weekly hours worked	0.0013	-0.0206***	0.0018	-0.0134*	-0.0153***	0.0101**
	(0.0041)	(0.0052)	(0.0050)	(0.0076)	(0.0054)	(0.0047)
Wage (reference £141-£180 per week						
Wage - £181-£220 per week	0.4201	0.6359*	0.6581**	-0.6062	0.5450*	0.4456
	(0.2833)	(0.3649)	(0.3243)	(0.4718)	(0.3281)	(0.3324)
Wage - £221-£260 per week	0.2948	0.6757*	0.5426*	-0.6291	0.2158	0.3289
	(0.2772)	(0.3526)	(0.3173)	(0.4631)	(0.3176)	(0.3272)
Wage -£261-£310 per week	0.1532	0.7039**	0.4521	-0.4291	-0.0614	0.2966
	(0.2646)	(0.3405)	(0.3087)	(0.4122)	(0.3084)	(0.3149)
Wage - £431-£540 per week	0.0993	-0.2102	-0.4058	-0.0638	-0.4230	-0.2214
	(0.2560)	(0.3327)	(0.3015)	(0.3801)	(0.2977)	(0.3092)
Wage - £681-£870 per week	-0.0547	-0.1739	-0.5362*	1.2575***	-0.6215*	-0.3124
	(0.2680)	(0.3498)	(0.3215)	(0.3846)	(0.3177)	(0.3292)
Wage - £871 or more per week	0.0520	-0.2159	-0.5475*	1.8179***	-0.6946**	-0.2581
	(0.2723)	(0.3562)	(0.3251)	(0.3911)	(0.3271)	(0.3345)
Market Area (reference-Local)						
Market Area-Regional	-0.2359***	-0.2701***	-0.1706*	0.3665***	-0.4192***	-0.3914***
	(0.0850)	(0.1015)	(0.0956)	(0.1246)	(0.0975)	(0.1035)
Market Area-National	-0.3443***	-0.1401*	-0.0518	0.3362***	-0.1776**	-0.2693***
	(0.0709)	(0.0845)	(0.0816)	(0.1045)	(0.0805)	(0.0840)
Market Area-International	-0.2433***	-0.3072***	-0.2540**	0.1262	-0.2386**	-0.2713**
	(0.0895)	(0.1085)	(0.1054)	(0.1316)	(0.1014)	(0.1083)
International competition (reference-Yes a lot)						
International competition-A little	-0.1323	0.0210	0.0218	0.0282	-0.1138	0.1136
	(0.0852)	(0.1100)	(0.1035)	(0.1187)	(0.0973)	(0.1066)
International competition-No	0.0228	0.1637*	0.0322	0.0860	0.0632	0.1451
	(0.0758)	(0.0976)	(0.0922)	(0.1111)	(0.0872)	(0.0969)
Observations	7,737	6,726	6,708	7,269	7,555	6,695
LR chi-square	982.73	1,745.60	1,462.63	1,530.09	1,469.27	736.23
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Wave-area specific clustered standard errors in parentheses, p-values within brackets, *** p<0.01, ** p<0.05, * p<0.1

Table 5. Propensity Score Matching and Fixed Effects for Job Satisfaction

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Flexible Time	0.1333***					
	(0.0188)					
Reduce hours		0.0664***				
		(0.0227)				
Increase hours			0.0803***			
			(0.0219)			
Teleworking				0.1395***		
				(0.0251)		
Change Shifts					0.1370***	
					(0.0213)	
Compress hours						0.1151***
						(0.0223)
Age (reference category 16-17)						
Age (18-19)	-0.2099*	-0.2165**	-0.2362**	-0.2820***	-0.2887***	-0.2353*
	(0.1139)	(0.1063)	(0.0997)	(0.1057)	(0.1011)	(0.1238)
Age (20-21)	-0.1112	-0.1200	-0.1035	-0.1983*	-0.2071**	-0.1200
	(0.1107)	(0.1055)	(0.0989)	(0.1044)	(0.0988)	(0.1207)
Age (22-29)	0.0314	0.0001	0.0176	-0.0429	-0.0349	-0.0216
	(0.0971)	(0.0944)	(0.0864)	(0.0904)	(0.0874)	(0.1075)
Age (30-39)	0.0916	0.0665	0.0620	-0.0004	0.0213	0.0243
	(0.0981)	(0.0959)	(0.0881)	(0.0914)	(0.0888)	(0.1089)
Age (40-49)	0.0874	0.0555	0.0523	-0.0099	0.0135	0.0248
	(0.0995)	(0.0973)	(0.0896)	(0.0928)	(0.0899)	(0.1101)
Age (50-59)	0.1220	0.0993	0.0819	0.0240	0.0356	0.0393
	(0.1002)	(0.0984)	(0.0907)	(0.0938)	(0.0910)	(0.1109)
Age (60-64)	0.3745***	0.3491***	0.3395***	0.2662***	0.2953***	0.2503**
	(0.1077)	(0.1075)	(0.1007)	(0.1024)	(0.0995)	(0.1182)
Age (65 and above)	0.3011**	0.2720**	0.2402*	0.1634	0.1467	0.2141
	(0.1274)	(0.1264)	(0.1261)	(0.1212)	(0.1236)	(0.1401)
Marital status (reference category single)						
Marital status-Married or couple	0.0879*	0.1073**	0.0900*	0.0918*	0.0992**	0.0923*
	(0.0484)	(0.0501)	(0.0509)	(0.0490)	(0.0486)	(0.0501)
Marital status-Divorced	0.1338***	0.0961**	0.0952**	0.0959**	0.0976**	0.1221***
	(0.0411)	(0.0437)	(0.0439)	(0.0427)	(0.0418)	(0.0437)
Marital status-Widowed	0.0547*	0.0339	0.0372	0.0447	0.0534*	0.0699**
	(0.0294)	(0.0314)	(0.0318)	(0.0300)	(0.0295)	(0.0311)
Education level (reference primary school)						
Education level- GCSE D-E levels	-0.0263	-0.0264	-0.0312	-0.0431**	-0.0354*	-0.0267
	(0.0206)	(0.0216)	(0.0217)	(0.0208)	(0.0204)	(0.0219)
Education level- GCSE B-S levels	-0.0619**	-0.0242	-0.0460	-0.0587**	-0.0411	-0.0529*
	(0.0280)	(0.0298)	(0.0305)	(0.0289)	(0.0288)	(0.0307)
Education level- GCSE A-AS levels	-0.0300	-0.0523**	-0.0252	-0.0559**	-0.0371	-0.0378
	(0.0243)	(0.0259)	(0.0261)	(0.0244)	(0.0249)	(0.0263)
Education level-First degree	-0.0570**	-0.0323	-0.0394	-0.0556**	-0.0273	-0.0216
	(0.0253)	(0.0272)	(0.0276)	(0.0258)	(0.0259)	(0.0272)
Education level-Higher degree	0.0541	0.0300	0.0672	0.0334	0.0098	0.0541
	(0.0402)	(0.0437)	(0.0439)	(0.0401)	(0.0424)	(0.0442)
Dependent children aged 0-2 (Yes)	-0.0116	-0.0529*	-0.0102	-0.0139	-0.0321	-0.0312
	(0.0268)	(0.0279)	(0.0284)	(0.0277)	(0.0279)	(0.0290)
Dependent children any age (No)	0.0067	-0.0076	0.0099	0.0002	0.0223	0.0245
	(0.0257)	(0.0273)	(0.0277)	(0.0259)	(0.0258)	(0.0270)
Skills matching with the job (much higher)						
Skills matching with the -bit higher	0.1955	0.2652	0.2051	0.1463	0.3105*	0.2508
	(0.1465)	(0.1753)	(0.1734)	(0.1524)	(0.1610)	(0.1659)
Skills matching with the job-the same	0.3987***	0.3982**	0.3929**	0.3714**	0.4613***	0.4565***
	(0.1388)	(0.1683)	(0.1656)	(0.1448)	(0.1538)	(0.1588)
Skills matching with the -bit lower	0.3520**	0.3207*	0.3496**	0.3244**	0.4242***	0.3996**
	(0.1390)	(0.1687)	(0.1657)	(0.1448)	(0.1541)	(0.1589)

Table 5 (cont.) Propensity Score Matching and Fixed Effects for Job Satisfaction

VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Skills matching with the -much lower	0.1469	0.1508	0.1408	0.1035	0.2092	0.1809
	(0.1398)	(0.1694)	(0.1663)	(0.1456)	(0.1547)	(0.1597)
Quality of relations (reference-very poor)						
Quality of relations-Poor	0.3882***	0.4092***	0.4098***	0.4261***	0.4077***	0.4131***
	(0.0706)	(0.0743)	(0.0756)	(0.0763)	(0.0711)	(0.0726)
Quality of relations-Neither good nor bad	0.6453***	0.7146***	0.7234***	0.7010***	0.7083***	0.7138***
	(0.0662)	(0.0696)	(0.0707)	(0.0718)	(0.0670)	(0.0682)
Quality of relations-Good	0.9780***	1.0448***	1.0627***	1.0281***	1.0206***	1.0255***
	(0.0653)	(0.0682)	(0.0695)	(0.0707)	(0.0659)	(0.0670)
Quality of relations-Very Good	1.3275***	1.4224***	1.4441***	1.3853***	1.3813***	1.4010***
	(0.0672)	(0.0702)	(0.0714)	(0.0724)	(0.0677)	(0.0689)
Years of experience in this workplace	0.0080	0.0056	0.0114	0.0040	0.0106	0.0079
	(0.0076)	(0.0081)	(0.0081)	(0.0076)	(0.0075)	(0.0081)
Ethnicity (reference British)						
Ethnicity-Irish	-0.1003	-0.0613	-0.1017	-0.1287	-0.0595	-0.0854
	(0.1045)	(0.1169)	(0.1231)	(0.1007)	(0.1090)	(0.1113)
Ethnicity-Other White	-0.1802***	-0.1597***	-0.1398**	-0.1587***	-0.1612***	-0.1728***
	(0.0532)	(0.0552)	(0.0566)	(0.0518)	(0.0543)	(0.0571)
Ethnicity-White and Black Caribbean	-0.3126	-0.2813	-0.2968	-0.2766	-0.3678*	-0.5628**
	(0.2243)	(0.2541)	(0.2137)	(0.2038)	(0.1996)	(0.2519)
Ethnicity-White and Black African	0.0204	-0.0154	0.0206	-0.0094	-0.0269	0.0314
	(0.1685)	(0.1781)	(0.1520)	(0.1685)	(0.1790)	(0.1411)
Ethnicity-White and Asian	-0.1201	0.1029	-0.0806	-0.3148	-0.1804	-0.3819
	(0.3301)	(0.4011)	(0.3671)	(0.3861)	(0.3294)	(0.3602)
Ethnicity-Indian	-0.0069	0.0310	0.0116	-0.0306	-0.0330	0.0034
	(0.0640)	(0.0648)	(0.0708)	(0.0654)	(0.0662)	(0.0640)
Ethnicity-Pakistani	0.1507	0.1689	0.1621	0.1570	0.1735	0.0984
	(0.1186)	(0.1237)	(0.1296)	(0.1371)	(0.1420)	(0.1284)
Ethnicity-Bangladeshi	-0.4250*	-0.1598	-0.2957	-0.2560	-0.3646	-0.4823**
	(0.2198)	(0.2038)	(0.2144)	(0.2685)	(0.2222)	(0.2086)
Ethnicity-Other Asian	0.0065	-0.0001	0.0352	-0.0632	0.0652	-0.0632
	(0.1108)	(0.1211)	(0.1258)	(0.1049)	(0.1102)	(0.1253)
Ethnicity-Caribbean	-0.3071**	-0.3310***	-0.2416**	-0.3157***	-0.3026**	-0.2806**
	(0.1208)	(0.1172)	(0.1076)	(0.1057)	(0.1177)	(0.1173)
Ethnicity-African	-0.1534	-0.0502	-0.0763	-0.1481	-0.1165	-0.1173
	(0.1048)	(0.1148)	(0.1035)	(0.1089)	(0.1009)	(0.1216)
Ethnicity-Other black	-0.3553**	-0.3201**	-0.3903**	-0.4665***	-0.3583**	-0.3655**
	(0.1623)	(0.1620)	(0.1641)	(0.1500)	(0.1575)	(0.1637)
Ethnicity-Chinese	-0.0432	-0.1741	-0.2257	-0.0075	-0.0237	-0.1378
	(0.1545)	(0.1640)	(0.1769)	(0.1450)	(0.1216)	(0.1711)
Ethnicity-Other group	0.2260	0.2263	0.1778	0.0751	0.4041**	0.2687
	(0.2353)	(0.2336)	(0.2310)	(0.2386)	(0.1632)	(0.2305)
Member of trade union (reference Yes)						
Member of union (No, but in the past)	0.0517*	0.0353	0.0314	0.0324	0.0163	0.0457
	(0.0287)	(0.0310)	(0.0309)	(0.0299)	(0.0290)	(0.0309)
Member of union (No never)	0.0763***	0.0808***	0.0565**	0.0962***	0.0543**	0.0702***
	(0.0246)	(0.0268)	(0.0268)	(0.0257)	(0.0253)	(0.0272)
Profit related payments (Yes)	0.0252	0.0197	0.0136	0.0149	0.0276	0.0317
	(0.0199)	(0.0212)	(0.0213)	(0.0201)	(0.0200)	(0.0215)
Proportion of appraisal (reference 100%)						
Proportion - (80-99%)	-0.0056	-0.0343	-0.0023	-0.0068	-0.0008	-0.0448
	(0.0442)	(0.0469)	(0.0473)	(0.0448)	(0.0436)	(0.0478)
Proportion - (60-79%)	0.0383	0.0604	0.0461	0.0714	0.0744	0.0996*
	(0.0477)	(0.0508)	(0.0510)	(0.0512)	(0.0478)	(0.0517)
Proportion - (40-59%)	0.0066	-0.0683	0.0303	0.0531	-0.0188	0.0100
	(0.0712)	(0.0818)	(0.0784)	(0.0718)	(0.0751)	(0.0795)
Proportion - (20-39%)	0.0010	0.0305	0.0348	0.0066	0.0210	0.0179
	(0.0459)	(0.0478)	(0.0477)	(0.0485)	(0.0455)	(0.0488)

Table 5 (cont.) Propensity Score Matching and Fixed Effects for Job Satisfaction

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Proportion - (1-19%)	0.0275	0.0121	0.0529	0.0339	0.0228	0.0303
	(0.0488)	(0.0518)	(0.0511)	(0.0516)	(0.0483)	(0.0509)
Number of weekly hours worked	0.0018	0.0020	0.0003	0.0022	0.0013	0.0007
	(0.0013)	(0.0014)	(0.0015)	(0.0014)	(0.0014)	(0.0014)
Wage (reference £141-£180 per week						
Wage - £181-£220 per week	0.1648*	0.2170**	0.2164*	0.1117	0.0981	0.1400
	(0.0927)	(0.1084)	(0.1127)	(0.1049)	(0.1061)	(0.1159)
Wage - £221-£260 per week	0.1673*	0.2603**	0.2665**	0.2005**	0.1909*	0.2347**
	(0.0894)	(0.1043)	(0.1100)	(0.1014)	(0.1039)	(0.1126)
Wage - £261-£310 per week	0.1174	0.1752*	0.2014*	0.1310	0.1019	0.1248
	(0.0890)	(0.1051)	(0.1100)	(0.1013)	(0.1036)	(0.1127)
Wage - £431-£540 per week	0.1538*	0.1909*	0.2238**	0.1398	0.1344	0.1840*
	(0.0870)	(0.1025)	(0.1073)	(0.0990)	(0.1007)	(0.1094)
Wage - £681-£870 per week	0.1831**	0.2008*	0.2758**	0.1668	0.1672	0.1699
	(0.0903)	(0.1055)	(0.1112)	(0.1023)	(0.1048)	(0.1117)
Wage - £871 or more per week	0.3141***	0.3576***	0.4381***	0.2953***	0.3436***	0.3824***
	(0.0904)	(0.1062)	(0.1110)	(0.1024)	(0.1051)	(0.1122)
Performance related payments (Yes)	0.0399**	0.0388*	0.0410*	0.0437**	0.0314	0.0306
	(0.0199)	(0.0211)	(0.0212)	(0.0202)	(0.0200)	(0.0215)
Number of establishments (reference many)						
Number of establ. (single)	0.0050	0.0182	0.0221	0.0125	0.0155	0.0101
	(0.0246)	(0.0259)	(0.0262)	(0.0255)	(0.0250)	(0.0264)
Number of establ. (sole in UK-foreign)	-0.0787	-0.0962*	-0.0945*	-0.1266**	-0.0601	-0.0890
	(0.0492)	(0.0550)	(0.0574)	(0.0538)	(0.0520)	(0.0564)
Company Status (reference Public)						
Company- Private Limited Company	0.0089	-0.0115	-0.0026	-0.0059	0.0013	-0.0015
	(0.0235)	(0.0250)	(0.0254)	(0.0234)	(0.0238)	(0.0252)
Company- Limited by guarantee	0.1008**	0.0756	0.0900	0.0960*	0.0745	0.0840
	(0.0501)	(0.0551)	(0.0565)	(0.0537)	(0.0537)	(0.0540)
Company- Partnership	0.0224	-0.0266	-0.0073	-0.0014	0.0245	0.0133
	(0.0439)	(0.0480)	(0.0471)	(0.0453)	(0.0454)	(0.0487)
Company-Trust/charity	0.0443	0.0217	0.0658*	-0.0006	0.0083	0.0140
	(0.0386)	(0.0406)	(0.0397)	(0.0400)	(0.0391)	(0.0420)
Company-Royal charter	0.0857	0.1635**	0.0898	0.1067*	0.0657	0.1077
	(0.0655)	(0.0737)	(0.0740)	(0.0645)	(0.0682)	(0.0738)
Company- Co-operative	-0.0130	0.0114	0.0463	-0.0407	-0.0654	0.0092
	(0.0677)	(0.0751)	(0.0724)	(0.0693)	(0.0719)	(0.0742)
Government-owned limited	-0.0757	-0.0127	0.0090	-0.0826	-0.0659	-0.0289
	(0.0693)	(0.0764)	(0.0751)	(0.0711)	(0.0678)	(0.0742)
Formal policy equal opportunities (No)	-0.0295	-0.0203	-0.0376	-0.0185	-0.0196	-0.0143
	(0.0371)	(0.0392)	(0.0396)	(0.0389)	(0.0369)	(0.0398)
Supervise other employees (No)	-0.1048***	-0.1198***	-0.1145***	-0.0921***	-0.1014***	-0.1152***
	(0.0208)	(0.0223)	(0.0222)	(0.0213)	(0.0212)	(0.0224)
Market Area (reference-Local)						
Market Area-Regional	0.0610**	0.0813**	0.0615*	0.0463	0.0682**	0.0465
	(0.0308)	(0.0323)	(0.0324)	(0.0315)	(0.0311)	(0.0336)
Market Area-National	0.0216	0.0112	0.0049	-0.0080	0.0013	-0.0043
	(0.0260)	(0.0273)	(0.0276)	(0.0259)	(0.0261)	(0.0280)
Market Area-International	0.0426	0.0423	0.0685*	0.0346	0.0425	0.0081
	(0.0325)	(0.0351)	(0.0350)	(0.0326)	(0.0329)	(0.0347)
International comp. (reference-Yes a lot)						
International competition-A little	-0.0152	-0.0232	-0.0265	-0.0153	-0.0013	-0.0200
	(0.0317)	(0.0335)	(0.0347)	(0.0320)	(0.0322)	(0.0342)
International competition-No	-0.0273	-0.0347	-0.0257	-0.0301	-0.0225	-0.0185
	(0.0288)	(0.0310)	(0.0316)	(0.0288)	(0.0293)	(0.0310)
Observations	7,737	6,726	6,708	7,269	7,555	6,695
R-squared	0.2634	0.2715	0.2738	0.2594	0.2668	0.2747

Wave-area specific clustered standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 6. Propensity Score Matching Test

Variables	PS test	Variables	PS test	Variables	PS test
Sex	-0.25	Ethnicity	-1.08	Number of weekly hours worked	-0.31
	(0.799)		(0.278)		(0.759)
Age	1.27	Member of trade	-0.96	Firm type	1.50
	(0.203)	union	(0.338)		(0.134)
Marital Status	-0.69	Profit-related	0.67	Formal polies for equal opportunities	1.85*
	(0.489)	payments	(0.500)		(0.064)
Education level	0.44	Proportion of non-	-0.40	Supervise others	-0.76
	(0.657)	managerial staff	(0.686)		(0.446)
		evaluated			
Dependent children	1.21	Performance related	1.62	Market area	-1.61
0-2 years old	(0.226)	payment	(0.105)		(0.156)
No dependent	0.10	Total employment	-1.52	competition	0.51
children	(0.922)		(0.139)		(0.611)
Skills matching	-0.64	Number of	-0.04	Standard occupation classification	0.68
with the job	(0.522)	establishments	(0.966)		(0.494)
Quality of relations	-0.71	Years working in the	0.15	Firm Location-Region	0.08
between managers	(0.478)	current workplace	(0.880)		(0.939)
and employees					
Wage	-0.99				
	(0.323)				

P-values in parentheses, * p<0.1

Table 7. Propensity Score Matching and Fixed Effects for Job Satisfaction Factor Index and Employee Loyalty

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: DV Job Satisfaction						
Flexible time	0.2150***					
	(0.0177)					
Reduce hours		0.1131***				
		(0.0217)				
Increase hours			0.1502***			
			(0.0206)			
Teleworking				0.2166***		
				(0.0241)		
Change shifts					0.2082***	
					(0.0201)	
Compress hours						0.1663***
						(0.0217)
Observations	7,459	6,481	6,473	7,022	7,284	6,427
R-squared	0.2197	0.2139	0.2219	0.2107	0.2139	0.2284
Panel B: DV Employee Loyalty						
Flexible time	0.1294***					
	(0.0186)					
Reduce hours		0.0365				
		(0.0222)				
Increase hours			0.0701***			
			(0.0221)			
Teleworking				0.1506***		
				(0.0251)		
Change shifts					0.0951***	
					(0.0212)	
Compress hours						0.0689***
						(0.0225)
Observations	7,732	6,727	6,719	7,263	7,560	6,691
R-squared	0.2158	0.2103	0.2125	0.2065	0.2104	0.2142

Wave-area specific clustered standard errors in parentheses, *** p<0.01

Table 8. Job Satisfaction Fixed Effects Estimates for total sample and movers

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Panel A- Total Sample						
Flexible time	0.1272***					
	(0.0176)					
Reduce hours		0.0577***				
		(0.0209)				
Increase hours			0.0768***			
			(0.0204)			
Teleworking				0.1264***		
				(0.0236)		
Change shifts					0.1355***	
					(0.0197)	
Compress hours						0.0985***
						(0.0205)
Observations	9,051	7,884	7,813	8,593	8,792	7,811
R-squared	0.2661	0.2752	0.2768	0.2616	0.2705	0.2792
Panel B: Movers Sample						
Flexible time	0.0638					
	(0.0492)					
Reduce hours		0.0672				
		(0.0533)				
Increase hours			0.0272			
			(0.0557)			
Teleworking				0.1363**		
				(0.0644)		
Change shifts					0.0888*	
					(0.0525)	
Compress hours						0.0284
						(0.0527)
Observations	1,314	1,158	1,105	1,324	1,237	1,116
R-squared	0.3855	0.4150	0.3975	0.3855	0.4074	0.4304

Wave-area specific clustered standard errors in parentheses, *** p<0.01, ** p<0.05

Table 9. 3SLS Estimates for Job Satisfaction and Employee Loyalty

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: DV Job Satisfaction						
Flexible time	0.0489***					
	(0.0175)					
Reduce hours		0.0551***				
		(0.0205)				
Increase hours			0.0492**			
			(0.0200)			
Teleworking				0.0580**		
				(0.0239)		
Change shifts					0.0915***	
					(0.0193)	
Compress hours						0.0560***
						(0.0203)
Employee loyalty (reference category strongly disagree)						
Employee loyalty -disagree	0.6183***	0.6674***	0.6288***	0.5935***	0.6017***	0.5646***
	(0.0573)	(0.0595)	(0.0604)	(0.0588)	(0.0562)	(0.0599)
Employee loyalty -neither agree nor disagree	1.2145***	1.2547***	1.2474***	1.2069***	1.2087***	1.1513***
	(0.0539)	(0.0559)	(0.0569)	(0.0550)	(0.0527)	(0.0566)
Employee loyalty -agree	1.8065***	1.8464***	1.8577***	1.7980***	1.7897***	1.7277***
	(0.0531)	(0.0550)	(0.0559)	(0.0542)	(0.0519)	(0.0557)
Employee loyalty –strongly agree	2.3797***	2.4238***	2.4204***	2.3763***	2.3508***	2.2909***
	(0.0556)	(0.0576)	(0.0585)	(0.0568)	(0.0544)	(0.0584)
Observations	7,732	6,726	6,708	7,263	7,555	6,691
R-squared	0.2507	0.2643	0.2655	0.2547	0.2570	0.2607
Panel B: DV Employee Loyalty						
Flexible time	0.0515***					
	(0.0174)					
Reduce hours		0.0182				
		(0.0206)				
Increase hours			0.0469**			
			(0.0199)			
Teleworking				0.0714***		
				(0.0236)		
Change shifts					0.0056	
					(0.0194)	
Compress hours						0.0511**
						(0.0234)
Job satisfaction (reference category-very dissatisfied)						
Job satisfaction-dissatisfied	0.6174***	0.5918***	0.5584***	0.6164***	0.6336***	0.5242***
	(0.0547)	(0.0580)	(0.0573)	(0.0562)	(0.0560)	(0.0585)
Job satisfaction-neither dissatisfied nor satisfied	1.0858***	1.0874***	1.0881***	1.0971***	1.1337***	1.0131***
	(0.0502)	(0.0532)	(0.0526)	(0.0519)	(0.0519)	(0.0541)
Job satisfaction- satisfied	1.7171***	1.7441***	1.7261***	1.7319***	1.7683***	1.6471***
	(0.0489)	(0.0519)	(0.0512)	(0.0506)	(0.0506)	(0.0529)
Job satisfaction- very satisfied	2.3177***	2.3361***	2.3265***	2.3240***	2.3623***	2.2411***
	(0.0524)	(0.0555)	(0.0548)	(0.0541)	(0.0541)	(0.0566)
Observations	7,732	6,726	6,708	7,263	7,555	6,691
R-squared	0.3117	0.3142	0.3124	0.3119	0.3083	0.3088

Standard errors in parentheses, *** p<0.01, ** p<0.05

Table 10. BN and DAG Estimates for Job Satisfaction, Employee Loyalty and Employee Arrangements

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: DV Job Satisfaction						
Flexible time	0.1298***					
	(0.0211)					
Reduce hours		0.0693***				
		(0.0232)				
Increase hours			0.0582**			
			(0.0231)			
Teleworking				0.1268***		
				(0.0300)		
Change shifts					0.1237***	
					(0.0217)	
Compress hours						0.1079***
						(0.0248)
Observations	7,732	6,726	6,708	7,263	7,555	6,691
Panel B: DV Employee Loyalty						
Flexible time	0.0885***					
	(0.0200)					
Reduce hours		0.0089				
		(0.0220)				
Increase hours			0.0389*			
			(0.0207)			
Teleworking				0.0803***		
				(0.0268)		
Change shifts					0.0506*	
					(0.0256)	
Compress hours						0.0482**
						(0.0221)
Job satisfaction (reference category-very dissatisfied)						
Job satisfaction-dissatisfied	0.3952***	0.3505***	0.3424***	0.3623***	0.4105***	0.2924***
	(0.0642)	(0.0684)	(0.0683)	(0.0603)	(0.0656)	(0.0674)
Job satisfaction-neither dissatisfied nor satisfied	0.5696***	0.5574***	0.6066***	0.5168***	0.6236***	0.4939***
	(0.0590)	(0.0692)	(0.0629)	(0.0528)	(0.0609)	(0.0624)
Job satisfaction- satisfied	0.9794***	0.9803***	1.0042***	0.9754 ***	1.0314***	0.9120***
	(0.0572)	(0.0612)	(0.0610)	(0.0517)	(0.0591)	(0.0607)
Job satisfaction- very satisfied	1.3645***	1.3497***	1.3723***	1.3507**	1.3917***	1.2775***
	(0.0618)	(0.0657)	(0.0656)	(0.0609)	(0.0635)	(0.0653)
Observations	7,732	6,726	6,708	7,263	7,555	6,691

Wave-area specific clustered standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.01