Industrial Labour Productivity and ICT Intensity as determinants of Individual Job Satisfaction

Agni Dikaiou[1], Michela Vecchi, Tim Jackson

Abstract

While global economies focus on continuous productivity growth and technological innovations, the question of whether these advancements are always positively related to workers' wellbeing has received less attention. This paper explores this question, by examining the effects of industrial labour productivity and ICT intensity on job satisfaction in an inter-industry, cross-country analysis. In order to explore the nature of these relationships, data from EU KLEMS were matched with data on individual job satisfaction from the European Social Survey (ESS) for eight advanced European countries. To estimate these relationships, job satisfaction from ESS5 in 2010 was regressed on lagged values of industry-level data for labour productivity (Model 1) and ICT intensity (Model 2) in 2006. In these econometric analyses an ordered probit model was employed. In all regression models, job satisfaction was conditioned by other factors, such as demographic, intrinsic, extrinsic and employment characteristics. Results showed that industrial labour productivity was negatively associated with job satisfaction across all the industries of the economy. This result could be attributed to stress factors and the form of production systems. In contrast, ICT intensity was positively correlated with job satisfaction, which could be attributed to the complementary role of technology in non-routine cognitive tasks and the effect of worker-friendly organizational changes that accompany the introduction of ICT at the workplace.

Keywords: Industrial labour productivity, job satisfaction, ICT intensity, intangible capital, organizational changes.

[1] Agni Dikaiou, corresponding author
agni.dikaiou@surrey.ac.uk
- PhD candidate at the Centre for the Understanding of Sustainable Prosperity (CUSP), University of Surrey (D3), GU2 7XH, Guildford, UK.
- Visiting Scholar at the University of Massachusetts (UMass), Amherst, MA 01003, USA.

1. Introduction

The introduction of Information and Communication Technology (ICT) in the workplace during the late 90s signalled the emergence of the “New Economy”, an era of increasing investment in new technologies that contributed significantly to economic growth, initially in the US and later in Europe. Continuous innovation in information technology and telecommunication networks made flexible work possible, eliminating time and distance, while facilitating virtual meetings and remote supervision. The introduction of ICT came hand in hand with changes in practices within the organizations destined to reap the full productivity benefits and facilitate the smooth transition to new technologies in the workplace.

The numerous efficiency boosting benefits afforded by this “New Economy” of ICT innovation and parallel structural changes within the organizations drove productivity upwards[2], even if this effect was initially not entirely captured by statistical indicators. Increases in productivity, an essential indicator for workers, organizations, industries and an important determinant of a county’s ability to achieve higher standards of living (Krugman, 1997), lead to economic growth, which is perceived to drive material wellbeing upwards. However, the relationship between material and emotional wellbeing is less clear and the way in which these changes affect the wellbeing of workers has been less explored.

The concept of workers’ wellbeing encompasses workers’ health, their sense of self-fulfilment, and security, the ability to afford resources for a decent life, and time availability for a satisfactory life outside work (McGillivray & Clarke, 2006). Self-reported job satisfaction is a hedonic measure of workers’ subjective wellbeing (SWB) and an empirical proxy for utility from work, and it has also been found to be a credible indicator for the quality of work (Ritter & Anker, 2002). Job satisfaction has been described as one of the most important life domains for an individual’s happiness, other than family and other social relations (Layard, Nickell, & Mayraz, 2008; Easterlin, 2005).

[2] For a review of the literature on this relationship see Kretschmer (2012), ‘Information and communication technologies and productivity growth: a survey of the literature,’ OECD Digital Economic Papers, 195.

Despite the evident importance of job satisfaction for the working life and happiness of individuals, productivity enhancements introduced across the centuries, from the industrial revolution to the digital one, came with direct and indirect implications for workers' wellbeing. In the past, the division of labour facilitated breakthroughs in labour productivity, operating via the separation of projects into small tasks performed by specialized workers, which, as Adam Smith (1776) argued, was the key to economic growth, However, Marx (1844) later argued that mechanization and division of work into sometimes meaningless small tasks, result in feelings of alienation from work. As he suggested, workers might feel alienated from the product of their labour and from each other, which might negatively affect their job satisfaction (Chiaburu, Thundiyil, & Wang, 2014). Furthermore, as economies strive to increase labour productivity, there is higher pressure put on production, which, above a certain level, may increase the stress levels of workers, hence negatively affecting their wellbeing.

In today's digital age, the introduction of ICT, a significant driver of productivity, sometimes coexists with negative feelings for workers, such as those of frustration and distress from the new demands of the job (Brod, 1984; Hudiburg, 1989). However, economists have not taken these feelings very much into account. The human-computer interaction has been mainly investigated by psychologists, who examined the ICT- job satisfaction relationship in management and in industrial organizational psychology literature. As most workers today have constant interaction with ICTs, they are required to remain up to date with the latest version of the software and hardware that they use. This new work pattern liberates them from repetitive tasks, while also having direct and indirect, positive and negative effects on their wellbeing. The effects of new technology could potentially vary by the special conditions that each worker faces in the workplace. These conditions, such as the workers' skill group, age group and the nature of the activities performed, need to be taken into account as well.

At the same time, managers and organizations, in their attempt to reap the full productivity benefits of the use of ICT at work, and in an attempt to smoothen the transition to new technologies, introduced new forms of working practices, with multiple impacts on the wellbeing of workers. The changes introduced to complement the use of ICT in the workplace included organizational changes and investment in human capital (Biagi & Parisi, 2012). Investment in these assets, so-called High Performance Workplace Practices (HPWP) or 'intangible capital', represented a fundamental shift in the nature of work, much like that stemming from the division of labour. HPWP replaced traditional Tayloristic practices with a holistic type of organization (Bauer, 2004). HPWP contribute to the 'humanization' of work in many cases, while affecting job satisfaction in multiple levels, both positively and negatively, very much depending on the type of change and its intensity.

While global economies focus on continuous productivity growth, the question of whether productivity increases are always positively related to workers' wellbeing has not been satisfactorily addressed. Similarly, economists seem to be primarily concerned with the effect of ICT on growth and ways to explain the productivity paradox, while paying little attention to the direct and indirect effects of ICT on workers' wellbeing. In an attempt to understand the underlying relations, this paper explores the effects of productivity, as a measure of performance, and ICT use, as a measure of technological innovation, on workers' wellbeing, and more specifically their job satisfaction. This is achieved through an inter-industry, cross-country analysis in a wellbeing regression model, during a period of economic crisis in eight advanced European countries. To the best of our knowledge, this is one of the few studies that addresses these relationships by matching individual and industry level data for a group of advanced economies. Hence, it provides a sector analysis in an international perspective, contributing significantly to the literature with its innovative method.

This paper has been organized in the following way. The next section contains a literature review of the relationships between job satisfaction, performance and ICT have been viewed to date. Section 3 presents the research design, which includes the method followed and data sources used in this paper. Section 4 describes the empirical analyses and the results from a regression model estimating these relationships. This section also includes a discussion of their implications, the limitations of the study and ideas for future research on this topic. Finally, chapter 5 concludes the paper.

2. Literature Review

2.1 The Job Satisfaction- Performance Relationship

The job satisfaction-performance relationship has been studied by different disciplines, with only occasional cross-referencing (Pugno & Depedri, 2010). This relationship has been extensively investigated in industrial-organizational psychology since the human relations movement in the 1930s and has been regarded as the "Holy Grail" of the literature (Landy, 1989). On the other hand, economic theories such as efficiency wages and agency theory, focus on job effort and utility from work, assuming that workers' effort (usually measured by the hours worked) is positively related to their production function and negatively related to their utility (disutility from work). In economic studies, satisfaction with pay, career opportunities, or other short-term rewards are often used as alternative proxies for utility (Pugno & Depedri, 2010).

One of the most influential reviews of the literature found a "minimal or no relationship" between job satisfaction and performance[3] (Brayfield & Crockett, 1955). However, this did not hinder researchers from re-examining the relationship more closely, mainly at the individual level. This research effort produced contrasting results, supporting a positive (Iaffaldano & Muchinsky, 1985), a negative (Green & Tsitsianis[4], 2005), or a spurious relationship (N. A. Bowling, 2007), depending on the theoretical approach used to analyse it and the exact measures of performance and job satisfaction in each study.

Only a few relatively recent studies have analysed the relationship between job satisfaction and performance at higher aggregation levels, such as the business-unit/department (e.g. Harter et al. 2002), the establishment (e.g. Böckerman & Ilmakunnas 2012) or the organization (e.g Bakotić, 2016; Ostroff[5], 1992). Results at the organizational level are as inconsistent as those found at the individual level, with some studies reporting a positive relationship between job satisfaction and

[3] In this study the measure of performance was either self-reported or provided by the immediate supervisor of the worker, with only one case using objective measures of sales by employee.
[4] When performance was measured as subjective work effort.
[5] Measuring the job satisfaction of teachers and the performance of their schools.

performance (Schneider[6] et al. 2003) and others reporting statistically insignificant results (Mohr & Puck, 2007).

In general, the direction of causality in the relationship between job satisfaction and labour productivity has also been found to be complex and ambiguous. The approaches followed in most of the early studies, do not always satisfy the necessary assumptions needed to draw causal inferences as Judge et al. (2001) note. In their meta-analysis, they summarized the ways in which the relationship between job satisfaction and performance at the individual level had been explained in the literature in a variety of specification models, with the direction of causality in each model varying according to the underlying theory.

They described each possible causal path through a model where satisfaction with one's work drives performance (model 1), performance affects job satisfaction (model 2), the relationship is bidirectional (model 3) or spurious (model 4), the relationship is moderated by other factors (model 5), there is no relationship at all (model 6), or the relationship needs to be approach by alternative conceptualizations (model 7). Model 5, the approach most frequently taken by researchers, analyses the relationship between job satisfaction and productivity controlling for other moderating factors. These can include organizational tenure (Norris & Niebuhr, 1984), job complexity, or feelings about self, such as self-esteem (Korman, 1970), need for achievement (Steers, 1975), or pressure for performance (a stress provoking factor) (Ewen, 1973), etc. One of the most cited factors that acts as moderator of the relationship is reward contingency, according to which performance-based rewards, such as income, affect one's satisfaction with work.

Judge et al.'s (2001) main result was that the correlation between job satisfaction and performance is positive and statistically significant. However there is no consensus on which is the most accurate factor for moderating the relationship or affecting its sign or the direction of causality in the relationship. In a recent study, Royuela and Suriñach (2013) used a simultaneous equations model for seven Spanish regions and seven industries over a 5-year period to explore the direction of causality in this relationship. They found significant results for both directions after

[6] Performance as financial and market outcomes at the organizational level and measuring satisfaction with various job facets, among which overall job satisfaction.

distinguishing between high and low human capital sectors, suggesting that there might be a loop connecting the two variables, as suggested by Judge's third model.

2.2 The Job Satisfaction- ICT intensity Relationship

Innovative work patterns established as a result of the explosive growth of networking technologies and end-user computing have had an effect on workers' wellbeing. One of the direct effects of ICT use is the experience of technostress (Brillhart, 2004; K. Clark & Kalin, 1996; Weil & Rosen, 1997). Technostress is the stress an individual experiences in his 'attempt to deal with constantly evolving ICTs and the changing physical, social, and cognitive responses demanded by their use' (Ragu-Nathan, Tarafdar, Ragu-Nathan, & Tu, 2008). Evidence (Brod, 1984; Weil & Rosen, 1997) suggests that technostress leads to negative feelings of end-users, such as anxiety and tension, due to the complexity of new technologies (Heinssen, Glass, & Knight, 1987), job dissatisfaction, due to perceived higher work pressures (Smith et al. 1981), information overload [7] (Ivancevich & Matteson, 1980) and ambiguity about job demands (Love, Simpson, & Walker, 1989). Technostress is provoked usually by techno-overload, techno-complexity, techno-insecurity and techno-uncertainty (Ragu-Nathan et al., 2008).

There is also evidence of another phenomenon experienced by end-users of ICT, that of flow, which is a mental state characterized by intense concentration and enjoyment of one's activity. Workers using ICT could experience flow when having a sense of control or when the task is perceived to be challenging enough (Ghani & Al-Meer, 1989). Bjorn-Andersen et al. (1986) found that computers have greater impact on individuals performing high scope tasks (tasks with variety, autonomy, identity and support) as it was enriching the work experience, while reducing stress by better structuring the job. Hence, flow, as a direct effect of ICT on end-users, could be improving their satisfaction with work.

An indirect way in which ICT intensity affects job satisfaction is through organizational changes. HPWP such as ICT literacy facilitation and provision of technical support, act as technostress inhibitors alleviating overwhelmed ICT end-users (Ragu-Nathan et al., 2008), hence mitigating any negative effect of ICT intensity on job satisfaction. However, organizational changes induced

[7] This is similar to role overload due to increased demands from the stressor.

by the introduction of ICT, such as new management practices allowing greater control and intensive monitoring of the activities of workers (Green, 2006) can sometimes negatively impact wellbeing at work. Other managerial changes that lead to decentralization of decision making, due to new technology adoption, can increase the workload and stress levels of workers. The pressure for production and work intensification, together with the shift of responsibility from management to shop floor levels, can potentially cause psychological and physical stress or cumulative trauma disorders (Antonioli, Mazzanti, & Pini, 2009).

Other changes in management systems, however, promote involvement and discussion, provide social and technical support and facilitate information exchange (Nelson, 1990; Wastell & Newman, 1993), acting once again as technostress inhibitors. One way in which the use of ICT is improving information sharing processes is by helping to spread best practices, such as health and safety information providing workers with greater sense of control, autonomy (Antonioli et al., 2009) and empowerment. These changes, urged by innovations associated with the deployment of ICT, could negatively or positively affect the wellbeing of workers on the basis of whether they are leading to labour intensification- causing stress- or enriching and complementing job tasks-encouraging empowerment (Bryson, Dale-Olsen, & Barth, 2009) and if both occur, which effect prevails. As Bryson et al. (2009) found, labour-related innovations were linked to lower job satisfaction of workers when labour unions were not in place.

New technologies at the workplace might as well alter the skills necessary for the new ICT-based job, requiring employee training, a fundamental provision among other HPWP. According to Beas and Salanova (2006), computer training facilitates ICT use and increases professional self-confidence, if the worker has a positive attitude towards computers. Nevertheless, the opposite happens if the worker has a negative attitude towards computers. Attitudes, therefore, moderate the relationship between training and feelings of professional self-confidence, which influences job satisfaction (Beas & Salanova, 2006). The interplay of these feelings has an impact on the job satisfaction of the worker.

Shifts in labour demand, due to the need for new skills in human capital, create divergent job paths. The literature provides contradictory evidence on the exact nature of this effect. There are two major tendencies, the deskilling and the skills upgrading. The deskilling or polarization of labour demand suggests that due to ICT there is a polarizing shift in the distribution of skills, meaning mass unskilled labour at the bottom, and a few highly skilled workers at the top, e.g. bosses and garbage collectors (Driscoll, 1982), with medium-skilled labour gradually being substituted by automation. An alternative to deskilling is the upgrading effect, or what has been named "Skill-Biased-Organizational-Changes". According to the upgrading theory, ICT substitutes unskilled labour in routine jobs while it complements labour in complex/cognitive demanding jobs (Autor, 2003). This favours the recruitment of skilled over unskilled labour, an increase in human capital[8]. Attewell & Rule (1984) observed that both processes could be taking place and more extensive data analyses would be needed to investigate which of the two tendencies predominates. Whichever the case, the "victim" skill-group is left feeling job insecurity, hence negatively impacting their level of job satisfaction.

3. The Research Framework

3.1 Methods

To estimate the relationships between worker's wellbeing, performance and ICT, a regression model is employed using job satisfaction as dependent variable, industrial labour productivity and ICT intensity at the industry level as well, as the core independent variables. Most studies have been conducted in lower aggregation levels, mostly at the individual level and with a few at the firm and organizational level. Therefore, the innovation of this method is the use of measures at the industry level, which reveal information on the use of skills, capital, labour and other inputs used in the production of goods and services, taking into account all the industries in the economy, across different countries.

The value for performance is given by the single factor measure of labour productivity, which is value added per hour worked. As measured in conventional growth accounting (Inklaar, O'Mahony, & Timmer, 2005), labour productivity is decomposed into the contributions of multifactor

[8] Wage gains may become also polarized going to those at the top and at the bottom of the income and skill distribution and not to the semi-skilled in the middle (Autor & Dorn 2013).

productivity and inputs per hour worked, such as ICT and non-ICT capital per hour worked or value added, labour services over the number of hours worked, representing labour quality, and intangible capital[9] (Niebel, O'Mahony, & Saam, 2017). Therefore, in this analysis ICT intensity, measured by ICT capital services per value added, is also partially a driver of labour productivity by industry as well.

Survey data are used for job satisfaction, which is a single-item measure of satisfaction. This means that one single question captures the notion of wellbeing at work: *"How satisfied are you in your main job?"*. Initially the answer options ranged from 0 "extremely dissatisfied" to 10 "extremely satisfied". However, since, the distribution of job satisfaction is left-skewed in most advanced countries it can be rescaled into less likert scales (e.g. Mysíková & Večerník, 2013; Sousa-Poza & Sousa-Poza, 2000). Therefore the dependent variable has been reclassified so that it only has five possible values that measure job satisfaction, still from extremely dissatisfied to extremely satisfied[10]. Rescaling is feasible as there are only a few observations in the categories of extreme satisfaction and there is some 'noise', as people usually cannot distinguish between too many categories of choice. With regards to the distributions of the answers, the majority of workers report high levels of job satisfaction. This feature of the data is common in most surveys of wellbeing at work (e.g. Clark, 1996).

Since the answer options in the question are ordinal, reported job satisfaction is treated as a latent variable and used in a regression analysis of an ordered probit model to test the desired effects. This model has been argued to be theoretically superior for ordinal data than the others (Georgellis & Lange, 2007). If the models were estimated through Ordinary Least Squares (OLS) the

[9] Measures of intangible capital usually consist of two components. The first component is technological innovation, which includes R&D and other components such as architectural design, new product development costs. The second component is economic competencies which includes spending on strategic planning, worker training, redesigning or reconfiguring existing products in existing markets, investment to retain or gain market share and investment in brand development (Niebel et al., 2017).

[10] The reclassification was as follows: categories 0-2 became scale 1 (extremely dissatisfied), categories 3-4 became scale 2, categories 5-6 became scale 3, categories 7-8 became scale 4 and categories 9-10 became scale 5 (extremely satisfied).

relationship would inaccurately illustrate both parameters and standard errors (Lange, 2014a). This non-linear regression model as typically used in the SWB literature, takes the following form:

Model 1 $JBS_{isj} = \alpha + \beta\log(\boldsymbol{P}_{sj}) + \sum_{c=1}^{c} \gamma_c X_{ci} + \sum_{j=1}^{j-1} \delta_j Cntry_j + u_{isj}$

Model 2 $JBS_{isj} = \alpha + \beta \boldsymbol{ICT}_{sj} + \sum_{c=1}^{c} \gamma_c X_{ci} + \sum_{j=1}^{j-1} \delta_j Cntry_j + u_{isj}$

Where the dependent variable named JBS_i represents overall job satisfaction of each individual measured in 5 Likert scales (extremely dissatisfied to extremely satisfied). The core independent variables are the logarithm of P_{sj} , reporting labour productivity of industry s in the country j that individual i works in Model 1, and $\boldsymbol{ICT}_{sj}$, reporting ICT intensity of each industry s in the country j that individual i works in Model 2. Both in Model 1 and Model 2, there are c=16 independent control variables X_{ci} that help explain and, at times potentially, moderate the level of job satisfaction, e.g demographic, intrinsic, extrinsic, and employment characteristics, of each individual i. $Cntry_i$ is a dummy variable that controls for the institutional or other differences between the countries in the estimation. The constant term is α and the standard normally distributed error terms u_i have been clustered by industry (32 clusters).

To permit the identification of the model, either one of the threshold parameters or the constant term must be excluded. In this application the constant term α is set equal to zero and therefore 4 thresholds (for the 5 job satisfaction categories) are computed. As with the standard probit, the variance (σ^2) of the error term u of the model is assumed constant and equal to 1. In other words, this is the homoscedasticity assumption. The estimates of the ordered probit are biased and inconsistent in the presence of heteroscedasticity. Since weights are used for the estimation of the model, the statistical software used (STATA) reports robust standard errors by default and therefore the homoscedasticity assumption is satisfied. Though this adjustment for robustness inflates both the absolute magnitude of the coefficients as well as their standard errors (Litchfield, Reilly, & Veneziani, 2012).

3.2 Data Sources

The analysis is based on secondary data from two different sources. Data for industrial labour productivity and ICT intensity from EU KLEMS[11] are matched with data on job satisfaction from the European Social Survey (ESS5), which is the primary dataset. The ESS has been conducted across Europe since 2001, with face-to-face interviews of newly selected, cross-sectional samples taking place every two years. It includes people over the age of 15 living in private households, selected by strict random probability methods. The module on family, work and wellbeing was first introduced in round 2 in 2004, including a job satisfaction question, and then it was enhanced and repeated in round 5 in 2010. In this study the ESS module from 2010 on family, work and wellbeing from round 5 is used, which comprises information for an initial sample of 52,458 individuals from 27 European countries[12]. This is a period of financially difficult times in Europe, an important factor to bare in mind, which might have implications for the levels of wellbeing at work.

Labour productivity and ICT intensity variables are both derived from the EU KLEMS database, which contains information for economic growth, labour productivity, employment, capital and technological change at the industry level[13] for all European Union member states from the year 1970 onwards. It has been constructed largely based on data from national statistical institutes (NSI)[14] and it is harmonised across countries to allow for international comparisons in a consistent way. The harmonisation procedure resulted in the specification of a common industrial classification, similar price concepts for inputs and outputs, and close definitions of types of labour and capital for all countries in the database. The year 2005 is set as the common reference year for all the variables in volumes. Values for labour productivity and ICT intensity retrieved for each industry across the following eight countries that have updated values for 2006: Netherlands, Spain, Finland, Sweden[15], Germany, United Kingdom, Belgium and France. These countries

---

[11] EU KLEMS 2012 release.

[12] The countries initially included in this dataset are: Belgium, Bulgaria, Switzerland, Cyprus, Czech Republic, Germany, Denmark, Estonia, Spain, Finland, France, United Kingdom, Greece, Croatia, Hungary, Ireland, Israel, Lithuania, Netherlands, Norway, Poland, Portugal, Russia, Sweden, Slovenia, Slovakia and Ukraine.

[13] Based on the Industry Classification ISIC rev. 4, which is directly equivalent to NACE rev. 2

[14] The statistics originate from the National Accounts and follow the System of National Accounts (SNA) framework, as well as its European equivalent (ESA).

[15] EU KLEMS does not report data for ICT capital services for Sweden and therefore is excluded from the ICT intensity analysis.

exhibit relative homogeneity in socioeconomic and institutional conditions and therefore it is safe to use them as a consistent sample.

Both labour productivity and ICT intensity are included in the specification using their four-year lagged values (since job satisfaction is reported in 2010), mitigating any reverse effect stemming from job satisfaction. Lagged explanatory variables mitigate potential problems of simultaneity (Michie & Sheehan, 2003) and lessen the possibility of endogeneity in the model by being aggregated at higher levels than the individual. As suggested, there is a five to seven years lag between the time ICT is introduced and the time its impact on productivity is observed (O'Mahony & Vecchi, 2005), in order to allow for any organizational changes to take place. It is assume that a similar amount of time is required for labour productivity and ICT intensity to have their full impact on job satisfaction.

Both variables are introduced in the estimation model of job satisfaction by matching individual-level data from ESS5 with industry-level data from EU KLEMS. To achieve this, the industry that each individual worked in 2010 is identified and attached to his/her industrial labour productivity and ICT intensity values 2006 from EU KLEMS (33 industries * 8 countries). Both datasets follow the NACE rev. 2 (2008) industry classification scheme, but in different aggregations. The 88 industry divisions from ESS5 were merged into 33 categories, in which EU KLEMS reported labour productivity and ICT intensity values.

From the initial sample[16], only 23,877 of those who had a paid job reported their level of job satisfaction. After excluding individuals who had missing values (responded: "Refusal", "Don't know", "No answer" or "Not applicable") in the other variables that affect job satisfaction the initial sample is reduced by 53.9%. The final sample size used in the regressions is approximately 5000 employees (no self-employed people), since industrial labour productivity and ICT capital data for 2006 were available for only 8 of the initial 27 European countries. This final sample is weighted

[16] For a minimum effective sample size, each country collects data from 800 (for countries with populations of less than 2 million people) to 1,500 people.

with post-stratification and population size weights, in order to reduce sampling error and ensure equal country representation in the sample.

3.2.1 Dependent Variable

Job Satisfaction

Both job satisfaction and performance receive different measures and interpretations from each line of inquiry. Job satisfaction has been defined as the 'positive emotional state resulting from the appraisal of one's job' (Locke, 1976). Self-reported measures, such as Subjective Wellbeing (SWB), are mainly used by psychologists, and increasingly also by economists, to capture thoughts and feelings on overall life satisfaction and happiness (Diener, Suh, Lucas, & Smith, 1999). SWB is subdivided into other subcategories of satisfaction. Job satisfaction has been found to be positively correlated with life satisfaction (Tait, Padgett, & Baldwin, 1989), a cognitive dimension of SWB, and with happiness (Weaver, 1978), an affective dimension of SWB.

These positive relationships point out that job satisfaction is a sub-dimension of the SWB of an individual (Judge & Locke, 1993), even though the causal relationship between job satisfaction and SWB has not been clearly identified in the literature (Bowling, Eschleman, & Wang, 2010). Despite concerns for its self-reported nature, SWB is shown to be a relatively robust indicator of a person's wellbeing (Dolan & White, 2007), as well as valid and reliable (Schimmack & Oishi, 2005). SWB measures such as satisfaction with life and happiness as well as job satisfaction (Kristensen & Westergaard-Nielsen, 2007) have been empirically validated[17]. According to the definition of (Boehm & Lyubomirsky, 2008) a happy person is someone frequently experiencing positive emotions, including satisfaction, and from their longitudinal and experimental findings happy people are more likely to be successful in their careers. Job satisfaction has nonetheless been questioned as an economic construct, being instead interpreted as a proxy for the intention to be absent from work, and to quit, with obvious negative effects on turnover.

[17] The reliability of self-reported data has been verified over time as well (Gallie, & Green, 2002).

3.2.2 Other Independent Variables

As Freeman (1977) argued, "satisfaction cannot be treated in the same way as standard economic variables". In the case of job satisfaction for example, he concluded that even though it provides better understanding and prediction of the behaviour of workers, its dependency on psychological states leads to complications. Due to this dependency on psychological states, there have been different analytical approaches in the research of job satisfaction, namely the bottom-up and the top-down psychological models.

Bottom-up models consider the effects of determinants such as external situations, demographic and employment characteristics on job satisfaction and SWB, by assuming that the sum of small pleasures in life partially determines how happy one feels (Sousa-Poza & Sousa-Poza, 2000). On the other hand, in top-down psychological models an individual's personality plays a critical role, as individuals' outlooks on life in general influence their perceptions of job satisfaction (Diener 1984). Another distinction between determinants of job satisfaction were indicated by Herzberg et al. (1967), who developed a Two-Factor theory by distinguishing between intrinsic-motivational factors, which positively influence job satisfaction, and extrinsic-hygiene factors, whose absence can generate dissatisfaction.

Intrinsic factors indicate the quality of work and the characteristics related to the task itself and are usually approximated by satisfaction with the work itself (Clark, 1996), the type of work (Skalli, Theodossiou, & Vasileiou, 2008), and the sense of achievement (Gazioglu & Tansel, 2006); whereas extrinsic factors are mostly quantitative and are necessary to satisfy basic needs (e.g. job security, flexibility, promotion, autonomy, etc.). Therefore, other independent variables were used as controls in the model in order to explain job satisfaction are demographic, intrinsic, extrinsic and employment characteristics of the individuals of the sample. More specifically:

<u>Demographic characteristics:</u> characteristics such as gender, education level and household income.

<u>Intrinsic characteristics:</u> subjective opinions concerning intrinsic aspects of work, such as work-variety, risky job, hard work, and work-life balance (reported in 4 to 10-scale indicators).

Extrinsic characteristics: mainly subjective opinions concerning extrinsic aspects of work, such as supportive colleagues, secure job, flexibility, advancement opportunities, autonomy, involvement, fair payment[18] (a similar concept with "relative income" that provides a subjective evaluation of one's own income compared to a benchmark income), living well (how well off is someone with her/his income ranging from living comfortably to finding it very difficult), etc. (reported in 4 to 10-scale indicators as well).

Employment characteristics: characteristics of the job and the conditions in which employees work, such as years of experience & tenure, monthly income[19], union membership, company size (small, medium, large), contract type (limited, unlimited, no contract) and working hours.

Countries: 8 dummies for the countries included in the sample, in order to control for the country-specific characteristics that could have an effect on job satisfaction.

More information on these variables can be found in the Appendix.

3.2.3 Core independent variables

Industrial Labour Productivity

Defining the exact measure of performance is crucial in understanding and interpreting the puzzling and quite conflicting results produced to date. Only input or only output from work are frequently used as measures of performance, which create confusion in the literature. As (hristen et al. (2006) emphasized, workers' effort is an input[20] to work which achieves an output. Job performance has so far been evaluated using either effort as its input, or directly measured as an outcome, reported by supervisors or end users/customers (Pugno & Depedri, 2010).

A clear distinction between performance and productivity needs to be made at this point. Productivity, which is the ratio of output per input, is another measure of performance, even if the

[18] A 5-scale categorical variable ranging from 1 strongly agree to 5 strongly disagree.

[19] The ESS5 data includes individual gross pay before deductions for tax and insurance. After standardization in monthly pay terms and Purchasing Power Parity (PPP) conversion, the monthly income variable provides a cross-country harmonized measure of own income.

[20] As the amount of effort is not easily observed, it is inferred from the output produced, even though, cases in which high effort produces low output and vice versa is often not considered (Christen et al., 2006).

words are used interchangeably in a vast literature investigating its relationship to worker's wellbeing. When performance is measured as the output of work, the relationship is usually found to be positive (Bowling, 2007; Judge et al., 2001). However, performance measured by the input/effort exerted by the workers has been found to be negatively[21] related to job satisfaction in a number of studies (A. Clark, Oswald, & Warr, 1996; Green & Tsitsianis, 2005; Sloane & Williams, 2000). This is due to the fact that working hours are usually used as a proxy for effort, which, according to economic theories, negatively impact the utility of workers and subsequently their job satisfaction (even though the results are mixed).

In the psychology, management and labour economics literature, various proxies for productivity measurement have been used at different aggregation levels. To begin with, the productivity of the world is a function of the productivity of the economy in each country. Simultaneously, the productivity of an economy is determined by the productivity in each industry (industrial labour productivity), which depends on the productivity of the organizations (organizational labour productivity) that constitute it; at the bottom of this chain of dependency, the organizations are as productive as their workers (individual labour productivity). At the individual level these mainly include self-reported performance measures, rates of quits or absences and supervisors' evaluations of employees' performance (Judge et al. 2001). Measurement concentrates on the number of repetitions of an activity in a specific time (Ruch, 1994).

At higher aggregation levels, such organization or industry sector levels, measures of productivity focus on the total amount of output produced (allocative efficiency) and total resources used (production efficiency) per unit of input (Ruch, 1994). Proxies for these measures are the ratio of revenues over expenses, return on assets (ROA), return on equity (ROE), revenue per employee, labour costs per employee, etc. (Bakotić, 2016). At the industry level, labour productivity is defined as the output-input ratio, primarily investigated from a macroeconomic perspective. This measure

[21] This negative relationship that varies by sector (blue/white collar) (Ghinetti, 2007), however, becomes positive as soon as team support is existent the relationship between satisfaction with effort and job satisfaction (Green & Gallie 2002).

of labour productivity is derived from the simplest form of a short-run production function:

$$Y_j = P_j * L,$$

where Y_j is the output produced and is a function of labour L times labour productivity P_j, which is assumed to capture any dependency on capital and technology. Assuming L is hours worked and that it remains constant, labour productivity P_j solely determines total output Y_j, measured either in prices/costs or volumes (gross volumes or value added to the product). To measure input productivity, single or multiple factors can be used. Single factor measures use only the labour input (labour productivity) or the capital input (capital productivity). Multifactor productivity (MFP) [22] measures, on the other hand, take into account the main inputs (capital and labour), as well as intermediate inputs such as energy, materials and services [23] (Schreyer & Pilat, 2001). Labour productivity in this study is measured as a single factor measure of industry sector productivity[24] representing gross value added per hour worked (in volumes) as in Böckerman et al. (2012) and Royuela et al. (2009).

2.2.1 ICT intensity at the Industry-level as an independent variable

Regarding measures of ICT, there have been various in the literature, depending on the scope of the analysis and the level of aggregation. The indicators for the intensity of ICT use vary from a mere measurement of computers and levels of broadband penetration at the firm level to more sophisticated measures that take into account in detail all the technological components[25] used at the industry level. Chen, et al. (2016) identify four different measures of ICT intensity at the industry level:

---

[22] Otherwise named Factor Productivity (TFP), it account for differences in capital quality & intensity, labour quality (human capital), economies of scale as well as intangible investment in education and skills, R&D, management techniques and other organizational innovations (Inklaar 2008). These are the drivers of productivity growth in the long run.
[23] MFP measures are less frequently used in international comparisons of productivity levels, as they heavily dependent on extensive data (Inklaar 2008).
[24] Named LP_I in the EU KLEMS dataset, where LP_I in 2005 (reference year) is set to 100. This variable does not incorporate any changes in the labour composition (educational attainment, etc.), which means that the labour productivity is quality unadjusted in terms of inputs.
[25] According to Oz (2005) these ICT components should include computing hardware, telecommunications hardware and software, purchased software, software development, consulting services, and personnel training.

(1) ICT capital services per labour services (e.g. Corrad & Jonathan 2014; Chen et al. 2016)

(2) ICT capital/ total value added (e.g. Michaels et al. 2014; Jorgenson & Timmer 2011)

(3) ICT capital/ total capital services (e.g. Goetz et al. 2012; Stiroh 2002) or

(4) ICT capital/ total capital compensation (Van Ark, Inklaar, & McGuckin, 2003).

A frequently used alternative to the above measures is a binary variable indicating intensive or non-intensive ICT-using industries, constructed by the median value of the above measures as the cut-off point. This measure has been used mainly due to the fact that the above continuous variables vary extensively both over time and across industries (Chen et al., 2016). The cut-off point however varies across the different ICT intensity indicators resulting in an arbitrary classification/ranking of ICT intensive or non-intensive industries[26]. The ICT intensity indicator in this study is defined as ICT capital services in volumes (CAPIT_QI)[27] per gross value added in volumes (VA_QI) as in Michaels et al. (2014) and Jorgenson & Timmer (2011).

3.3 Research Design

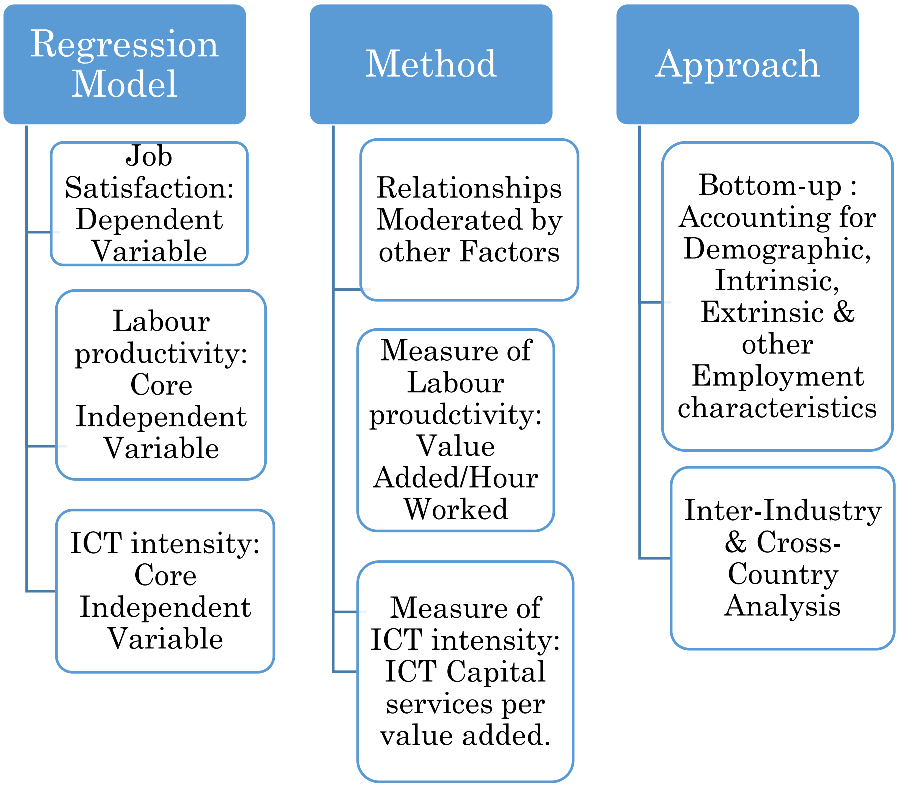
The method followed is based on Judge's (2001) conceptual model 5 in which other factors are assumed to moderate the relationship, without explicitly investigating the direction of causality. This is the assumption most frequently encountered in the literature. It is also supported by the cross sectional nature of the data used, which allows the examination of one direction of the possible loop existing between job satisfaction and performance (as suggested in Model 3). The approach in this wellbeing model is therefore to control for factors such as demographic characteristics (age, sex, education, etc.), intrinsic characteristics (work-variety, risky job, hard work, and work-life balance), extrinsic characteristics (supportive environment, flexibility, advancement opportunities, autonomy, etc.) and employment characteristics (income, years of experience & tenure, company size, etc.). Among these factors, some play a moderating role within the relationships investigated. This approach is in line with the bottom-up[28] psychological models

[26] The arbitrariness of a binary variable has been confirmed in the results of Van Ark & Inklaar (2003). Their cluster analysis shows no clear-cut distinction of industries between these two categories.

[27] CAPIT_QI accounts for computing equipment (IT), communication equipment (CT) and software.

[28] Due to unavailability of data that account for personality traits that influence SWB and job satisfaction, a top-down approach cannot be followed.

followed extensively in the labour economics literature (e.g. Sousa-Poza 2000). A schematic representation of the research design can be seen in the figure below:



4. Empirical Analysis

4.1 Findings

Table 1 displays the estimation results for a sample of approximately 5000 individuals from seven to eight European countries. Columns (1)-(3) represent different specifications of the ordered probit model, where job satisfaction is regressed on the log of industrial labour productivity, ICT intensity and the rest of the explanatory variables. The categories of variables used as controls are: demographic, intrinsic, extrinsic and employment characteristics. All specification models include country dummies. The pseudo R squared and the Akaike Information Criterion (AIC)[29] are reported at the bottom of the table.

[29] It is a measure that allows comparisons of maximum likelihood models. Defined as AIC = -2*ln(likelihood) + 2*k it combines measures of fit and complexity. Between two models the one with the small AIC value is considered to be better.

Column (1) represents the aggregate model, which is the regression of job satisfaction on the log of labour productivity and on ICT intensity together with all the controls. Both labour productivity and ICT intensity appear to be individually statistically insignificant. This is likely due to their high collinearity, as ICT is one of the drivers of labour productivity in that same year. Therefore, an F test for joint significance is performed, revealing that the jointly they are marginally insignificant (α=11,11%).

Column (2) represents model 1 regressing job satisfaction on the log of labour productivity only. Labour productivity becomes statistically significant at the 10% level. The estimated coefficients of the ordered probit model can only give information on the sign of the effect on the dependent variable, in which case labour productivity has a negative effect on job satisfaction. In column (3) Model 3 shows that ICT intensity is found to have a statistically significant and positive effect on job satisfaction.

Even though the value of the coefficients is not very informative, the signs of the coefficients show the effect of each variable on job satisfaction. The analysis of the other independent variables shows that having a higher household income or being female increase the probability of being more satisfied with work. Though having a higher education level is negatively correlated with being satisfied with work, which is not much of a surprise if the "curse of high aspirations" is considered (Clark & Oswald 1996). Furthermore, having a balanced work-life relationship, a lot of variety at work, supportive colleagues, security, good advancement opportunities, flexible work, autonomy in organizing one's own work and fair payment pushes the respondent further up the real line of job satisfaction. Surprisingly, not having a working contract at all is associated with higher levels of job satisfaction. Another surprising result is that as the working hours increase, job satisfaction (of the employees) increases as well.

Table 1. Regressing job satisfaction on labour productivity and ICT intensity in different specification forms

	(1) Combined	(2) Model 1	(3) Model 2
Job Satisfaction5			
lnLP_I_2006	-0.845	-1.371**	
	(0.710)	(0.635)	
ICT intensity 2006	0.339		0.524*
	(0.288)		(0.286)
Household Income	0.0136*	0.0130*	0.0136*
	(0.00764)	(0.00777)	(0.00767)
Female	0.150***	0.156***	0.151***
	(0.0550)	(0.0507)	(0.0543)
Education level	-0.0701***	-0.0703***	-0.0698***
	(0.0163)	(0.0161)	(0.0162)
interesting	0.561***	0.558***	0.562***
	(0.0646)	(0.0617)	(0.0648)
Support	0.102***	0.0969***	0.103***
	(0.0272)	(0.0260)	(0.0271)
Advancement	0.110***	0.113***	0.108***
	(0.0159)	(0.0155)	(0.0153)
Work-life balance	0.227***	0.227***	0.227***
	(0.0107)	(0.0103)	(0.0106)
Safety at risk	-0.0232	-0.0228	-0.0231
	(0.0330)	(0.0332)	(0.0327)
Variety in work	0.179***	0.180***	0.180***
	(0.0252)	(0.0251)	(0.0249)
Paid appropriately	-0.186***	-0.188***	-0.187***
	(0.0195)	(0.0193)	(0.0198)
Flexible work	0.0307	0.0276	0.0294
	(0.0277)	(0.0265)	(0.0283)
Autonomy	0.0340***	0.0354***	0.0339***
	(0.00690)	(0.00697)	(0.00682)
Secure Job	0.0821***	0.0794***	0.0829***
	(0.0243)	(0.0240)	(0.0240)
Working Hours	0.0107***	0.0105***	0.0106***
	(0.00209)	(0.00208)	(0.00211)
No contract	-0.00761	0.0379	-0.0119
	(0.127)	(0.127)	(0.129)
Experience	0.00277	0.00312*	0.00274
	(0.00168)	(0.00161)	(0.00168)
Observations	4868	5477	4890
Pseudo R-squared	0.177	0.178	0.176
AIC	16146.2	16784.8	16167.4

Standard errors in parentheses
The dependent variable is Job satisfaction, measured in a 5-likert scale.
All regressions include country dummies.
* p<0.1, ** p<0.05, *** p<0.01

To identify and interpret the effects of the core variables in a more suitable and meaningful way, the marginal effects need to be computed. The results from the computation of the marginal effects of labour productivity and that of ICT intensity using the delta method appear in the tables below. As seen in **Table 2**, labour productivity increases are associated with higher probabilities of belonging to the lower job satisfaction levels (first four categories) and lower probabilities of being extremely satisfied with one's work (job satisfaction category five). On average and *ceteris paribus* an increase in labour productivity by 10% increases the probability of a worker expressing him/herself as "extremely dissatisfied" (job satisfaction category 1) by approximately 0.62 percentage points (0.062*0.1=0.0062). On the other hand, an increase in labour productivity by 10% decreases the probability of a worker expressing him/herself as "extremely satisfied" (job satisfaction category 5) by approximately 3.7 percentage points (0.366*0.1=0.037).

Table 2. Average Marginal effects of Labour productivity on Job Satisfaction

```
Average marginal effects                        Number of obs     =      5,477
Model VCE    : Robust

dy/dx w.r.t. : lnLP_I_2006
1._predict   : Pr(jbs5==1), predict(pr outcome(1))
2._predict   : Pr(jbs5==2), predict(pr outcome(2))
3._predict   : Pr(jbs5==3), predict(pr outcome(3))
4._predict   : Pr(jbs5==4), predict(pr outcome(4))
5._predict   : Pr(jbs5==5), predict(pr outcome(5))
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
lnLP_I_2006						
_predict						
1	.0620381	.0302533	2.05	0.040	.0027428	.1213334
2	.0747071	.0348715	2.14	0.032	.0063602	.1430541
3	.1712768	.0796264	2.15	0.031	.0152119	.3273417
4	.0576791	.0267627	2.16	0.031	.0052252	.110133
5	-.3657011	.1691498	-2.16	0.031	-.6972286	-.0341737

In **Table 3** below, the average marginal effects of ICT intensity are shown. As with labour productivity, the effect differs for each satisfaction category. As above, on average and *ceteris paribus* an increase in ICT intensity by 10 percentage points decreases the probability of a worker expressing him/herself as "extremely dissatisfied" (job satisfaction category 1) by approximately 0.24 percentage points (0.024*0.1=0.0024) On the other hand, an increase in ICT intensity by 10 percentage point increases the probability of a worker expressing him/herself as "extremely satisfied" (job satisfaction category 5) by approximately 1.4 percentage points (0.139*0.1=0.014).

Table 3. Average Marginal effects of ICT intensity on Job Satisfaction

```
Average marginal effects                        Number of obs     =      4,890
Model VCE    : Robust

dy/dx w.r.t. : ICT2006
1._predict   : Pr(jbs5==1), predict(pr outcome(1))
2._predict   : Pr(jbs5==2), predict(pr outcome(2))
3._predict   : Pr(jbs5==3), predict(pr outcome(3))
4._predict   : Pr(jbs5==4), predict(pr outcome(4))
5._predict   : Pr(jbs5==5), predict(pr outcome(5))
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
ICT2006						
_predict						
1	-.0240161	.0125826	-1.91	0.056	-.0486775	.0006454
2	-.0288647	.0164106	-1.76	0.079	-.0610289	.0032995
3	-.0652584	.0351596	-1.86	0.063	-.1341699	.0036532
4	-.0216561	.0132702	-1.63	0.103	-.0476652	.004353
5	.1397953	.0766888	1.82	0.068	-.010512	.2901025

In addition to the above analyses, a series of tests were conducted in order to shed some light on the reasons behind some of the results obtained. Dividing the sample between workers that have received any kind of training during the last 1 year and those who had not. This test revealed that ICT intensity had a really higher positive effect on job satisfaction if workers has received training. The effect was also a lot higher for highly skilled workers, while ICT was a statistically insignificant factor for only low or only middle skilled workers. ICT had a slightly higher positive effect on the job satisfaction on people whose work tasks involved mainly non-routine cognitive tasks, i.e. activities most frequently performed by highly skilled people.

4.3 Discussion

Regarding model 1, a negative relationship was found between labour productivity at the industry level and individual job satisfaction. Since previous studies have been conducted at different aggregation levels (at organizational or individual) and with different definitions of productivity (either as output or as input/effort), these results of productivity as output/input at the industry level are not comparable to other findings in the literature in a straightforward way and any comparisons need to be made cautiously. Assuming that there is a possibility of loops in this relationship and the broad spectrum of activities and interconnections taking place at the industry level, it is hard to pinpoint the exact mechanisms that drive this negative relationship. The possible mechanisms can only be speculated, ranging from measurement discrepancies to the form of production systems in the countries of the sample.

This negative result is contradictory to the majority of the literature and only similar to a result of Royuela & Suriñach (2013). While examining the effect of productivity (defined as output/input) on job satisfaction in low human capital sectors, they also found a negative relationship (not using all the sectors however and without controlling for all the variables necessary for a workers' wellbeing model). The surprising factor is that this negative relationship cannot be explained by the increased effort in terms of hours worked exerted in the job, as this variable had a positive effect on job satisfaction, even though all of the sample were employees and not self-employed workers.

This result is not very surprising however, since the literature has exhibited mixed evidence on the effect of working hours on job satisfaction as well. For example, Diaz-Serrano et al. (2005) find a positive relationships for the UK and a negative for the rest of the countries. On the other hand, (Skalli et al., 2008) found workers increasingly dissatisfied with their working hours in Greece, Italy and Spain and Green & Tsitsianis (2005) had similar results for Germany and the UK. As Pugno and Depedri (2010) suggest, these mixed results might reflect both the positive route from output as achievements to satisfaction and the negative route from input as effort to disutility. Furthermore, the fact that labour productivity is statistically significant from the baseline model suggest that income does not moderate the performance-satisfaction relationship, as suggested in the literature. Also, findings of a positive and statistically significant effect of few of the most cited moderating factors, such as household income and perception of fair payment (inversely measured in the regression), on job satisfaction is not consistent with the theory that income levels are driven in the same direction as productivity levels.

What could potentially explain the negative relationship, which was not controlled for in this analysis, is the factor of pressure. Pressures on production have been found to affect the correlation between labour productivity and job satisfaction (Ewen, 1973). Therefore, pressure for higher labour productivity could be correlated with higher stress levels, which affect job satisfaction negatively. Organizational structures, also, allow employers to exert outcome-based control (e.g. pay for performance) and behaviour-based control, such as monitoring in order to push workers beyond the level of minimal effort (Anderson and Oliver 1987).

Regarding Model 2, ICT intensity was found to have a positive and statistically significant effect on job satisfaction, a result partially supported by the literature. As Antonioli et al. (2009) discovered, ICT, measured by the intensity of ICT innovation, is more correlated with the content and the characteristics of the job and less with physical and psychological stress, thus, increasing the sense of empowerment without harming the sense of safety and security or increasing work-related stress. As they suggest, innovative breakthroughs, among which ICT, could be increasing the sense of autonomy and the amount of information that workers have access to and are able to share.

Organizational changes might have played an indirect role in this positive result, even though this analysis did not include any information related to changes in work practices, as immediately reported but the respondents of the survey. Work practices related to new processes resulting from the use of new technologies could have facilitated adaptation and new learning. As shown in some further tests performed in the analysis, receiving training, one of the most frequently applied HPWP currently, proved to have increased the positive effect of ICT on job satisfaction.

The positive effect of ICT on job satisfaction is also stronger for people performing non-routine cognitive tasks, as well as for highly skilled people[30] (95% of which perform these kind of tasks), hence, suggesting that technology plays a significant complementing role in cognitively demanding

[30] However, this result is not quite indicative of a job polarization in the labour market.

tasks. Since it has been found that intensive use of computers could be generating experiences of flow at the workplace, this might be also reflected by this positive effect. This is in line with (Bjorn-Andersen et al., 1986)Bjorn-Andersen et al. (1986) who found that if the involved high scope tasks, computers were enriching the work experience, while reducing work-related stress.

Finally, since the negative relationship between labour productivity and job satisfaction cannot be attributed to technology

4.3.1 Data Limitations and Future Research Recommendations

One of the issues that can be raised, lies in the problematic nature of output measurements in certain sectors of the economy. For example, output measures in the service sector where the output is not quantifiable and is derived from the input measure in the national accounts creates a source of bias. This shortcoming has been highlighted by O' Mahony and Timmer (2009), warning that the reliability of the EU KLEMS data is lower for the service industries, especially for non-market services such as public administration and personal services. As neither labour productivity not ICT intensity, which both make use of output measures, do not properly reflect the quality of output produced, it results in an underestimation of its value. This is the case in the services industries, where quality matters more than quantity. However if output is quality-adjusted, then the relationships investigated in this study are likely to change.

These models make no inferences on the direction of causality in the relationships investigated, but only on the existence of mere correlation. The job-satisfaction literature is full of reverse causality issues (Diener et al., 1999) and a solution to this problem would be the employment of instrumental variables. This would require the linear transformation of the non-linear ordered probit model into what van Praag and Ferrer-i-Carbonell (2008) refer to as a probit-adapted OLS.

Regarding of job satisfaction, which is measured by a single-item, its critics suggest that it might not be presenting the whole picture and the exact connections between productivity and ICT with the wellbeing of workers, while hindering the assessment of internal consistency (Lange, 2014b; Sousa-Poza & Sousa-Poza, 2000). There has been a lot of discussion on the suitability of single or multiple-item[31] measures of job satisfaction. According to Rose (2003), single-item measures, reporting global or overall or job satisfaction, were initially thought to be less precise than multiple-item measures, reporting satisfaction with different facets of jobs (Smith, Kendall, and Hulin 1969). However, findings from (Scarpello & Campbell, 1983) have shown that both measures are stable and reliable. They reported that the effects of the independent variables on job satisfaction were equivalent regardless of using multiple-item or single-item measures of job satisfaction.

Alike most SWB measures, self-reported job satisfaction data depend on the ordering of the satisfaction categories, the current mood at the timing of measurement, among other factors (see Diener et al., 1999). As this study makes use of cross-sectional data for these wellbeing models, heterogeneity in individual unobservable characteristics, such as personality traits or intrinsic abilities that influence job satisfaction, might be present. Ferrer-i-Carbonell and Frijters (2004) analysing SWB, highlight this drawback. A way to eliminate this heterogeneity is the use of panel data with an extensive temporal dimension (Litchfield et al. 2012). Though, this would require data for the same individuals across time, something that the ESS dataset does not provide, as in every survey round they have newly selected, cross-sectional samples.

A recommendation for future work is using industrial labour productivity and ICT growth rates in a panel data analysis, which take into account temporal changes across time. The effect of on job satisfaction is another subject of immense interest for research as well. Furthermore, incorporating data for intangible capital (measuring organizational changes through innovation and economic competencies) and its interaction with ICT to get their combined effect on job satisfaction, would showcase the possibly complementing effects of organizational changes across different industries.

5. Conclusions

This paper adds to the literature by uncovering some of the least straightforward relationships in the economics literature. This is attained by the investigation of the effects of industrial labour

[31] Multiple-item measures use a variety of questions which are weighted accordingly in order to produce a Job Descriptive Index, first introduced by Smith, Kendall and Hulin (1969).

productivity and those of ICT intensity on job satisfaction in an inter-industry, cross-country analysis. In order to explore the nature of these relationships, data from EU KLEMS) were matched with data on individual job satisfaction from the European Social Survey (ESS) for eight advanced European countries. To estimate these relationships, job satisfaction from ESS5 in 2010 was regressed on lagged values of industry-level data for labour productivity (Model 1) and ICT intensity (Model 2) in 2006. In these econometric analyses an ordered probit model was employed and the estimated effect of labour productivity on job satisfaction was found to be negative. The reasons that attest this finding could possibly be attributed to stress factors related to increased pressures for production and mechanisms in the production system of excessive controlling and monitoring of work activities by management.

The penetration of computers in knowledge-intensive jobs and the instantaneous communication possibilities offered by ICT have changed radically the work patterns in every organizational environment, directly and indirectly impacting the wellbeing of workers. The findings suggest that there is a positive effect of ICT intensity at the industry level on individual job satisfaction. across all the industries of the economy in those eight European countries. This result could be attributed to the complementary role of technology in non-routine cognitive tasks and the effect of worker-friendly organizational changes that accompany the introduction of ICT at the workplace such as training, and HPWP related to increased levels of autonomy, empowerment and information sharing. This result was stronger for workers performing non-routine cognitively demanding tasks, as well as for high skilled workers, the majority of which performs these kinds of tasks.

Concluding, there is a great need in our times for investment in jobs that provide high job satisfaction, regardless of their labour productivity and their contribution to growth. It is crucial to motivate a structural change towards economic measures that take into account the emotional wellbeing of workers and not just measures that promote economic growth. Since using ICT in the workplace proved to have a positive effect on the wellbeing of workers it seems like a viable route for investment in ICT-related skills and training. Productivity enhancements that are stress provoking seem to have a negative impact on the emotional wellbeing of workers and subsequently on the wellbeing of society. Higher labour productivity levels pursued through task-complementing technological innovation, in the sector where this is possible, translates into better quality of working life. But, striving to achieve productivity enhancements in all sectors of the economy on any cost, might, on average, not be beneficial for the wellbeing of workers.

References

Antonioli, D., Mazzanti, M., & Pini, P. (2009). Innovation, Working Conditions and Industrial Relations: Evidence for a Local Production System. *Economic and Industrial Democracy*, *30*(2), 157–181. https://doi.org/10.1177/0143831X09102418

Attewell, P., & Rule, J. (1984). Computing and Organizations: What We Know and What We Don't Know. *Communications of the ACM*. https://doi.org/10.1145/2135.2136

Autor, D. H. (2003). Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing. *Journal of Labor Economics*, *21*(1), 1–42.

Autor, D. H., & Dorn, D. (2013). The Growth of Low Skill Service Jobs and the Polarization of the U . S . Labor Maret. *American Economic Review*, *103*(5), 1553–97. https://doi.org/10.1257/aer.103.5.1553

Bakotić, D. (2016). Relationship between job satisfaction and organisational performance. *Ekonomska Istraživanja*, *29*(1), 118–130.

Bauer, T. K. (2004). High Performance Workplace Practices and Job Satisfaction: Evidence from Europe, (1265), 1–33. Retrieved from http://ftp.iza.org/dp1265.pdf

Beas, M. I., & Salanova, M. (2006). Self-efficacy beliefs, computer training and psychological well-being among information and communication technology workers. *Computers in Human Behavior*, *22*(6), 1043–1058. https://doi.org/10.1016/j.chb.2004.03.027

Biagi, F., & Parisi, M. L. (2012). *Are ICT , Human Capital and Organizational Capital Complementary in Production ? Evidence from Italian Panel Data*. https://doi.org/10.2791/99567

Bjorn-Andersen, N., Eason, K., & Robey, D. (1986). Managing computer impact. *Norwood NJ: Ablex Publishers*.

Böckerman, P., & Ilmakunnas, P. (2012). The job statisfaction productivity nexus: A study using matches survey an register data. *Industrial and Labor Relations Review. Forthcoming*, *65*(April). https://doi.org/10.1177/001979391206500203

Boehm, J. K., & Lyubomirsky, S. (2008). Does happiness promote career success? *Journal of Career Assessment*, *16*(1), 101–116.

Bowling, N. A. (2007). Is the job satisfaction-job performance relationship spurious? A meta-analytic examination. *Journal of Vocational Behavior*, *71*(2), 167–185. https://doi.org/10.1016/j.jvb.2007.04.007

Bowling, N. a, Eschleman, K. J., & Wang, Q. (2010). A meta-analytic examination of the relationship between job satisfaction and subjective well-being. *Journal of Occupational and Organizational Psychology*, *83*(4), 915–934. https://doi.org/10.1348/096317909X478557

Brayfield, A. H., & Crockett, W. H. (1955). Employee attitudes and employee performance. *Psychological Bulletin*, *52*(5), 396–424. https://doi.org/10.1037/h0045899

Brillhart, P. E. (2004). Technostress in the workplace: Managing stress in the electronic workplace. *Journal of American Academy of Business*, *5*(1/2), 302–307.

Brod, C. (1984). *Technostress: The human cost of the computer revolution*. Addison Wesley Publishing Company.

Bryson, A., Dale-Olsen, H., & Barth, E. (2009). How does innovation affect worker well-being? *Social Research*, *2004*(173591).

Chen, W., Niebel, T., & Saam, M. (2016). Are intangibles more productive in ICT-intensive industries? Evidence from EU countries. *Telecommunications Policy*, *40*(5), 471–484. https://doi.org/10.1016/j.telpol.2015.09.010

Chiaburu, D. S., Thundiyil, T., & Wang, J. (2014). Alienation and its correlates: A meta-analysis. *European Management Journal*, *32*(1), 24–36.
Christen, M., Iyer, G., Soberman, D., Anderson, E., Mitchell, A., Russell, G., & Staelin, R. (2006). Job Satisfaction, Job Performance, and Effort: A Reexamination Using Agency Theory. *Journal of Marketing*, *70*(January), 137–150. https://doi.org/10.1509/jmkg.2006.70.1.137
Clark, A. E. (1996). Job satisfaction in Britain. *British Journal of Industrial Relations*, *34*(2), 189–217. https://doi.org/10.1111/j.1467-8543.1996.tb00648.x
Clark, A., Oswald, A., & Warr, P. (1996). Is job satisfaction U-shaped in age? *Journal of Occupational and Organizational Pshychology*, *69*, 57–81. https://doi.org/10.1111/j.2044-8325.1996.tb00600.x
Clark, K., & Kalin, S. (1996). Technostressed Out? How to Cope in the Digital Age. *Library Journal*, *121*(13), 30–32.
Corrad, C., & Jonathan, H. (2014). E c o n o m i c s P r o g r a m W o r k i n g P a p e r S e r i e s Know ledge Spillovers , ICT and Productivity Grow th, (May), 0–27.
Diaz-Serrano, L., & Cabral Vieira, J. A. (2005). Low Pay, Higher Pay and Job Satisfaction within the European Union: Empirical Evidence from Fourteen Countries. *IZA Discussion Papers*, *1558*(1558), 1–25.
Diener, E., Suh, E. M., Lucas, R. E., & Smith, H. L. (1999). Subjective well-being: Three decades of progress. *Psychological Bulletin*, *125*(2), 276.
Dolan, P., & White, M. P. (2007). How can measures of subjective well-being be used to inform public policy? *Perspectives on Psychological Science*, *2*(1), 71–85.
Driscoll, J. (1982). Office Automation: The Dynamics of a Technological Boondoggle, Emerging Office Systems, Landau, RM and Blair, JH Eds. *Norwood, NJ*.
Easterlin, R. A. (2005). Is There an'Iron Law of Happiness?'.
Ewen, R. B. (1973). Pressure for production, task difficulty, and the correlation between job satisfaction and job performance. *Journal of Applied Psychology*, *58*(3), 378.
Felstead, A., Gallie, D., & Green, F. (2002). Work skills in Britain 1986-2001. *Methodology*, *14*(January 2002), 17.
Ferrer-i-Carbonell A, Frijters P (2004) How important is methodology for the estimates of the determinants of happiness. Economic Journal 114: 641–659
Freeman, R. B. (1977). *Job satisfaction as an economic variable*. National Bureau of Economic Research Cambridge, Mass., USA.
Gazioglu, S., & Tansel, A. (2006). Job satisfaction in Britain: individual and job related factors. *Applied Economics*, *38*(10), 1163–1171.
Georgellis, Y., & Lange, T. (2007). Participation in continuous, on-the-job training and the impact on job satisfaction: longitudinal evidence from the German labour market. *The International Journal of Human Resource Management*, *18*(6), 969–985. https://doi.org/10.1080/09585190701321112
Ghani, J. A., & Al-Meer, A. R. (1989). Effect of end-user computing on job satisfaction: An exploratory study. *Information and Management*, *17*(4), 191–195. https://doi.org/10.1016/0378-7206(89)90042-6
Ghinetti, P. (2007). The public–private job satisfaction differential in Italy. *Labour*, *21*(2), 361–388.
Goetz, K., Campbell, S. M., Broge, B., Dörfer, C. E., Brodowski, M., & Szecsenyi, J. (2012). The impact of intrinsic and extrinsic factors on the job satisfaction of dentists. *Community Dentistry and Oral Epidemiology*, *40*(5), 474–480. https://doi.org/10.1111/j.1600-0528.2012.00693.x

Green, F. (2006). *Demanding work: The paradox of job quality in the affluent economy*. Princeton University Press.
Green, F., & Tsitsianis, N. (2005). An investigation of National trends in job satisfaction in Britain and Germany. *British Journal of Industrial Relations*, *43*(3), 401–429. https://doi.org/10.1111/j.1467-8543.2005.00362.x
Heinssen, R. K., Glass, C. R., & Knight, L. A. (1987). Assessing computer anxiety: Development and validation of the computer anxiety rating scale. *Computers in Human Behavior*, *3*(1), 49–59.
Hudiburg, R. A. (1989). Psychology of computer use: VII. Measuring technostress: Computer-related stress. *Psychological Reports*, *64*(3), 767–772.
Iaffaldano, M. T., & Muchinsky, P. M. (1985). Job satisfaction and job performance: A meta-analysis. *Psychological Bulletin*, *97*(2), 251–273. https://doi.org/10.1037/0033-2909.97.2.251
Inklaar, R., O'Mahony, M., & Timmer, M. (2005). ICT And Europe's Productivity Performance: Industry-Level Growth Account Comparisons With The United States. *Review of Income and Wealth*, *51*(4), 505–536.
Ivancevich, J. M., & Matteson, M. T. (1980). Stress and Work Glenview. *IL: Scott, Foresman and Co*.
Jorgenson, D. W., & Timmer, M. P. (2011). Structural Change in Advanced Nations: A New Set of Stylised Facts. *Scandinavian Journal of Economics*, *113*(1), 1–29. https://doi.org/10.1111/j.1467-9442.2010.01637.x
Judge, T. A., & Locke, E. A. (1993). Effect of dysfunctional thought processes on subjective well-being and job satisfaction. *Journal of Applied Psychology*, *78*(3), 475.
Judge, T. A., Thoresen, C. J., Bono, J. E., & Patton, G. K. (2001). The Job Satisfaction-Job Performance Relationship: A Qualitative and Quantitative Review. *Psychological Bulletin*, *127*(3), 376–407. https://doi.org/10.1037/0033-2909.127.3.376
Korman, A. K. (1970). Toward an hypothesis of work behavior. *Journal of Applied Psychology*, *54*(1p1), 31.
Kretschmer, T. (2012). Information and Communication Technologies and Productivity Growth. *OECD Digital Economy Papers*, (195), 1–27. https://doi.org/10.1787/5k9bh3jllgs7-en
Kristensen, N., & Westergaard-Nielsen, N. (2007). Reliability of job satisfaction measures. *Journal of Happiness Studies*, *8*(2), 273–292.
Krugman, P. R. (1997). *The age of diminished expectations: US economic policy in the 1990s*. MIT press.
Landy, F. J. (1989). *Psychology of work behavior*. Thomson Brooks/Cole Publishing Co.
Lange, T. (2014a). Social capital and job satisfaction: The case of Europe in times of economic crisis. *European Journal of Industrial Relations*, *21*(3), 275–290. https://doi.org/10.1177/0959680114542907
Lange, T. (2014b). Social capital and job satisfaction: The case of Europe in times of economic crisis. *European Journal of Industrial Relations*, *21*(3), 275–290. https://doi.org/10.1177/0959680114542907
Layard, R., Nickell, S., & Mayraz, G. (2008). The marginal utility of income. *Journal of Public Economics*, *92*(8–9), 1846–1857. https://doi.org/10.1016/j.jpubeco.2008.01.007
Litchfield, J., Reilly, B., & Veneziani, M. (2012). An analysis of life satisfaction in Albania: An heteroscedastic ordered probit model approach. *Journal of Economic Behavior & Organization*, *81*(3), 731–741.
Locke, E. A. (1976). The nature and causes of job satisfaction. *Handbook of Industrial and*

Organizational Psychology.
Love, J. H., Simpson, D. R. F., & Walker, J. (1989). The impact of new technology on labour flexibility and working practices: A management perspective. *Journal of General Management*, *14*(3), 13–25.
Marx K (1972) The Marx- Engels reader (Vol. 4). New York: NortonMcGillivray, M., & Clarke, M. (2006). Understanding human well-being. *New York*, 422. https://doi.org/10.1080/00220380701437154
Michaels, G., Natraj, A., & Van Reenen, J. (2014). Has ICT polarized skill demand? Evidence from eleven countries over twenty-five years. *Review of Economics and Statistics*, *96*(1), 60–77.
Michie, J., & Sheehan, M. (2003). Labour market deregulation, "flexibility" and innovation. *Cambridge Journal of Economics*, *27*(1), 123–143. Retrieved from http://dx.doi.org/10.1093/cje/27.1.123
Mohr, A. T., & Puck, J. F. (2007). Role conflict, general manager job satisfaction and stress and the performance of IJVs. *European Management Journal*, *25*(1), 25–35.
Mysíková, M., & Večerník, J. (2013). Job satisfaction across Europe: differences between and within regions. *Post-Communist Economies*, *25*(4), 539–556. https://doi.org/10.1080/14631377.2013.844934
Nelson, D. L. (1990). Individual adjustment to information-driven technologies: A critical review. *MIS Quarterly*, 79–98.
Niebel, T., O'Mahony, M., & Saam, M. (2017). The Contribution of Intangible Assets to Sectoral Productivity Growth in the EU. *Review of Income and Wealth*, *63*(s1).
Norris, D. R., & Niebuhr, R. E. (1984). Organization tenure as a moderator of the job satisfaction-job performance relationship. *Journal of Vocational Behavior*, *24*(2), 169–178.
O'Mahony, M., & Vecchi, M. (2005). Quantifying the impact of ICT on output growth: a heterogeneous dynamic panel approach. *Economica*, *72*, 615–633. https://doi.org/10.1111/j.1468-0335.2005.0435.x
Ostroff, C. (1992). The relationship between satisfaction, attitudes, and performance: An organizational level analysis. *Journal of Applied Psychology*, *77*(6), 963–974. https://doi.org/10.1037/0021-9010.77.6.963
Pugno, M., & Depedri, S. (2010). Job performance and job satisfaction: An integrated survey. *Economia Politica*, *27*(1), 175–210.
Ragu-Nathan, T. S., Tarafdar, M., Ragu-Nathan, B. S., & Tu, Q. (2008). The consequences of technostress for end users in organizations: Conceptual development and validation. *Information Systems Research*, *19*(4), 417–433. https://doi.org/10.1287/isre.1070.0165
Ritter, J. A., & Anker, R. (2002). Good jobs, bad jobs: Workers' evaluations in five countries. *International Labour Review*, *141*(4), 331–358. https://doi.org/10.1111/j.1564-913X.2002.tb00244.x
Rose, M. (2003). Good Deal, Bad Deal? Job Satisfaction in Occupations. *Work, Employment and Society*, *17*(3), 503–530. https://doi.org/10.1177/09500170030173006
Royuela, V., López-Tamayo, J., & Suriñach, J. (2009). Results of a quality of work life index in Spain. A comparison of survey results and aggregate social indicators. *Social Indicators Research*, *90*(2), 225–241.
Royuela, V., & Suriñach, J. (2013). Quality of Work and Aggregate Productivity. *Social Indicators Research*, *113*(1), 37–66. https://doi.org/10.1007/s11205-012-0081-1
Ruch, W. A. (1994). Measuring and managing individual productivity. *Organizational Linkages: Understanding the Productivity Paradox*, 105–130.

Scarpello, V., & Campbell, J. P. (1983). Job satisfaction: Are all the parts there? *Personnel Psychology*, *36*(3), 577–600.
Schimmack, U., & Oishi, S. (2005). The influence of chronically and temporarily accessible information on life satisfaction judgments. *Journal of Personality and Social Psychology*, *89*(3), 395.
Schreyer, P., & Pilat, D. (2001). MEASURING PRODUCTIVITY Paul Schreyer and Dirk Pilat. *OECD Economic Studies*, (33), 127–170.
Skalli, A., Theodossiou, I., & Vasileiou, E. (2008). Jobs as Lancaster goods: Facets of job satisfaction and overall job satisfaction. *Journal of Socio-Economics*, *37*(5), 1906–1920. https://doi.org/10.1016/j.socec.2008.04.003
Sloane, P. J., & Williams, H. (2000). Job satisfaction, comparison earnings, and gender. *Labour*, *14*(3), 473–502.
Smith A, Nicholson JS (1887) An Inquiry into the Nature and Causes of the Wealth of Nations... T. Nelson and Sons
Sousa-Poza, A. A. A. A., & Sousa-Poza, A. A. A. A. (2000). Well-being at work: a cross-national analysis of the levels and determinants of job satisfaction. *The Journal of Socio-Economics*, *29*(6), 517–538. https://doi.org/10.1016/S1053-5357(00)00085-8
Steers, R. M. (1975). Effects of need for achievement on the job performance-job attitude relationship. *Journal of Applied Psychology*, *60*(6), 678.
Stiroh, K. J. (2002). Information Technology and the U . S . Productivity Revival : What Do the Industry Data Say ? Federal Reserve Bank of New York.
Tait, M., Padgett, M. Y., & Baldwin, T. T. (1989). Job and life satisfaction: A reevaluation of the strength of the relationship and gender effects as a function of the date of the study. American Psychological Association.
Van Ark, B., Inklaar, R., & McGuckin, R. H. (2003). The contribution of ICT-producing and ICT-using industries to productivity growth: A comparison of Canada, Europe and the United States. *International Productivity Monitor*, *6*, 56–63.
Van Praag BMS, Ferrer-i-Carbonell A (2008) Happiness Quantified: A Satisfaction Calculus Approach. Oxford University Press. Paperback and Revised edition
Wastell, D., & Newman, M. (1993). The behavioral dynamics of information system development: A stress perspective. *Accounting, Management and Information Technologies*, *3*(2), 121–148.
Weaver, C. N. (1978). Job satisfaction as a component of happiness among males and females. *Personnel Psychology*, *31*(4), 831–840.
Weil, M. M., & Rosen, L. D. (1997). *Technostress: Coping with technology@ work@ home@ play*. Wiley.

Appendix

- Demographic characteristics
  - Living with a partner: There is a possibility of reversed causality here as cheerful and happy people have more chances to attract a partner (Stutzer and Frey 2006). By belonging to an occupation or industry affiliation that offers higher income, an individual probably increases his/her marriage/ partnering prospects as Pischke (2011) mentions. Hence, this variable could be endogenous.
    I constructed it as a dummy taking the value 1 if the respondent lives with a husband, wife or partner, both *de jure* and *de facto*.

  - Gender: According to Clark (1997) women report higher job satisfaction than men, possibly because women do different types of jobs, are more dedicated to their job, are more likely to quit if they are not satisfied, or expect less from their work. Other studies, though, do not find any substantial difference between genders (Sousa-Poza 2000).
    The gender dummy was constructed to take the value 1 if the individual is female and 0 if it is a male. Since there was no option in the survey to report transgendered/binary people, those not reporting their gender were treated as missing values and therefore were dropped from the sample.

  - Education level: Education does not have a straight-forward effect on job satisfaction. Clark and Oswald (1996) report a negative relationship, due to the so-called "curse of high aspirations", as more education sometimes makes you overqualified for some jobs and landing on a post inferior to your skills and competencies makes you less satisfied.
    I follow Mysíková (2013) that uses the same dataset, and use 7 classifications of educational attainment, harmonised across countries according to the International Standard Classification of Education (ISCE) system.
  - Income: In the existing literature various types of income measures have been used, namely absolute income, comparison income (Ferrer-i-Carbonell 2005) or wage changes (Clark 1999, Clark and Oswald 1996, Grund and Sliwka 2003). There is no consensus on which is the most accurate measure that predicts job satisfaction or on the sign of the effect of each type on job satisfaction. The ESS5 data includes individual gross pay before deductions for tax and insurance but this variable is reported in different measures by different individuals and has many missing

values. Therefore the variable for household income, reported in deciles per country is instead used as in Lange (2014) and Mysíková et al. (2013).

- Intrinsic characteristics

  These variables are subjective opinions concerning intrinsic aspects of work, such as work-variety, risky job, hard work, and work-life balance. All of them are reported in scales and are not transformed into dummy variables, so that they explain as much of the variation in job satisfaction as possible.

- Extrinsic characteristics

  These variables are mainly subjective opinions concerning extrinsic aspects of work, such as supportive colleagues, secure job, flexibility, advancement opportunities and autonomy. For the reason explained before, they are reported in scales and not in dummy variables. Other subjective variables in this category are:

  - Fair payment: The subjective evaluation of one's own income incorporates ideas on how s/he should be compensated for the effort put at work. Feeling satisfied with pay is a significant determinant of overall job satisfaction. Green & Gallie (2002) confirm that the lack of fair pay, has a significant deteriorating impact on satisfaction with work.

    To capture this effect a 5-scale categorical variable was used reporting how the individual feels about the appropriateness of the pay he/she receives.

  - Living well: Easterlin (1974) argued that an individuals' perception of their income is relative to how much those around them earn. Moreover, it may not be just the absolute value of the income that matters, but how much that income can offer you in terms of living well. To this end, a 4-scale categorical variable was used indicating how well off one is with his/her household income, ranging from living comfortably to finding it very difficult. The feeling towards household income reflects the individuals' perception of his/her own income and in turn, indirectly influences overall job satisfaction and vice versa (Mysíková 2013).

- Employment characteristics

  These variables illustrate the characteristics of the job and the conditions in which employees work, such as: years of experience & tenure, monthly income, union membership, company size, working contract type (limited, unlimited, etc.), working hours, etc.

- Company size: Idson (1990), using US data, found a negative relationship between job satisfaction and the size of the company that an individual belonged to. Even though bigger companies normally offer higher wages, this factor does not drive overall satisfaction upwards.
  The variables that controls for the effect of company size on job satisfaction are four, controlling for less than 10 to more than 500 workers in each company/organization.

- Hours Worked: The findings concerning hours worked are contradictory in the literature. There is evidence from the UK suggesting that full time work is associated with higher life satisfaction among men than part-time work (Schoon, Hansson, & Salmela-Aro 2005). Though, no difference between part-time and full-time work is reported in other studies using international data (Blanchflower & Oswald 2004). Given the positive connection between life satisfaction and job satisfaction the effects are expected to be similar on job satisfaction.