Productivity Gains from Worker Well-Being in Europe

Chiara Peroni,
Maxime Pettinger and
Francesco Sarracino
STATEC Research[1]

Abstract

This article investigates the relationship between well-being in the workplace and labour productivity using a combined dataset covering the business economies of 30 European countries. The dataset combines information on working conditions and on the structure and performance of industries in manufacturing, construction and services. Data are sourced from representative surveys on individuals' working conditions and official structural business statistics. Regressions of labour productivity on measures of worker well-being — job satisfaction and a multidimensional index of job quality — provide evidence that a link between the two variables operates at the aggregate level: industries where worker well-being is higher have higher levels of labour productivity. This result implies that well-being in the workplace is not just desirable in itself, but it also contributes to labour productivity. This is relevant to firms, managers, unions, and policy makers as policies that foster worker well-being consequently can contribute to productivity growth.

This article investigates the relation between well-being in the workplace and labour productivity in European countries using a matched dataset which combines information on working conditions and economic performance from representative surveys.

Well-being in the workplace carries societal and economic consequences. It is increasingly recognized as being connected to health, socio-economic outcomes, and the overall well-being of the population. Worker well-being has gained further relevance due to the transformations of jobs

1 Chiara Peroni is Head of the Research Division, Maxime Pettinger is Data Manager, and Francesco Sarracino is Senior Economist at STATEC Research. The authors wish to thank participants at the IPM Workshop on Productivity and Well-being: Measurement and Linkages held in November 2021 and especially Chris Warhurst for useful comments and discussion. The authors also thank STATEC Research colleagues, Anita Moiseeva and Sarah El-Joueidi and two anonymous referees for comments. Views and opinions expressed in this article are those of the authors and do not reflect those of STATEC and STATEC Research. Emails: Chiara.Peroni@statec.etat.lu, Maxime.Pettinger@statec.etat.lu, Francesco.Sarracino@statec.etat.lu

(emerging of the gig economy, increase of zero-hour contracts), and, recently, the COVID-19 pandemic. These events induced dramatic changes in working conditions and practices, as well as in workers' attitudes towards their jobs, and pose major challenges to decision makers. As an example, in many countries manufacturing and service firms face dramatic labour shortages — what has been referred to as "the Great Resignation" — which impact the overall economy (Brignall, 2021). Among economic outcomes, the relationship between well-being in the workplace and productivity is not only of interest to firms, managers, and unions, but also to policy makers. This is because firm- and industry-level labour productivity are sources of aggregate productivity growth. The link between worker well-being and productivity is the focus of this article.

Throughout the article, we employ the terms worker well-being and well-being in the workplace interchangeably, to indicate the overall evaluation of one's experience in relation to one's job. In the analysis, we use two measures of worker well-being: job satisfaction, which refers to an overall evaluation of the work experience — including relations with colleagues, sense of purpose, autonomy, and economic conditions; and a job quality index, which is based on specific evaluations of several aspects of the experience on the workplace. The main difference between the two measures is that the compilation of job quality draws on a wide array of questions on various dimensions of the work experience, while job satisfaction is measured from answers to a single question. They do, however, intend to capture the same latent concept.

This article contributes to the literature on the relationship between productivity and worker well-being by providing evidence that the relationship exists at the industry level. The evidence is drawn from a matched dataset that combines well-established standard measures of labour productivity with indicators of well-being in the workplace, sourced, respectively, from official statistics and nationally representative surveys.

We use the 2010 and 2015 wave of the European Working Conditions Survey (EWCS) to build the indicators of worker well-being, namely job satisfaction and the index of job quality. The latter is based on workers' explicit evaluation of several dimensions of their job, including income, health and safety, social dialogue, mental health, and work-life balance. Data on labour productivity, employment, investment and other structural and performance indicators come from the 2010-2018 waves of the Eurostat's Structural Business Statistics (SBS). The resulting, pooled dataset, covers much of the business economies — 68 manufacturing, service, and construction industries — in 30 European countries. We use this combined dataset to estimate an empirical model of labour productivity.

Regression results show that industries with higher worker well-being display higher levels of labour productivity. Moreover, well-being in the workplace predicts productivity growth, with industries with higher satisfaction displaying higher future productivity growth. The size of the partial correlations of our measures of worker well-being is comparable in magnitude to that for investment per worker, and in some cases it is larger than the coefficients for wages. This result has policy relevance as it shows that worker well-being is not only a desirable goal *per se*, but it also contributes to productivity growth and, as a result, to economic prosperity. This suggests that a virtuous cycle of increasing well-being and growth can be established with appropriate actions.

The article consists of five main sections. Section 1 provides a literature review of the relationship between job satisfaction and productivity. Section 2 describes the data. Section 3 presents the framework. Section 4 provides the results from the analysis. Finally, section 5 discusses limitations of the data and analysis, and provides some concluding remarks.

Literature Review

The relationship between worker well-being, incentives and performance at work has been addressed by several disciplines, from psychology to organizational sciences and economics, both in theoretical and empirical settings. Many studies in the field of psychology investigate the link between well-being in the workplace — conceptualized as positive emotions, affect and engagement — and job performance from an individual perspective. These studies show that happier workers are more pragmatic, less absent, change jobs less often, make fewer mistakes in performing tasks, have less accidents, earn more money, have better relationships with colleagues and customers (Bateman and Organ, 1983; George and Brief, 1992; Pavot and Diener, 1993; Spector, 1997; Wright and Cropanzano, 2000). All these aspects are linked to productivity and profitability. Judge *et al.* (2001) provide an overview of studies in organizational psychology on the job performance – job satisfaction relationship. They conduct a meta-analysis on 312 samples and find a mean correlation of 0.3 between the two variables (job performance assessment is mainly based on supervisors' evaluation.)

Oswald *et al.* (2015) provide experimental evidence showing that positive shocks to happiness generate productivity gains. Such gains stem from increased effort rather than from higher precision in executing standardized tasks. The authors find that productivity is affected by short-run and artificially-induced increases in happiness, as well as by long-lasting shocks such as family bereavement, parental divorce and health problems.

The studies above have been conducted on individual-level data and focused on individual performances. Other studies have addressed the link between worker well-being and workplace performances. Using a meta-analysis approach, Harter *et al.* (2020) study the relationship between worker engagement and various indicators of business outcomes. The authors show that companies in which employees report higher engagement with their jobs experience less absenteeism, higher employees retention, higher customer satisfaction, fewer safety incidents, less theft, and higher product quality. What is more, engagement positively correlates with worker well-being and organizational participation, on the one hand, and broader business outcomes such as profitability and sales on the other. For the period 1984-2009, Edmans (2011) show that companies listed in the

"100 Best Companies to Work For in America" exhibit superior long-run stock market returns (compared to a benchmark), which suggests that employees' satisfaction has a significant positive impact on firm value.

All the studies above suggest the existence of a link between worker well-being and a variety of worker and firm outcomes. The evidence, however, is primarily based on small samples, case studies, or experiments, and as such is not generalizable. Studies based on representative datasets are scarce. Among the latter, two notable analyses are those of Bryson *et al.* (2017) and Bockerman and Ilmakunnas (2012): these authors study the link between job satisfaction and labour productivity for, respectively, the United Kingdom and Finland using establishment-level data. Bockerman and Ilmakunnas (2012) find a positive effect of job satisfaction on labour productivity in a sample of Finnish manufacturing plants. The study is conducted on a matched dataset which combines a measure of job satisfaction from a survey on European households to plant-level administrative data, from 1996 to 2001. The authors find that a one point increase in job satisfaction (measured on a 1 to 6 Likert scale) increases plants' labour productivity by nearly 5 percentage points. The positive significant effect of job satisfaction on labour productivity remains when applying an instrumental variable approach.

Bryson *et al.*(2017) analyse data from the Workplace Employment Relations Survey, conducted on a sample of British workplaces from 2004 to 2011. The authors measure job satisfaction by aggregating employee satisfaction scores concerning nine aspects of their working environment, and by an indicator of affect. They estimate cross-section and panel regressions (to account for unobservables), and find that job satisfaction has a positive and significant effect on the various (evaluative) measures of business performance. In contrast, job-related affect is never significant.

Another stream of literature investigates the link between productivity and intangible factors of production using firm and plant-level data. Recently, these studies have increasingly focused on the role of human factors and workplace practices, including management and HR practices, in explaining productivity patterns and variations. Overall, they find that intangible human factors impact productivity. For example, Black and Lynch (2001) address the relationship between productivity, workplace practices, human capital and the adoption of information technology by estimating a production function on data from a representative sample of US businesses. They find evidence that employee participation and profit sharing, aspects that are linked to worker satisfaction, are associated with higher productivity at the establishment level. Other contributions investigate the role of management (Bloom *et al.*, 2019), worker skills (Criscuolo *et al.*, 2021), and specific aspects of working conditions on work-life balance (Bloom and Van Reenen, 2006).

Data

The dataset used in this analysis provides information on labour productivity and factors used in production, measures of well-being in the workplace, working conditions and workforce characteristics from, respectively, Eurostat's Structural Business Statistics (SBS) and the European Working Conditions Survey (EWCS). Observations are at the industry level and cover manufacturing, construction and service industries for European countries. To the best of our knowledge, no single representative cross-country dataset is available which permits to observe both productivity and worker well-being, so we combined information from the two datasets.

The European Working Conditions Survey (EWCS) (Eurofound, 2010 and 2015) is a nationally-representative survey conducted by Eurofound every five years on random samples of workers in European countries. The latest survey interviewed about 44,000 workers in 35 countries.[2] The survey provides detailed information on respondents' working conditions, employment status, characteristics of the workplace, and selected socio-demographics. It has, however, limitations in terms of periodicity and sample sizes (Warhurst *et al.*, 2018). The survey is conducted every five years, which limits considerably the possibility to exploit the time-series dimension of the data. It is representative of workers at the country level; due to limited sample sizes, however, certain cells at the industry level may contain a small or very small number of observations. Despite these limitations, the EWCS is the only source of exhaustive information on working conditions for European countries. As such, it is the workhorse of studies on job quality for these countries (Wright *et al.*, 2017). Here, we use the 2010 and 2015 waves.[3]

The SBS is a harmonized dataset which provides information on the business economy's performance and structure, including labour productivity, turnover, value added, investments, and employment at the industry level (NACE 2-digit).[4] It is compiled from surveys conducted on firms by the EU and European Economic Area (EEA) national statistical offices, and harmonized by Eurostat. It covers manufacturing, construction, and business services, and has yearly frequency. The survey does not cover agriculture, financial services, public administrations and certain non-market activities (culture, health and personal services). We use all the waves for the period from 2010 to the latest available, 2018.

As EWCS and SBS observational units differ, we combined the two datasets using the country-NACE codes as matching variables. We proceeded by first aggregat-

2 The European Foundation for the Improvement of Living and Working Conditions (Eurofound) is a tripartite European Union Agency established in 1975 to provide research-based input for the development of social, employment and work-related policies. This survey can be accessed at https://www.eurofound.europa.eu/surveys/european-working-conditions-surveys/sixth-european-working-conditions-survey-2015. A useful summary of the survey methodological features is available at https://www.eurofound.europa.eu/sites/default/files/wpef17036.pdf.

3 We did not consider previous waves because we would have not been able to construct comparable job quality indices due to missing information. To mitigate EWCS sample size concerns, involving the number of individual observations available at the industry level, we have run the analysis on a restricted sample of industries, as well as at the NACE 1-digit level. Our results are robust to these robustness checks.

4 Industries are classified according to the classification of economic activities known as NACE rev.2. See https://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF. According to NACE, SBS covers Sections B to N and Division S95 of NACE Rev.2.

ing the individual-level observations in the EWCS data, to construct industry-level indicators of well-being, working conditions and workforce characteristics. Then, we matched this dataset with the industry-level observations from the SBS, using the NACE 2-digit level and country codes available in both datasets. The matching is performed for two periods, which correspond to the 2010 and 2015 waves of the EWCS. We use SBS waves from 2010 to 2018 to compute growth rates of variables of interest.

The resulting combined dataset covers 68 manufacturing, construction and service industries for 30 countries.[5] We observe 2,040 unique industry-country pairs in two years, 2010 and 2015, which gives a total of 4,080 observations. The set of variables includes labour productivity, investment, persons employed, selected employee and business characteristics, working conditions, wages, and worker well-being. The dataset includes also the growth rates of productivity, investment and employment for the 3-periods ahead, i.e. for the periods 2011-2013 and 2016-2018.

As mentioned above, the dataset carries the drawbacks of the EWCS. In addition, its coverage is limited by the geographic and economic scope of the SBS, which excludes public services and financial industries. Despite these limitations, this dataset has the advantage of combining information on working conditions and job satisfaction with a conventional measure of productivity, which would not be available otherwise. To better gauge the information content of the dataset, we computed how much of total economy value added and employment the observed industries account for. Our sample accounts for, on average, 60 per cent of the economy total employment, and 50 per cent of total value added. The country-level employment coverage varies from a low of 48 per cent for Greece, to a high of 73 per cent for Latvia. We have also analysed patterns of missing values in the combined dataset and in the EWCS. In the combined dataset, missing values are more frequent for Eastern European countries, and for mining and quarrying activities (section B of the NACE) for the productivity variables. For job satisfaction and job quality variables, missing values are more frequent for certain service activities (sections B, J, M and N).[6] In the following section, we detail the variables used in our analysis.

Measures of worker well-being

We use two measures of worker well-being: job satisfaction and job quality. These measures are intended to capture. the same latent concept: well-being in the workplace. Job satisfaction comes from answers to the question "On the whole, are you very satisfied, satisfied, not very satisfied or not at all satisfied with working conditions in your main paid job?". Individual answers are coded on a scale rang-

5 Countries in the dataset are listed in the online Appendix D. Found at http://www.csls.ca/ipm/43/IPM_43_Peroni_Appendix.pdf.

6 This analysis is available from the authors upon request.

ing from 1 to 4, where higher scores indicate higher well-being. Job satisfaction is regarded as one of the satisfaction domains contributing to subjective well-being — an overall, self-reported evaluative measure of how people fare with their life as a whole. Previous studies indicate that surveys' single-item questions on job satisfaction provide valid and reliable measures of people's experience in the workplace (Van Saane *et al.*, 2003; Dolbier *et al.*, 2005). Job satisfaction is increasingly used in the economic literature to capture well-being in the workplace.

The job quality index is a composite indicator which combines several dimensions of the working experience. Specifically, it is compiled drawing on survey respondents' evaluations of the following aspects of the work experience: income and benefits, working time and work-life balance, social dialogue, skills development and training, safety and ethics, and stress at work.

The literature on the quality of work proposes a variety of indices of job quality. This reflects a lack of consensus on the definition of job quality, but also problems related to data quality and availability (Warhurst *et al.*, 2018).[7] Warhurst *et al.* (2017) recommends the following dimensions to construct job quality indicators for the UK: pay and other rewards; intrinsic characteristics of work; terms of employment; health and safety; work-life balance; and representation and voice. Bryson *et al.* (2017) use the following domains of job satisfaction: pay, sense of achievement, scope for using initiative, influence over the job, training, opportunity to develop skills, job security, involvement in decisions, and the work itself. Job quality indices based on EWCS data have been proposed by Green and Tarek (2012) and Munoz de Bustillo *et al.* (2011). The latter has been subsequently employed by Anton *et al.* (2012) to analyse the characteristics of poor quality jobs in Europe. This index includes five dimensions: pay, intrinsic characteristics of work (including autonomy, meaningfulness and skills), work-life balance, health and safety, and terms of employment. One can see that, despite the differences, there is a considerable degree of overlap across these proposals.

For the construction of our index, we followed the framework outlined in the United Nations Handbook on measuring quality of employment (UNECE, 2015), as this represents one of the two most recent contributions on the topic by an international organization concerned with the measurement of human development (OECD, 2017). We adapted it to the data at hand. Compared to the UN framework, we added a stress dimension to capture mental well-being, an aspect which is becoming increasingly relevant in the debate on working conditions. We could not account for the domains on employment-related relationships and motivation, and security of employment and protection, due to lack of available data. Another limitation of our job quality index is that it does not incorporate much information on intrinsic job characteristics, such

7 On the notion and operationalization of job quality one can see Warhurst *et al.* (2017), Green (2021), and Wright*et al.* (2017).

Table 1: Correlation Table: Selected Variables

	Labour prod.	Job quality	Job satisfaction
Labour prod.	1		
Job quality	0.1143	1	
Job satisfaction	0.1021	0.4774	1

Source: authors' calculations

as, for example, meaningfulness or sense of achievement. These aspects are the main departures of our index from the proposal by Munoz de Bustillo *et al.* (2011).

Note that the literature on job quality tends to view job quality and workplace well-being as two distinct concepts. The dimensions of job quality are rather seen as determinants of well-being (Green, 2021; Warhurst *et al.*, 2017; OECD, 2017). Here we depart from this view, and we employ a job quality index as a multi-dimensional measure of well-being in the workplace. The specific wording and methodology underlying the job quality index make it a measure of worker well-being that is complementary to job satisfaction. This allows us to ensure that the results do not depend exclusively on a single-item variable.

Note that we aggregated individual answers to obtain average measures of worker well-being at the level of the industry.[8] We also constructed a measure capturing the industries' share of satisfied and very satisfied workers.

Labour productivity is measured by gross value added per employee. An alternative indicator of labour productivity, value added per person employed, yields similar results. Thus, we omitted it from the presentation.[9] Workforce and industry characteristics are: age of employees; employees' education level; firm size (defined in terms of number of employees); industries' employment share; investment per worker; sector the industry belong to (manufacturing, construction and services). The education variable has three categories, corresponding to aggregations of the ISCED classification of educational levels. Category one, two, and three include, respectively: primary and lower secondary education; upper secondary and vocational training; tertiary, that is, graduate and post-graduates degrees. All economic variables are expressed in constant Euros, and the base year is 2015.

Table 1 presents pairwise correlations of labour quality, job satisfaction and labour productivity in the dataset. All correlations in the table are positive and significant. The correlation between the two measures of worker well-being – job quality

8 On-line Appendix A provides further details on the construction of the job quality index. http://www.csls.ca/ipm/43/IPM_43_Peroni_Appendix.pdf.

9 Labour productivity per person employed is an alternative, commonly used measure of labour productivity. In contrast to labour productivity per employee, which considers the number of people who are in the payroll, it takes into account the number of people involved in production. Thus, it is regarded as better suited to capture productivity performances of self-employed, family firms, and certain activities, such as professional services. In our case, difference in results are negligible. Another commonly used productivity indicator, labour productivity per hour of work, is not available in our data sources.

Table 2: Descriptive Statistics (pooled sample)

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Labour productivity	3,495	69.378	213.204	-355.714	23.676	77.728	10,686.05
Labour prod (total growth)	3,368	0.019	0.293	-4.516	-0.082	0.126	5.047
Labour prod (yearly growth)	3,308	0.012	0.129	-1.501	-0.026	0.044	4.498
Investment per worker	3,389	16.903	80.657	0	2.159	10.4	3,494.00
Investment pw (total growth)	3,253	-0.008	0.639	-4.156	-0.279	0.283	4.132
Investment pw (yearly growth)	3,143	0.039	0.28	-1.322	-0.075	0.115	5.172
Employment share	3,376	0.016	0.023	0	0.003	0.019	0.22
Empl. share (change)	3,279	-0.001	0.003	-0.032	-0.001	0.0002	0.046
Job quality	3,188	6.324	1.603	0	5.333	7.308	12
Job satisfaction	3,241	3.028	0.448	1	2.833	3.25	4
Age	3,239	41.944	7.214	18	38	46	72
Education	3,185	2.117	0.483	1	1.875	2.429	3
Wage	3,051	1,557.10	1,777.73	1.194	880.968	1,754.59	37,851.14
Large firms	2,895	0.196	0.278	0	0	0.333	1

Note: Pooled sample (2010 and 2015). *Labour productivity* is gross value added per employee, in thousands of Euros (volumes, 2015); *Investment per worker* is the investment per employee, also in thousands of Euros (volumes, 2015); *Employment share* is the share of total employment accounted for by a given industry in a country; *Age* is in years; *Education* is coded from 1 to 3 (1: primary and lower secondary, 2: upper secondary and vocational, 3: tertiary education); *Large firms* is the proportion of large firms ($\geq$ 250 employees) in a given industry. *total growth* and *yearly growth* denote respectively: the variable's total, cumulated growth over a 3-years period; the variable's average yearly rate of growth computed for a 3-year period.

and job satisfaction – is about 0.5 and statistically significant.[10]

Table 2 presents descriptive statistics for the variables in the dataset. Descriptives have been calculated by pooling the observations across countries and the two years of observations, 2010 and 2015. On average, labour productivity grew by 1 per cent yearly, and by 2 per cent over a 3-years period. The "average" worker is 42 years old with a secondary degree. The proportion of large firms in a given industry is, on average, 20 per cent. The average level of reported labour satisfaction is 3 (on a scale from 1 to 4) corresponding to "satisfied" (with a standard deviation of 0.45).

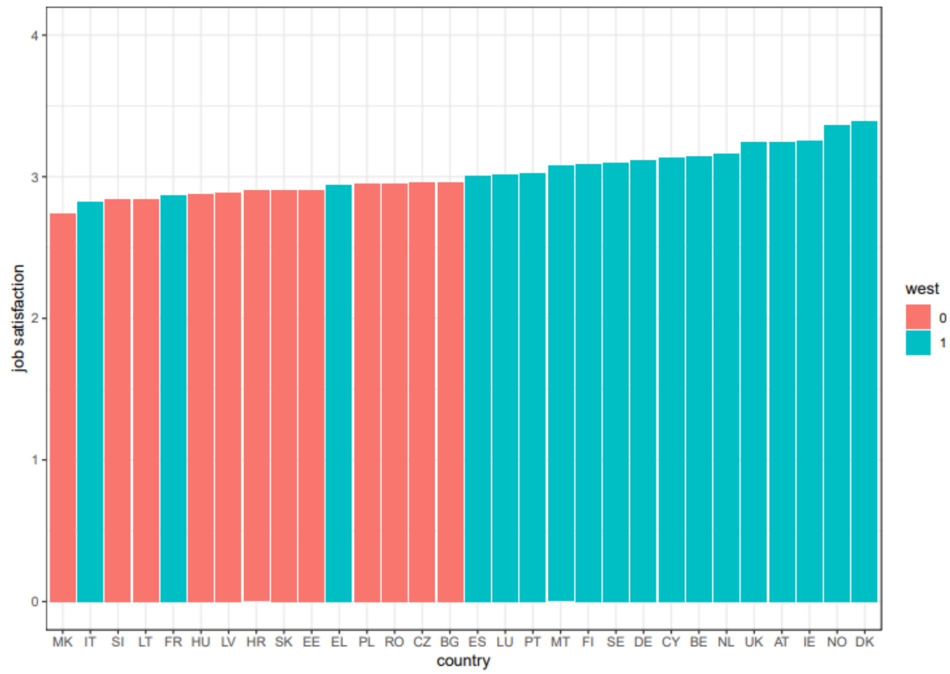
Charts 1-4 present aggregate average levels of job satisfaction and job quality by country and by groups of economic activity.[11] Job satisfaction is higher in Western European countries (denoted by blue boxes), with some notable exceptions, such as Italy, France and Greece. Job quality has its highest average levels in Scandinavian countries, and its lowest average in Greece. Across broad groups of economic activities, the data suggest that job satisfaction is about the same across sectors, whereas job quality is somewhat lower in construction — a feature that is more marked in Eastern European countries.

Chart 5 depicts average levels of labour productivity by country. Western European countries are characterized by higher levels of labour productivity compared to Eastern European countries. The lowest levels of productivity are recorded for Makedonia, followed by Bulgaria and Ro-

10 The correlation between the two measures of productivity is significant and close to 1, specifically 0.9968, so we do not report correlations for labour productivity per person employed in the table.

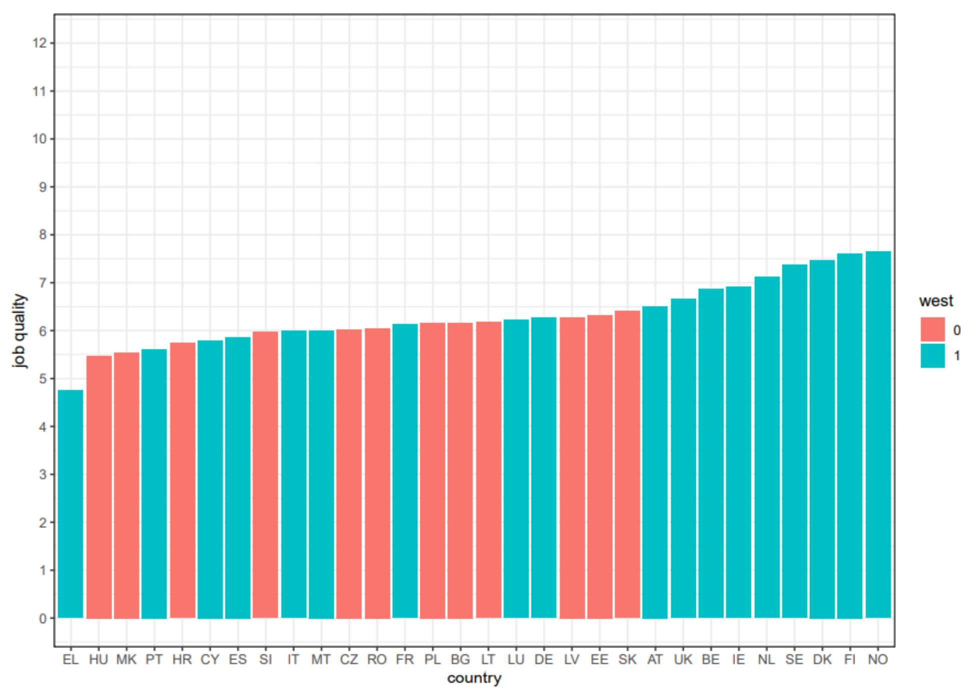
11 Country codes and corresponding country names are listed in Appendix D. http://www.csls.ca/ipm/43/IPM_43_Peroni_Appendix.pdf.

Chart 1: Job Satisfaction: Average by Country



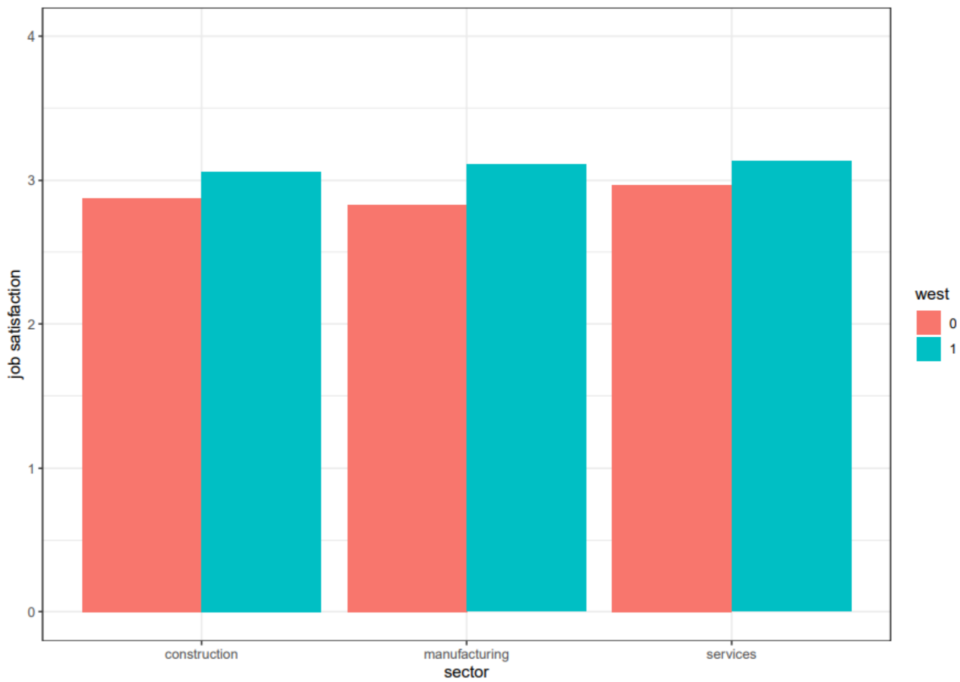
Note: Country averages of job satisfaction (pooled sample). The blue and red boxes denote, respectively, Western and Eastern European countries.
Source: EWCS.

Chart 2: Job Quality: Average by Country



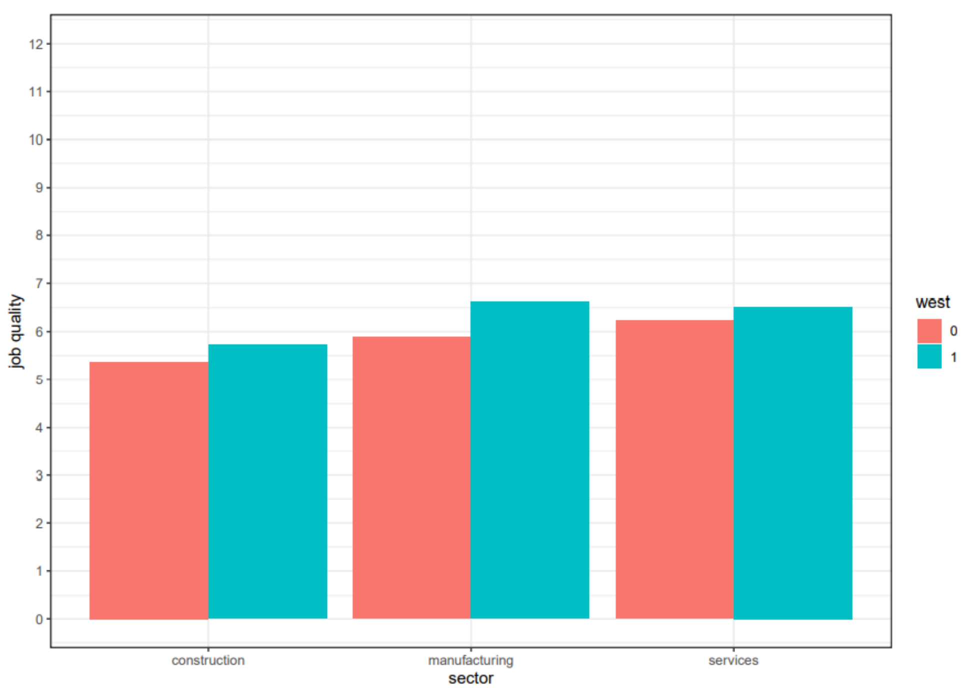
Note: Country averages of job quality (pooled sample). The blue and red boxes denote respectively, Western and Eastern European countries.
Source: EWCS.

Chart 3: Job Satisfaction: Average by Sector



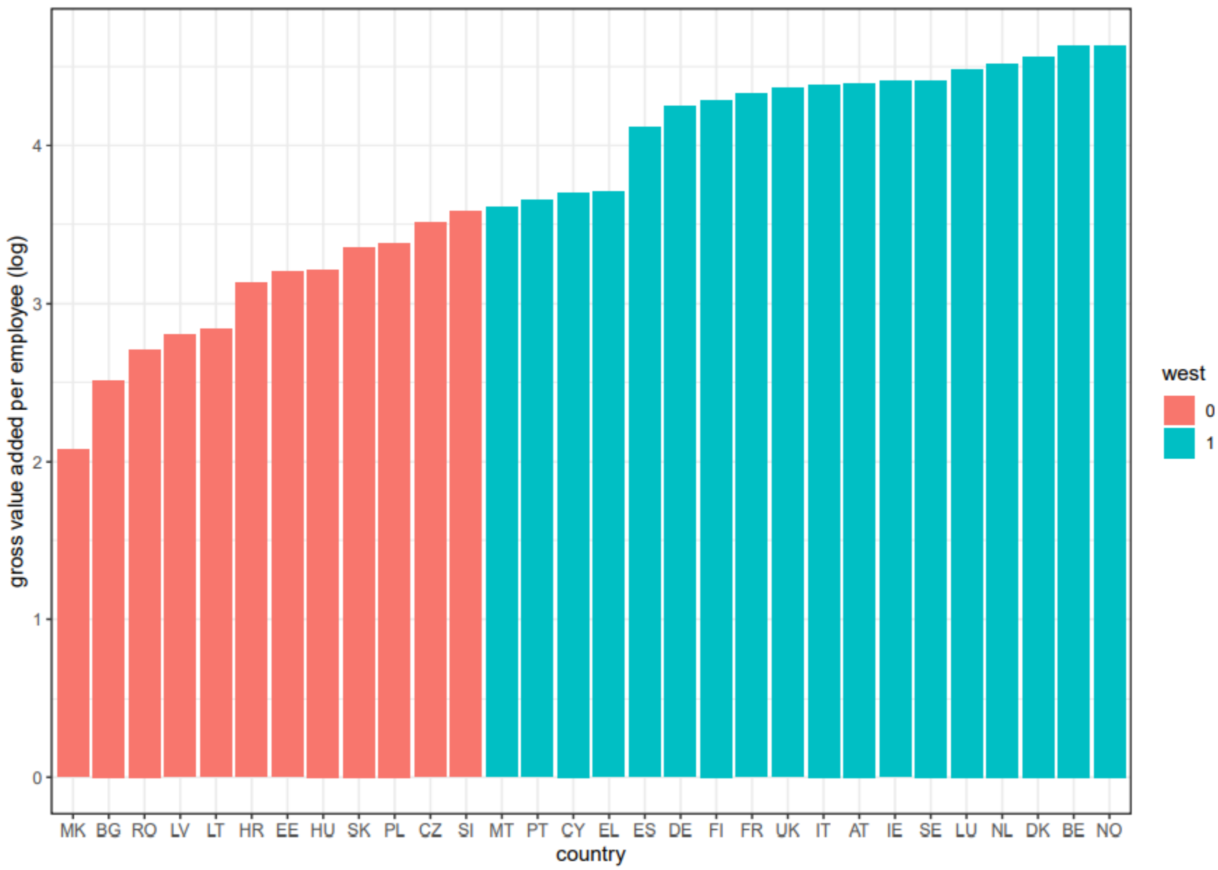
Note: Sector averages of job satisfaction (pooled sample). The blue and red boxes denote, respectively, Western and Eastern European countries.
Source: EWCS.

Chart 4: Job Quality: Average by Sector



Note: Sector averages of job quality (pooled sample). The blue and red boxes denote, respectively, Western and Eastern European countries.
Source: EWCS.

Chart 5: Labour Productivity: Average by Country



Note: (Log of) Labour productivity; the blue and red boxes denote, respectively, Western and Eastern European countries.
Source: SBS.

mania, while highest levels are those of Norway, Belgium and the Netherlands.

Method

Our empirical analysis rests on a standard model of labour productivity growth, derived from a Cobb-Douglas production function. The function links output to standard inputs to production — capital stock and labour — and to a residual, referred to as total factor productivity (TFP), which typically captures efficiency in inputs uses, technological improvements, and intangible factors of production. The term "intangibles"[12] refers to variables, or assets, such as human capital and skills, knowledge and organizational capital, management and HR practices. Intangibles are now a focus of at-

12 Increasing availability of data, and theoretical developments, have resulted in an increasing number of empirical studies on the role of intangibles assets in production and in explaining productivity patterns. Certain types of intangibles are now included in labour productivity decomposition and in datasets such as those produced by the OECD and EU-KLEMS. The set of intangible capital considered by economists has broadened over time from the initial set of human-related capital, such as personnel skills, and innovation-related variables such as R&D and software, to include aspects of the working environment, such as management and HR practices. On intangibles, one can see, for example, Corrado *et al.* (2022), and reference therein, and Bloom *et al.* (2016).

tention of productivity studies, as evidence shows they play a considerable role in explaining productivity patterns. The set of intangibles has also broadened over time, as more data sources have become available. Present analysis follows DiMaria *et al.* (2020) in considering well-being in the workplace as an intangible factor of production.

The Cobb-Douglas production function can be written as follows:

$$Y = e^{A(JS)} * K^{\alpha} * L^{(1-\alpha)} \tag{1}$$

Here, we assume constant returns to scale in labour and capital. Note that the TFP residual A captures the effect of worker well-being (denoted by JS). Thus, we regard worker well-being as an intangible factor of production.[13] Dividing by L and taking logs we obtain:

$$ln(Y/L) = A(JS) + \alpha * ln(K/L) \tag{2}$$

Based on the equation above, labour productivity growth can be expressed as the sum of (a function of) capital deepening (the change in capital per worker) and the change in the "residual" A, which depends on the intangible factors:

$$\Delta ln(Y/L) = \Delta A(JS) + \alpha \Delta ln(K/L) \tag{3}$$

The framework above lays the ground for our empirical models. The baseline model is a regression of the level of labour productivity on average job satisfaction and a set of controls:

$$ln(Y/L)_j = \alpha + \beta ln(I/L)_j + \gamma JS_j + \rho X_j + \epsilon_j, \tag{4}$$

where labour productivity depends on investment per worker (I/L), worker well-being (JS - which denotes either job satisfaction or job quality), and a vector of control variables X. The vector of controls includes workforce characteristics (age and education), the proportion of large firms in the industry j, the industries' labour shares, and average wages by industry and country. The characteristics of the workforce are known to affect economic outcomes, so it is reasonable to include them in the regression. In addition, large firms are typically characterized by higher productivity. The labour share captures the use of the labour input by industries. The dataset does not include capital stock, so we approximate capital stock by investment. The error term is ϵ. The subscript j denotes the industry.

The model also includes year, country and sector dummies. Dummies allow us to capture sector-specific effects and country-level characteristics. Country dummies capture country institutional features. The inclusion in the model of the sector dummy is motivated by the descriptives presented in the the previous section.

We also specify and estimate the model for the response variable's growth rates. We regress labour productivity growth on the levels of job satisfaction and the con-

13 One could specify the function $A(JS)$ as follows $A = \delta * JS^{\lambda}$.

trols:

$$\Delta ln(Y/L)_{j,t} = \alpha + \beta \Delta ln(I/L)_{j,t} + \gamma JS_{j,t} + \rho Z_{j,t} + \epsilon_j \quad t = 2010, 2015. \tag{5}$$

where the vector Z includes controls for industry-workforce characteristics, as for the model in levels. Additionally, we control for the "initial" level of productivity and the change in industries' employment shares. The level of productivity in the beginning of the period typically captures time persistence and, possibly, a convergence mechanisms. The changes in industries' employment shares, i.e. in the number of workers employed by each industry, possibly captures between-industries reallocation effects. We also include year, country, and sector dummies. We compute labour productivity growth in two different ways: we take the cumulated (log) change in productivity between t and $t+3$, and the yearly growth rate of labour productivity computed by averaging the labour productivity growth of the three periods ahead, $t : t+1, t+1 : t+2, t+2 : t+3$. We use two different measures of productivity growth to check the robustness of the findings

Considering the relation between job satisfaction in a given period and the *change* in labour productivity in the following periods is interesting *per se*. This amounts to check whether industries "endowed" with different amounts of job satisfaction exhibit significant differences in productivity growth. Moreover, the specifications in growth rates allow us to mitigate the possible presence of reverse causality.[14]

The models are estimated on the pooled datasets for the years 2010 and 2015 using Ordinary Least Squares (OLS) and robust standard errors clustered by year.[15]

Results

Table 3 reports results from the estimation of the regression models in levels. The coefficients of job satisfaction and job quality are small, but positive and statistically significant. The magnitude of the coefficients is, respectively, 0.047 and 0.044. This indicates that a unit increase in average job satisfaction in an industry is associated to about a 5 per cent increase in labour productivity. Note that, as job satisfaction is measured on a scale from 1 to 4, a unit increase in job satisfaction represents a sizeable increase in the variable.[16] Our baseline results are comparable with the estimate by Bockerman and Ilmakunnas (2012), which report a coefficient of job satisfaction on standard labour productiv-

14 The lack of sufficient time lags does not allow us to estimate a fixed-effect model. In other words, our dataset, which observes working conditions variables in two years only, does not permit to fully exploit the time series dimension of the data.

15 Overall, empirical results are not very sensitive to the errors' variance-covariance matrix specification for the model including job satisfaction. In contrast, results do change for the model with job quality, which now retains significance across specifications, compared to the assumption of homoskedasticity.

16 While individual responses are ordinal, we take averages at the industry level, so we can regard the well-being variables as continuous, albeit bounded.

Table 3: **Regression of Labour Productivity on Job Quality and Job Satisfaction (levels)**

	Dependent variable:		
	Labour productivity		
	(1)	(2)	(3)
job quality	0.044***		
	(0.000)		
job satisfaction		0.047***	
		(0.006)	
satisfied (share)			0.077 ***
			(0.005)
age	0.000	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
education	0.241***	0.257***	0.260***
	(0.026)	(0.026)	(0.027)
large firms	0.076***	0.097***	0.096***
	(0.016)	(0.017)	(0.017)
employment share	-2.278***	-2.425***	-2.432***
	(0.075)	(0.122)	(0.123)
investment p.w.	0.327***	0.333***	0.333***
	(0.004)	(0.006)	(0.006)
wage	0.080***	0.083***	0.084***
	(0.014)	(0.003)	(0.003)
sector: construction	0.013	-0.008	-0.009
	(0.013)	(0.017)	(0.017)
sector: services	0.027***	0.035***	0.037***
	(0.010)	(0.010)	(0.011)
Country dummies	*Yes*	*Yes*	*Yes*
Year dummy	*Yes*	*Yes*	*Yes*
Constant	*Yes*	*Yes*	*Yes*
Observations	2,165	2,188	2,188
R^2	0.836	0.832	0.832
Adjusted R^2	0.833	0.829	0.829

Note: $^*p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. Robust standard errors clustered by year. Standard errors are reported in brackets.

ity of 5 per cent in the baseline OLS regression (though job satisfaction is measured on a 1 to 6 Likert scale in their study).

Controls have the expected signs. Ceteris paribus, industries with higher proportions of large firms, more educated workers, and higher wages are characterized by higher productivity levels. Industries with higher intensity of investment (higher investment per worker) are more productive. In contrast, industries which employ larger shares of workers are less productive.

Tables 4 and 5 present estimation results for the models where the dependent variable, productivity, is specified in growth rates (respectively a three-year period growth, and average yearly growth rates). The job satisfaction coefficient is, once again, positive and significant. The job quality coefficient now appears small and only weakly significant. The coefficients on job quality and job satisfaction for the model in average yearly growth rates are positive, significant, with a magnitude of, respectively, 0.003 and 0.029 (Table 5). Controls have the expected signs.

The regression results show that a positive statistically significant association exists between well-being in the workplace and labour productivity at the aggregate, industry level. In other words, industries where workers are on average more satisfied, are also characterized by higher levels

Table 4: Regression of Labour Productivity on Job Quality and Job Satisfaction (Total Growth)

	Dependent variable:		
	Labour productivity		
	(1)	(2)	(3)
job quality	0.006*		
	(0.003)		
job satisfaction		0.059***	
		(0.002)	
satisfied (share)			0.088***
			(0.009)
labour prod. (t_0)	-0.093***	-0.095***	-0.094***
	(0.013)	(0.015)	(0.016)
age	0.000	0.001	0.001
	0.000	0.000	0.000
education	0.037***	0.032**	0.036**
	(0.012)	(0.016)	(0.017)
large firms	(0.023)	(0.016)	(0.018)
	(0.017)	(0.015)	(0.015)
empl. share	-0.537**	-0.544***	-0.550***
	(0.216)	(0.201)	(0.209)
Δ empl. share	-3.394***	-3.204***	-3.210***
	(0.381)	(0.403)	(0.325)
Δ invest. p.w.	0.067***	0.067***	0.067***
	(0.009)	(0.010)	(0.010)
wage	0.015**	0.011***	0.013***
	(0.007)	(0.004)	(0.004)
sector: construction	0.024***	0.021***	0.020***
	(0.002)	(0.001)	(0.001)
sector: services	0.035	0.031	0.033
	(0.029)	(0.029)	(0.029)
Country dummies	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes
Constant	Yes	Yes	Yes
Observations	2,104	2,127	2,127
R^2	0.186	0.190	0.187
Adjusted R^2	0.170	0.174	0.172

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors clustered by year. Standard errors are reported in brackets.

of labour productivity. What is more, they are characterized by higher labour productivity growth.

The last columns in the Tables 3-5 report results for regressions where the explanatory variable of interest is the share of satisfied and highly satisfied workers within an industry. The variable retains its positive significant effect on productivity in all specifications. This shows that results are robust to an alternative specification of the variable of interest.

The tables in on-line Appendix B present regression results in detail, as controls are included in the regressions incrementally.[17] Results indicate that job satisfaction and job quality remain positive and significant following the inclusion of the controls, although the magnitude of the coefficient decreases.

We ran separate regressions replacing the country dummies with a "west" dummy (a dummy for the group of western European countries), in light of the system-

17 http://www.csls.ca/ipm/43/IPM_43_Peroni_Appendix.pdf.

Table 5: Regression of Labour Productivity on Job Quality and Job Satisfaction (yearly growth).

	Dependent variable:		
	Labour productivity		
	(1)	(2)	(3)
job quality	0.003**		
	(0.001)		
job satisfaction		0.029***	
		(0.003)	
satisfied (share)			0.036***
			(0.006)
labour prod. (t_0)	-0.042***	-0.042***	-0.041***
	(0.009)	(0.009)	(0.010)
age	0	0	0
	0.000	0.000	0.000
education	0.018***	0.015***	0.017***
	(0.001)	(0.004)	(0.003)
large firms	-0.001	0.002	0.001
	(0.004)	(0.004)	(0.004)
empl. share	-0.278**	-0.283**	-0.284**
	(0.124)	(0.116)	(0.119)
Δ empl. share	-3.782***	-3.488***	-3.520***
	(0.128)	(0.033)	(0.137)
Δ invest. p.w.	0.045***	0.047***	0.046***
	(0.005)	(0.004)	(0.004)
wage	0.011*	0.009*	0.010*
	(0.006)	(0.005)	(0.005)
sector: construction	0.009***	0.008***	0.007***
	(0.003)	(0.002)	(0.002)
sector: services	0.015	0.014	0.015
	(0.011)	(0.011)	(0.011)
Country dummies	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes
Constant	Yes	Yes	Yes
Observations	2,035	2,056	2,056
R^2	0.154	0.161	0.155
Adjusted R^2	0.137	0.144	0.139

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors clustered by year. Standard errors are reported in brackets.

atic differences in the average value of the outcome variable between the two regions. The estimation of the models yields positive and significant coefficients for both measures of well-being.[18]

Overall, these results indicate that job satisfaction and job quality are positively and significantly associated to productivity and productivity growth, so that increases in the quality of work and worker well-being are correlated to higher productivity levels or growth rates. This association is not only statistically significant, but it is also economically meaningful.

To gauge the economic relevance of results, we have standardized the variables to obtain comparable regression coefficients. The tables in on-line Appendix C provide the corresponding results.[19] For instance, if we compare the coefficient of the share of satisfied workers (0.019 in Table 13 in Appendix C) with the size of the coefficient

18 Results not reported for reasons of space, but available from the authors.

19 http://www.csls.ca/ipm/43/IPM_43_Peroni_Appendix.pdf.

Table 6: Economic Significance of Worker Well-being. Percentages are Based on Estimates Using Standardized Variables

	Models		
	levels	total growth	yearly growth
job satisfaction	4.5%	61.6%	98.0%
job quality index	15.9%	22.6%	36.7%
share of satisfied workers	3.7%	46.6%	62.0%

Note: The coefficients of job satisfaction and job quality are expressed as a percentage of the coefficients of investment per worker. The complete set of regressions is available in online Appendix C. The model in levels (first column) refers to the coefficients from Table 13, the model using cumulative growth (second column) refers to the results from Table 14, the model with yearly growth (third column) refers to results from Table 15.

of investment per worker (the largest correlate of productivity, with a coefficient of 0.505), we see that the coefficient of job satisfaction is 4.5 per cent the size of the coefficient of investment per worker. This can be regarded as a small contribution. However, it is nearly half the size of wages (0.056). Moreover, this is the worst case we found: if we consider job quality, its coefficient (0.079) is 16 per cent the size of investment per worker (0.496). These percentages are larger when we consider the models in growth terms. For instance, the share of people satisfied with their job is 62 per cent the size of the yearly growth rate of investment per worker (see the coefficients in Table 14 in Appendix C). Such percentage jumps to 98 per cent when we consider average job satisfaction.

Table 6 shows the size of our measures of worker well-being as a share of the coefficient of investment per worker for each model considered. In sum, this evidence suggests that the size of the effect of worker well-being is comparable to one of the most important predictors of labour productivity, and in some cases it is larger than the effect of wages.

Discussion and Conclusions

The review of the literature highlighted two main obstacles to studies of the link between worker well-being and economic outcomes. First, observing jointly job satisfaction and sound measures of economic performance in representative datasets is difficult. The only study that observes both variables in a representative dataset is Bryson *et al.* (2017), at the expense, however, of having to use self-reported measures of firm performances. Second, the bulk of the evidence reports statistical correlations, rather than a "causal" effect. The relationship between worker well-being and economic outcomes, however, could suffer from an endogeneity bias stemming from reverse causality, or the presence of omitted/unobservable variables.

The only study based on data from representative surveys which addresses reverse causality is Bockerman and Ilmakunnas (2012). These authors instrument job satisfaction with satisfaction with housing, and conclude that the effect of job satisfaction on labour productivity is free from endogeneity bias. This evidence, however, is limited to one country, and is for the period 1996–2001. Here, we address the first of these issues through the use of a combined dataset.

This study provides evidence on the economic consequences of well-being in the workplace, by analysing a novel combined dataset at the industry level. To the best of our knowledge, we are the first to carry out this exercise. The dataset is built by matching two waves of the European Working Conditions Survey with information on the business economy from Eurostat's Structural Business Statistics. Among the different measures of economic outcomes considered in the literature, the use of SBS data allows us to include in the study an official measure of labour productivity, an important variable for decision makers.

The empirical results provide evidence that there is a statistically significant link between worker well-being and labour productivity in industries. We estimate regressions of labour productivity on two measures of worker well-being, namely job quality — an index summarizing various dimensions of working conditions — and job satisfaction, and various controls. The results vary depending on the measure of worker well-being employed and on model specification. For the model in levels, the effects of both measures are positive, statistically significant, and of similar magnitude. Job satisfaction also correlates significantly with future productivity growth. We also gauge the economic significance of results, by comparing the size of coefficients to those of economic variables in the dataset. Data limitations, however, do not allow us to correct for the possible presence of endogeneity bias, stemming from reverse causality or omitted variables. We mitigate this risk by estimating a model in growth rates, and by including as many controls as possible, including industry average wage levels.

The value added of this article can be summarized follows: 1) a novel matched dataset based on representative surveys; 2) a composite indicator of job quality based on the EWCS, a very rich source of information on workers' conditions; 3) evidence that job satisfaction and job quality predict productivity level, and that job satisfaction predicts productivity growth, at the aggregate-industry level.

The study has several limitations which one should keep in mind when interpreting results. There are data limitations. First, the dataset coverage is limited by the Structural Business Statistics. The SBS does not include economic activities which might account for large shares of certain economies in the sample, such as those countries that are service-intensive, or in which public administrations and non-market services are very large. The SBS, however, is the most widely used dataset in the analysis of business sector productivity performances. Indeed, the analysis of the relationship between productivity and worker well-being would be limited by the difficulties of measuring productivity for the industries excluded from the SBS. It is well known that the extension of the concept and measurement of productivity to activities such as non-market and financial services is difficult, if possible at all. Second, sample sizes for the EWCS can be severely restricted at the industry level.

A further issue concerns the measure of job quality adopted in the article. This broadly follows the relevant dimensions indicated by the UN framework, partly departing from it due to data availability issues. The literature lacks consensus on a definition of multidimensional job quality index and implementations vary. Thus, a further limitation is that it is difficult to compare results from this article to other studies in the literature, due to the varied definitions of worker well-being adopted in the literature. Limitations also include the inability to identify causal effects, as discussed above. Moreover, the issue of costs and returns on investments in worker well-being for firms would merit further investigation. To do this, however, one would have to resort to firm-level data which are currently not available.

Despite its limitations, we believe this study contributes to the literature on economic outcomes of worker well-being, and to building a body of evidence based on the relationship between well-being in the working place and economic performance. The results of this study are relevant for managers and policy makers alike as policies that foster worker well-being consequently can contribute to productivity growth. Well-being and economic efficiency (productivity) are often perceived as competing objectives. We show instead that worker well-being has positive impacts on industry-wide productivity. Economic development and well-being do not need to be alternatives; they can reinforce each other.

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