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Summary

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SPLIT-PLOT DESIGNS AND MULTI-RESPONSE PROCESS OPTIMIZATION: A COMPARISON BETWEEN TWO APPROACHES

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Abstract: *Nowadays split-plot designs play a crucial role in technological fields, both for their flexibility when applying a robust design approach and in relation to the modelling step, by considering mixed Response Surface models and/or the class of Generalized Linear Mixed Models (GLMMs). In this paper, a split-plot design is studied in a process optimization scenario involving several response variables, a multi-response situation, where two optimization methods are compared. More precisely, by considering a real case study related to the improvement of a measurement process of a Numerical Control machine for measuring dental implants, the optimization is carried out with the Pareto front approach and then compared with an analytical optimization method obtained starting from the definition of a risk function. In the final discussion advantages and disadvantages of application for both methods are evaluated.*

Keywords: *split-plot designs, multi-response process optimization, Pareto front approach, analytical optimization methods*

1. INTRODUCTION

Process optimization is a key issue for statistical quality control, and its relevance has increased since the long and fruitful scientific debate related to Taguchi's two-step procedure for robust design (Nair, 1992). Currently, the robust design approach involves three key-steps: experimental design, modelling, and optimization. For a successful implementation, it is important to

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involve noise factors starting from the experimental planning, and then modelling them through a suitable analysis in the subsequent optimization phase. Therefore, the concept of process optimization is extended to robust process optimization, where control and noise variables are jointly studied to attain the best set of control factor levels that simultaneously achieves the target value and minimize the process variability with a robust configuration. In this context, the process optimization strictly depends on the designed experiment and on the class of statistical models applied. Specifically, Response Surface Methodology (RSM) approaches (Myers et al., 2016) may be used, or, alternatively, an experimental design may be planned outside the RSM context, modelling the experimental data with a more flexible class of statistical models, e.g. Generalized Linear Models-GLMs (McCullagh and Nelder, 1989; Nelder and Lee, 1991; Lee and Nelder, 2003) or Generalized Linear Mixed Models-GLMMs (Dror and Steinberg, 2006; Robinson et al., 2006; Berni and Bertocci, 2018).

Undoubtedly, the two choices of experimental design and modelling are related to what is known about the process to be studied and optimized; the same line of reasoning should be applied when deciding on which, how many, and the type of response variables have to be considered. In fact, the multi-response situation should be evaluated when the real scenario shows that several response variables are naturally involved, and they are important to the overall process under study. If this is not the case, then a simpler choice should be used, since collinearity, often present among responses (Box et al., 1973; Chiao and Hamada, 2001), can lead to serious complications both in analysis and optimization.

Moreover, in a multi-response situation, the optimization step is crucial, since it is generally not feasible in practical terms to reach an ideal optimum simultaneously for all the responses. In literature there are several methods for achieving optimal solutions as a compromise among several response variables, including Derringer and Suich (1980), Khuri and Conlon (1981), Del Castillo et al. (1996), Copeland and Nelson (1996).

A further issue concerns the conjunction of a multi-response case and the dual response approach. The simultaneous optimization of several variables, jointly with the consideration of two statistical models, e.g., location and dispersion, complicates the analysis and interpretation of results. Indeed, we should make a distinction when considering the differences between the dual response approach, or, alternatively, when a single response model, opportunely weighted with respect to the estimated dispersion values, is applied in a "true" multi-response case. In the latter case, the application of analytical methods for optimizing can give fruitful and satisfactory results, particularly by considering recent developments involving noise factors.

To this end, several optimization measures are suggested in the literature (Lin and Tu, 1995; Tang and Xu, 2002). The Pareto front approach is a multi-response optimization method of the analytical-qualitative type, consisting of two sequential steps: a first step based on objective conditions identifies the dominant solutions, and a second step based on examining the identified alternatives and then selecting the best solution conditions that subjectively match the experimenters' priorities (Lu et al., 2011; Chapman et al., 2014a).

In this paper, data from a split-plot experiment (Berni, 2010) are optimized through the Pareto front approach (Chapman et al., 2014b), and following, the results obtained are compared with a proposal of the analytical optimization method. More specifically, both methods are compared and discussed through an empirical example in the orthodontic field, in order to improve the accuracy in the measurements of a Numerical Control (N/C) machine, which provides some automatic control of machining tools.

This paper is structured as follows: in Section 2, the basics of split-plot designs are reviewed and briefly illustrated. Section 3 provides a short description of both optimization methods, and Section 4 presents the case study including optimization results. The paper ends with a general comparison between the two approaches, and final remarks.

2. SPLIT-PLOT DESIGNS FOR STATISTICAL QUALITY CONTROL: A REVIEW

The split-plot design (Cochran and Cox, 1957) has been developed and characterized over the years, proving to be an experimental design widely used in industrial, technological, and environmental fields, because of the need to restrict randomization on expensive or hard-to-change factors in the experiment.

By considering the developments that the fractional factorial and RSM designs, and modelling have had since the 1980s, the split-plot design has experienced a particular renewal (Box and Jones, 1992), expounding its theoretical features, specific usefulness for the statistical quality control and robust design concepts, initially introduced by Genichi Taguchi, (Nair, 1992). In this context, the two seminal papers of Vining and Myers (1990) and Myers et al. (1992) extended the two-step procedure into the dual response approach, and the combined-array is considered as a milestone for recent developments and robust process optimization. Within this methodological framework, the split-plot design plays a central role, starting from the tutorial by Box and Jones

(1992), in which the authors proposed the split-plot design as an efficient alternative in many experiments, for example with hard-to-change factors, to Taguchi's product-array for a robust design approach, and also in a fractional factorial setting (Bisgaard, 2000).

Recently, split-plot designs have great relevance for the latest developments in robust process optimization, extending the initial concept of the robust design approach, with a focus on the design and modelling steps (Kowalski and Potcner, 2003; Kowalski et al., 2007; Jones and Nachtsheim, 2009). More recently, the split-plot design has been revised and included in the class of *crossed bi-randomized* experimental designs (Myers et al., 2016), given the possibility of including environmental/noise factors as Whole-Plot (WP) factors and process factors as Sub-Plot (SP) factors. The standard allocation of the environmental/noise factors as WP allows for the most accurate estimate of the factors of interest, as well as the estimate of the 1^{st} order interactions, e.g., the 1^{st} order interaction between a WP factor (for example a noise factor) with a SP (process) factor, in order to perform a robust design (Berni and Nikiforova, 2022). This structure is common in many applications, given the generally high cost of controlling the noise factors in production.

Nevertheless, a split-plot design in a RSM context generally requires that all the variables included in the experimental plan (irrespective of whether WP or SP factors) must be quantitative in nature. In fact, in case of a qualitative process variable, the optimization step is conditioned to the levels of the categorical variable involved. To this end, the inclusion of a qualitative variable should be limited (Berni, 2010) or restricted to two levels where they can be treated as quantitative in standard models. Moreover, the presence of measurable noise factors, involved as random effects, is possible when the split-plot design is applied through mixed Response Surface (RS) models, or alternatively, through GLMMs.

Additional developments in the literature have contributed significantly to the inclusion of the split-plot design in RSM, showing the equivalence of *Ordinary Least Squares* (OLS) with *Generalized Least Squares* (GLS) for split-plot designs and mixed RS models (Vining et al., 2005); and improving inference issues (Vining and Kowalski, 2008).

2.1. THEORY ABOUT THE SPLIT-PLOT DESIGN

When implementing a split-plot design, it is essential to begin with a primary classification between WP factors and SP factors. It is therefore desirable to carefully evaluate what is possible in the experimental set-up for the specific process (industrial process, laboratory experiment) under study, considering the exact definition of the response (quantitative) variables. Also, it is necessary to define the role of each variable in the study, in order to plan the split-plot design based on the most efficient arrangement for the specific scenario. This step plays a central role, not only in the attribution of factors as whole-units or sub-units, but also determines the subsequent model estimation, in which each variable plays a specific role, according to its nature (qualitative, discrete quantitative or continuous). It is also a crucial point to clarify the distinction between fixed and random effects.

In short, a Whole-Unit (WU) is defined by runs involving the set of WP factors, and the run order of all the WUs is randomized. Subsequently, the Sub-Units (SUs), defined through the combination of levels (runs) of the SP factors within the WUs, are associated with a particular WU and randomized separately.

In this study, we consider a split-plot design in a RSM context. More precisely, we are interested in applying a standard second-order polynomial model with random effects. The model with random effects for the single experimental observation y_u $(u = 1, \dots, n)$ and J variables $(x_1, \dots, x_j, \dots, x_J)$ is (Khuri, 1996):

$$y_u = \beta_0 + \boldsymbol{f}'(\boldsymbol{x}_u)\boldsymbol{\beta} + \boldsymbol{z}'_u\boldsymbol{\gamma} + \boldsymbol{g}'(\boldsymbol{x}_u)\boldsymbol{\Delta}\boldsymbol{z}_u + \varepsilon_u \tag{1}$$

where β_0 is the intercept; $\boldsymbol{\beta} = (\beta_1, \dots, \beta_p)'$ is the column vector $[p\times 1]$ of the unknown fixed parameters $(p \geq J)$; $\boldsymbol{x}_u = (x_{u1}, \dots, x_{uj}, \dots, x_{uJ})'$ is the vector of design settings at the u-th experimental run; $\boldsymbol{f}(\boldsymbol{x}_u)$ is a vector function of dimension $[p\times 1]$ defined for each $\boldsymbol{x}_u$ and related to the p second-order effects for the J variables. Therefore, $\boldsymbol{F}$ is the so-called "extended" matrix of dimension $[n\times p]$, formed by the n rows $\boldsymbol{f}'(\boldsymbol{x}_u)$; ε_u is the residual error. For the random effects, $\boldsymbol{z}_u = (z_{u1}, \dots, z_{ub})'$ is the vector of binary values $(0,1)$ to describe the presence and structure of the block factors; $\boldsymbol{\gamma} = (\gamma_1, \dots, \gamma_b)'$ is the column vector $[b\times 1]$ of the unknown coefficients relating to the random effects. The matrix $\boldsymbol{\Delta}$ characterizes the 1st order interactions between polynomial effects (fixed) and random effects. The maximum dimension of $\boldsymbol{\Delta}$ is achieved if the interactions of all fixed effects with random effects are included in model (1). Note that this matrix contains the key estimated coefficients for evaluating the robust design as the control-by-noise interactions that can be exploited to achieve robustness.

Starting from the model expression (1), the second-order polynomial model of response surfaces from a split-plot design is outlined, considering quantitative variables only. For further details, see Myers et al. (2016).

Let's consider two sets of factors: $\boldsymbol{z} = (\boldsymbol{z}_1, \dots \boldsymbol{z}_i, \dots, \boldsymbol{z}_I)$ are WP random factors/variables and $\boldsymbol{x} = (\boldsymbol{x}_1, \dots \boldsymbol{x}_j, \dots, \boldsymbol{x}_J)$ are SP variables/factors.[2] Furthermore, let y_u be the u-th observation of the k-th block, for the i-th WP factor and the j-th SP factor respectively $(i = 1, \dots, I; j = 1, \dots, J; k = 1, \dots, K)$; therefore, the second-order mixed RS split-plot model for a single replicate $(K = 1)$ and a single observation u is defined as follows:

$$y_u(\boldsymbol{z}, \boldsymbol{x}) = \beta_0 + \boldsymbol{z}_i'\boldsymbol{\gamma} + \boldsymbol{z}_i'\boldsymbol{\Gamma}\boldsymbol{z}_i + \boldsymbol{x}_{ij}'\boldsymbol{\beta} + \boldsymbol{x}_{ij}'\boldsymbol{B}\boldsymbol{x}_{ij} + \boldsymbol{z}_i'\boldsymbol{\Delta}\boldsymbol{x}_{ij} + \psi_u + \varepsilon_u \qquad (2)$$

where β_0 is the intercept; $\boldsymbol{z}_i = (z_{i1}, \dots, z_{iu}, \dots, z_{in})'$ is the vector of the i-th WP factor; $\boldsymbol{\gamma}$ contains the unknown coefficients of linear terms of the WP variables; $\boldsymbol{\Gamma}$ is the array related to the coefficients of the 1st order interaction and quadratic terms of the WP variables; $\boldsymbol{x}_j = (x_{j1}, \dots, x_{ju}, \dots, x_{jn})'$ is the vector of the j-th SP factor; $\boldsymbol{\beta}$ contains the unknown coefficients of linear terms of the SP variables; $\boldsymbol{B}$ is the array containing 2nd order coefficients for the fixed effects of SP variables; the matrix $\boldsymbol{\Delta}$, contains coefficients of the 1st order interaction effects between the WP and SP factors. The model terms in the matrix $\boldsymbol{\Delta}$ are of primary interest in the context of robust design evaluation. Regarding the two error components, ψ_u is the WP error component and ε_u is the SP error component, where in general the two error components are assumed to be independent and identically Normally distributed, i.e. $\psi \sim iid\, N(0, \sigma_\psi^2)$ and $\varepsilon \sim iid\, N(0, \sigma_\varepsilon^2)$, respectively. In addition we also assume that $Cov(\psi_u, \varepsilon_u) = 0\ \forall u$. The assumptions about the error variances and covariances are equivalent to assume constant covariance between two observations belonging to the same WU, across all its observations.

In the case study illustrated in Section 4, the multi-response case is related to the optimization involving three split-plot models, one for each response, estimated applying the RSM model above.

3. OPTIMIZATION METHODS

This Section includes a short description of both optimization methods considered. The Pareto front approach (Lu et al., 2011; Chapman et al., 2014a; Chapman et al., 2014b) is also illustrated within the case study, considering the application (Subsections 4.2 and 4.3); a brief introduction of the analytical

[2] Please note that we are referring to a factor/variable considering that the experimental region χ is defined by the factor ranges; a finite number of experimental points, forming the experimental design, is then selected by the experimental region. Following, the model estimation is performed within the whole experimental region, by inferring from a discrete set of points, e.g., the experimental points, to a continuous one.

method is illustrated in Subsection 3.2. For further details see (Berni and Gonnelli, 2006; Berni, 2010; Berni and Burbui, 2014).

3.1. THE PARETO FRONT APPROACH

The Pareto front approach is a multi-response analytical-qualitative optimization method, which allows the search for optimum to take subjective priorities and constraints into account, such as those due to a company's requirements (for example, costs or technical/engineering specifications). It consists of two sequential steps (Chapman et al., 2014a; Myers et al., 2016; Anderson-Cook, 2017), as outlined below.

Suppose that χ defines the entire experimental region; within this region a finite set, possibly a grid, of points, is selected and used to estimate the responses of interest and used to define a Pareto-optimal set. A possible solution is called non-inferior (or Pareto-optimal), if and only if, there is no other combination within the set for which the values of all the responses are at least as good, and the value of at least one response is strictly better; otherwise, the solution is called inferior or dominated. The set of non-inferior (or Pareto-optimal) input combinations is called the Pareto-optimal set, and the corresponding set of vectors for the responses under consideration is known as the Pareto front or frontier. Since the inferior solutions are not rational choices conditional on the choice of responses under consideration, they are not considered further and definitively discarded (Zitzler, 1999; Marler and Arora, 2004; Coello Coello et al., 2007). This leads to a reduced number of alternative solutions to be considered further in later stages of the optimization.

The Pareto front approach can be summarized with the following two steps:

1. An objective step, where the Pareto-optimal set is identified from the initial set of choices, based on the corresponding estimated response values;
2. A subjective step, in which the points belonging to the Pareto-optimal set are examined and then compared. Only points that provide the best combination of responses are considered as a compromise among all the estimated response values (quantitative considerations). This choice is based on evaluation and incorporation of the priorities/preferences of the company.

It must be noted that several optimal points corresponding to input combinations could be considered and compared for selection, by considering the priorities of different teams (decision-makers) involved in the study. Therefore, the best optimal solution combines the quantitative results with the decision-makers' priorities. Moreover, graphical methods are a useful tool for discussion, comparison and achieving a consensus among all stakeholders (Anderson-Cook and Lu, 2018).

3.2. THE ANALYTICAL METHODS FOR A ROBUST PROCESS OPTIMIZATION

When dealing with several response variables, it is generally not feasible in practical terms to simultaneously achieve the optimum for each of them with a single input combination. To this end, many authors, starting from the methods suggested by Derringer and Suich (1980) and Khuri and Conlon (1981), have proposed methods to synthetize and optimize the responses, such as Ames et al. (1997), Del Castillo et al. (1996), Rajagopal et al. (2005).

In addition, a further issue emerges when considering the multi-response case and the dual response approach. Here, the simultaneous optimization of several variables jointly with the consideration of two statistical models, e.g., location and dispersion models, increases the complexity and dimensionality of the problem.

In order to solve the latter issue, which could imply a notable computational burden, analytical optimization methods can be defined and simplified starting from the dual approach theory and the building of a suitable performance measure (Leon et al., 1987). To this end, we consider a multiplicative relationship between the expected value $\left(E(y) = \mu(\boldsymbol{x})\right)$ and the process variance $\left(Var(y) = \sigma^2(\boldsymbol{z}, \boldsymbol{x})\right)$ defined as the variance of the response variable. Moreover, the expected value of the response could be identified in relative to the target value (e.g., $E(y) = \tau$), according to the Nominal the Best (NTB), Smaller the Better (STB), or Larger the Better (LTB) situations. At the beginning a general risk function is expressed as follows:

$$R(\boldsymbol{z}, \boldsymbol{x}) = (\mu(\boldsymbol{x}) - \tau)^2 + f\left(\mu(\boldsymbol{x})\right)\sigma^2(\boldsymbol{z}, \boldsymbol{x}) \tag{3}$$

Formula (3) explicitly involves two terms: i) $(\mu(\boldsymbol{x}) - \tau)^2$ which expresses the adjustment to the target value, while ii) $f\left(\mu(\boldsymbol{x})\right)\sigma^2(\boldsymbol{z}, \boldsymbol{x})$ is related to the multiplicative relation between location (adjustment) and process variance (dispersion). Therefore, formula (3) allows for defining specific objective functions in a dual response approach perspective, (Berni and Gonnelli, 2006), and particularly, to optimize several response variables without separately estimating the two statistical models for each response. This approach provides a simplification as well as a weighting of the responses according to their relative importance.

More recently, split-plot designs and modelling have been optimized by explicitly involving one model only for each response in a robust process optimization context, in which random effects are also evaluated (Berni and Bertocci, 2018; Berni and Nikiforova, 2022).

Let's start by defining a general response surface model, y_t $(t = 1, \dots, T)$, for each of the T responses. The simultaneous optimization may be performed considering the T estimated surfaces; each estimated model is evaluated as a single function to be included in the objective function to be optimized. Starting by formula (3) and considering the concept of a dual response approach, a general objective function can be defined as the distance between the estimated surface $\hat{y}_t$ and the corresponding desired target value τ_t:

$$S_t(\boldsymbol{z}, \boldsymbol{x}) = (\hat{y}_t(\boldsymbol{z}, \boldsymbol{x}) - \tau_t)^2 \quad \forall t$$

The approach can be easily adapted for responses where the goal is to achieve a maximum or minimum value. Subsequently, the minimization on the coded experimental region χ is performed by minimizing the sum of all the distances, as follows:

$$\min_{\chi} \left\{ \sum_t S_t(\boldsymbol{z}, \boldsymbol{x}) \right\} \tag{4}$$

The objective function (formula (4)) is optimized conditional on the whole experimental region χ defined by the process variable ranges (and potentially any limiting constraints for other technological issues), as well as involving the estimated confidence interval for each random coefficient when random noise factors are present.

In the following section, we compare the two optimization methods, the Pareto front approach (Subsection 3.1), and the objective function of formula (4), where the goal is to improve the accuracy of the measurement process of a N/C machine, used in the orthodontic field; the measurements of which are analyzed for a generic dental implant.

4. THE CASE STUDY: DATA DESCRIPTION AND PROCESS OPTIMIZATION

In this Section, comparison of multi-response optimization methods is made, after a short description of the experimental planning and data. For further details see Berni (2010).

4.1. SPLIT-PLOT DESIGN AND DATA DESCRIPTION

The aim of the study is to improve the accuracy in measurements for a N/C machine, jointly with a reduction of the measuring time. The machine uses a feeler pin with a movable bridge framework to facilitate the positioning of the measured piece (dental implant). The machine needs specific environmental conditions to function properly, all of which were ensured previously (see Berni and Gonnelli, 2006).

In Berni (2010), five response variables, $T = 5$, were optimized simultaneously applying formula (4) and related to the different positionings of the feeler pin on the dental implant during the process measurement steps. In this paper we focus on the optimization comparison by looking at a subset of three response variables.

By considering the dental implant used to set the measurement process, the three responses are (with their respective targets in brackets): maximum circle diameter-$crmax$ (τ_1: 3.000), minimum circle diameter-$crmin$ (τ_2: 2.790), and eccentricity-$eccen$ (τ_5: 0.000). There is no problem with correlation among the three dependent variables, since each type of measurement is carried out as a distinct step; moreover, each response variable is independent from the others during the measurement of the piece. In order to reduce the measuring time, it is possible to intervene on the process phase related to the identification of the cone frustum, identified by three circles, at three different distances. In Figure 1, the frustum of cone is shown by highlighting the three circles used to locate it.

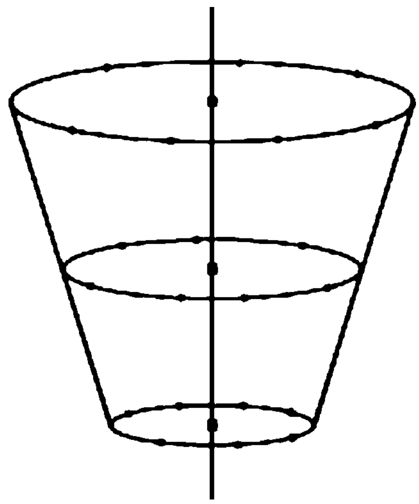

Fig. 1: Location of the frustum of cone by three circles and definition of the "circle-point" factor

In the initial setting, the N/C machine measures 7 points on each circle (7,7,7), each point is denoted with a dot in Figure 1. A categorical input factor "circle-point-*cp*" is then defined at four levels with each level corresponding to a different number of points measured on each circle: (1) 7,7,7; (2) 7,5,7; (3) 5,7,5; (4) 5,5,5.

Two other variables are involved in the split-plot design: measurement speed-*mspeed* (mm/sec), and drift speed-*dspeed* (mm/sec). Therefore, a split-plot design with three factors is planned: two WP process factors, both at two levels (measurement and drift speeds), and only one SP control factor, the *cp* categorical factor at four levels. The final split-plot has 112 runs with seven replicates.

Standardization of the responses was carried out (Berni, 2010) to compensate for differences in magnitude among responses, even though both responses and WP factors are expressed with the same unit of measurement.

4.2. THE PARETO FRONT APPROACH: OBJECTIVE PHASE

In order to identify the Pareto-optimal set, a series of 1764 combinations of the factor *mspeed*, *dspeed* and *cp* levels were identified, from which, the predicted response values $\widehat{crmax}$, $\widehat{crmin}$ and $\widehat{eccen}$ were estimated using the model form described in formula (2). The set of possible input combinations (Figure 2) was formed by constructing a grid of points based on discrete levels of *mspeed* and *dspeed* for each level of the factor *cp*. The fineness of the mesh of each grid is 0.1, since this choice balances the complexity of calculation and valid coverage of the two-dimensional region, (ranges of *mspeed* and *dspeed* factors). The combinations of the possible solutions are labelled from 1 to 1764 according to the approach described in Chapman et al. (2014a): i) from the first grid on the upper left to the lower right grid; ii) inside each grid starting from the bottom row and moving from left to right, then starting at the end of each row, from the leftmost point of the next row.

The obtained Pareto-optimal set consists of 61 combinations, highlighted by the solid circles in Figure 2. These all combinations involve $cp = 4$, which requires the smallest number of measured points. Therefore, irrespective of the choice in the subjective phase, the Pareto front results ensure that an improvement in the measurement time is always obtained.

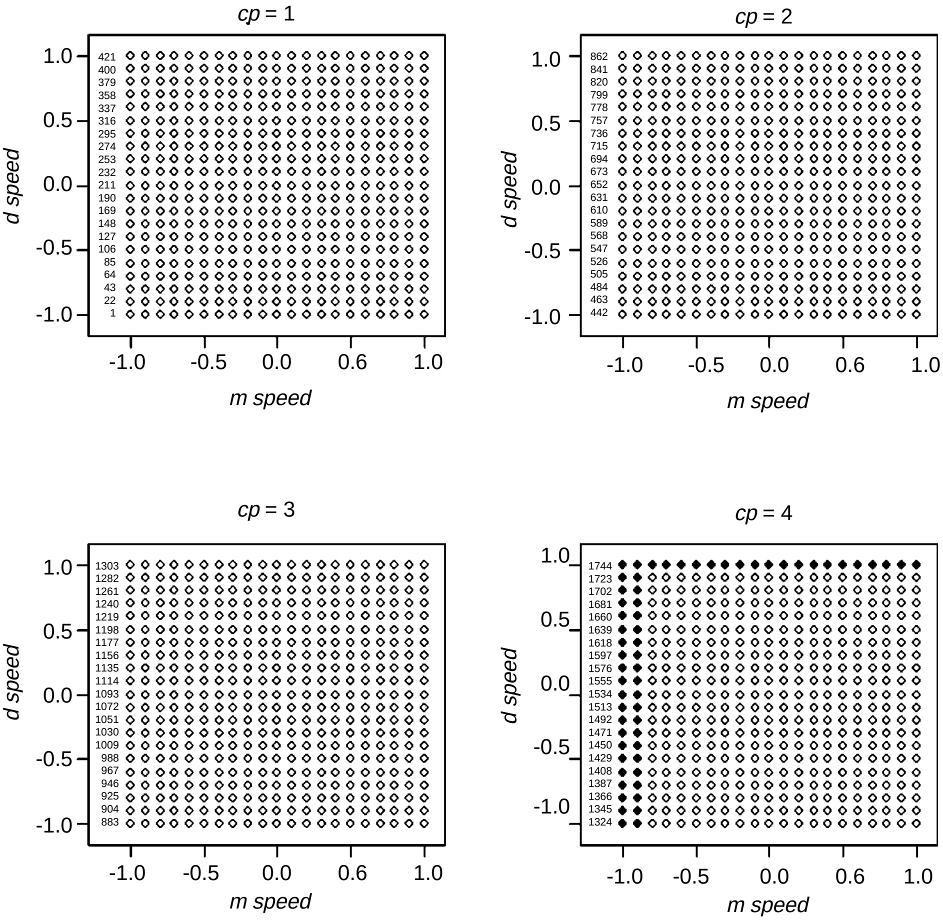

Fig. 2: Input grid plot

Figure 3 shows the pairwise scatterplots of the points belonging to the Pareto front (Chapman et al., 2014a; Anderson-Cook, 2017). The analysis of this set of points shows that there is a strong trade-off between the maximum circle diameter and eccentricity. The trade-offs between the other two pairs of response variables appear less important. Finally, by observing the relatively small ranges of the predicted responses, we note that all 61 combinations of the Pareto-optimal set lead to values of $\widehat{crmax}$, $\widehat{crmin}$ and $\widehat{eccen}$, close to the respective desired targets.

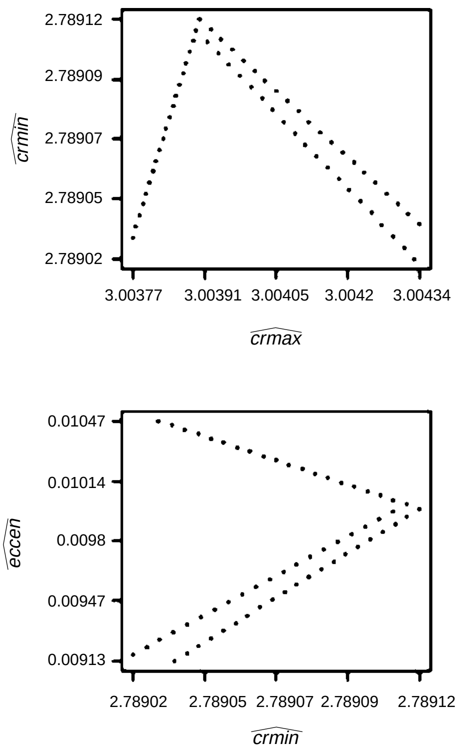

Fig. 3: Pairwise scatterplots of the points belonging to the Pareto front

4.3. THE PARETO FRONT APPROACH: SUBJECTIVE PHASE

In order to compare the 61 combinations of the Pareto-optimal set, the following procedure is carried out (Chapman et al., 2014a; Myers et al., 2016; Anderson-Cook, 2017): i) the Pareto front values of each predicted response are transformed into desirability values, so that the best value obtained (from the set of solutions comprising the front) for each response is scaled to one, while the worst value is scaled to zero; ii) for each combination of the Pareto-optimal set, the respective desirability values are combined in a single global desirability function. Since it was considered appropriate to heavily penalize undesirable predicted response values, we choose the standard multiplicative desirability form, based on the geometric mean expression, as follows:

$$D(\boldsymbol{x}_{\mathcal{P}}, \boldsymbol{w}) = d_{crmax}(\boldsymbol{x}_{\mathcal{P}})^{w_{crmax}} \, x \, d_{crmin}(\boldsymbol{x}_{\mathcal{P}})^{w_{crmin}} \, x \, d_{eccen}(\boldsymbol{x}_{\mathcal{P}})^{w_{eccen}}$$

where $\boldsymbol{x}_{\mathcal{P}}$ is a combination of the Pareto-optimal set; $d_{crmax}(\boldsymbol{x}_{\mathcal{P}})$, $d_{crmin}(\boldsymbol{x}_{\mathcal{P}})$,

$d_{eccen}(\boldsymbol{x}_{\mathcal{P}})$ the single desirability values related to the three predicted responses; $\boldsymbol{w} = (w_{crmax}, w_{crmin}, w_{eccen})'$ a weight vector, with $w_{crmax}, w_{crmin}, w_{eccen} \geq 0$ representing the weights assigned to the three response variables and $w_{crmax} + w_{crmin} + w_{eccen} = 1$. We note here that the small deviations of the response values from their desired targets mean that even small misses from the target are being strongly penalized, because one minimal error in measurements can lead to a serious risk for a patient.

Figure 4 shows the mixture plot, which identifies the best combination (i.e., the optimum point for achieving the highest value of the global desirability function) for each possible weighting of the response variables. Each point of the mixture plot represents a weight vector (e.g., the left bottom vertex represents $\boldsymbol{w} = (1,0,0)'$, the centroid marked with a black cross represents $\boldsymbol{w} = (1/3, 1/3, 1/3)'$, and the bottom edge represents the weight vectors with $w_{crmax}, w_{crmin} > 0$ and $w_{eccen} = 0$). For further details see Cornell (2002).

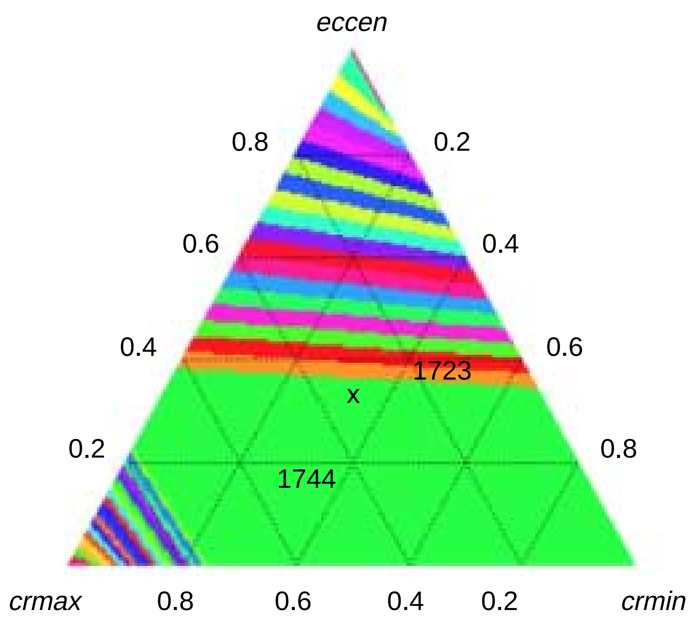

Fig. 4: Mixture plot

In the case study, 41 of the 61 combinations belonging to the Pareto-optimal set appear in the mixture plot (each colored area identifies a different combination), that is, they are best for at least one weight vector. Assuming that the three response variables are thought to be of equal importance, the weights reflecting company priorities/preferences are those around the centroid of the triangle. The two best points for these weight combinations are 1723 and 1744. In particular, 1744 is better for most of these weights, including the one directly at the centroid of the triangle as well. Table 1 shows the detailed results obtained for these two points, (1723 and 1744), differing only in the *dspeed* level value, and providing similar predicted responses.

Tab. 1: Factor levels and predicted response values for the combinations 1723 and 1744

Combination	Factors			Predicted responses		
	mspeed	*dspeed*	*cp*	$\widehat{crmax}$	$\widehat{crmin}$	$\widehat{eccen}$
1723	-1	0.9	4	3.00392	2.78911	0.00994
1744	-1	1	4	3.00390	2.78912	0.00998

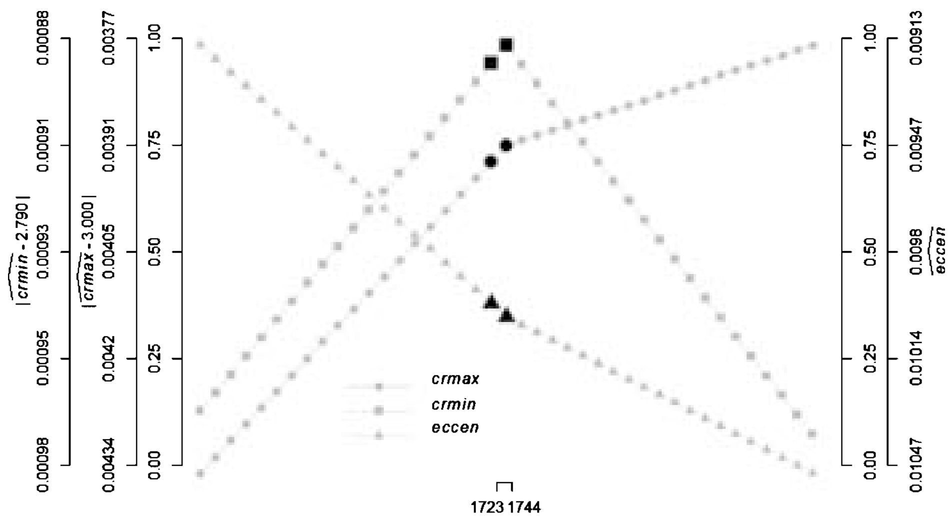

Fig. 5: Trade-off plot of the 41 best point combinations for at least one weight combination

Figure 5 contains the trade-off plot illustrating the desirability values (internal vertical axes) and absolute value differences between the predicted response values and the respective targets (external vertical axes) considering the 41 solutions that are best for at least one weight combination. In Figure 5, the trade-offs between the pairs of responses are similar to those highlighted by the pairwise scatterplots in Figure 3. Moreover, as shown in the mixture plot (Figure 4); the point combinations 1723 and 1744 provide an ideal balance among the three responses when they are all prioritized as being equally important.

In order to better analyze and compare these two combinations of interest, Figure 6 shows the synthesized efficiency plots (Lu and Anderson-Cook, 2012) which allow comparison of the relative efficiency of individual solutions with the best available across all the possible weight vectors.[3] The synthesized efficiency of a point combination (belonging to the Pareto-optimal set) $\boldsymbol{x}_{\mathcal{P}}$, with weight vector $\boldsymbol{w}$, is defined as follows:

$$\frac{D(\boldsymbol{x}_{\mathcal{P}}, \boldsymbol{w})}{max_{\boldsymbol{x}_{\mathcal{P}}}[D(\boldsymbol{x}_{\mathcal{P}}, \boldsymbol{w})]}$$

The shading, from white to black, represents the transition from high to low values of the synthesized efficiency. Each of the 19 shades of grey, starting from the lightest, corresponds to a decrease in the synthesized efficiency of 0.05.

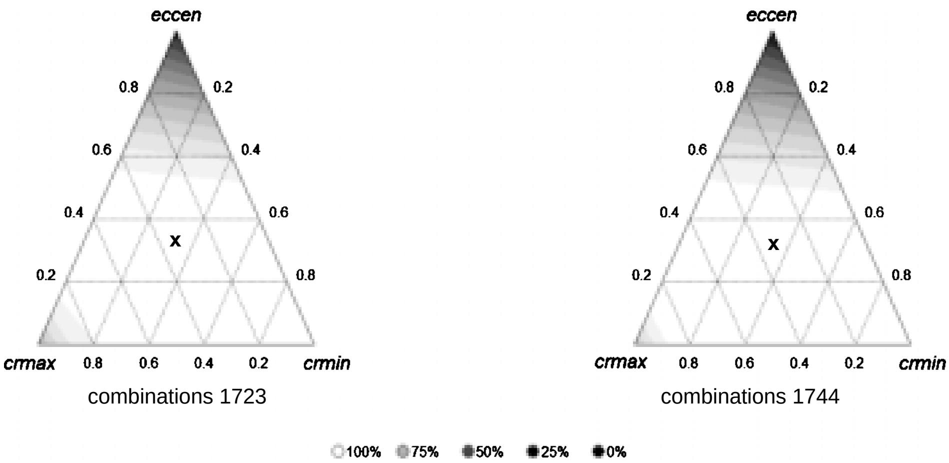

Fig. 6: Synthesized efficiency plot for the point combinations 1723 and 1744

[3] It should be noted that for the construction of the synthesized efficiency plots (Figure 6) and the mixture plot (Figure 4), a set of 20301 weight combinations has been defined, where adjacent weights related to a same response variable are separated by a distance equal to 0.005.

The large white region characterizing the two graphs, represents approximately 75% and 74% of the triangles, respectively, and indicates that both points have a synthesized efficiency of at least 0.95 for a substantial number of weight combinations. In particular, the white region around the centroid of the triangle, indicated in Figure 6 with a black cross, shows that both point combinations give excellent performance at the weighting region, which reflects the company's priorities/preferences. The graphical plots provide detailed information about the relative performance of the different contending solutions and allow the experimenter to understand what alternatives are available.

Moreover, we select the optimal solution as represented by combination 1744, since it is slightly better for a large number of weight combinations, and in particular, for the weighting giving equal importance to the three response variables. However, input combination 1723 provides a similar performance, thus representing a valid competitive alternative.

4.4. RESULT COMPARISON BETWEEN THE TWO APPROACHES

Table 2 shows the results from both multi-response optimization methods: the Pareto front approach and the analytical method applied in Berni (2010). By comparing (Table 2) the optimum point combination 1744 (Piattoli, 2020) and the optimal analytical solution, we can observe how only one process factor, *cp*, shows the same optimal level; nevertheless, it must be noted that the circle-point variable is the main process variable that we are interested in optimizing. Although both combinations provide similar predicted response values, the analytical method allows for obtaining a better value for the response $\widehat{eccen}$. This is an important result in view of the relevance that this response variable has in the actual process. The constructed Pareto front contains similar solutions to those identified by the optimal analytical solution, but corresponding to different weight combinations. Hence, with a more thorough exploration of the solution set identified with the Pareto front, a similar solution could be selected relaxing the assumption that all the responses were of equal importance.

Tab. 2: Optimization results: the comparison

Method	Factors			Predicted responses		
	$mspeed$	$dspeed$	cp	$\widehat{crmax}$	$\widehat{crmin}$	$\widehat{eccen}$
Pareto front	-1	1	4	3.00390	2.78912	0.00998
Analytical	0.710	0.362	4	3.00300	2.78500	0.00100

It is important to note, however, that although a Pareto front can be constructed for any number of responses of interest, the graphical tools considered here only used three response variables, unlike the five considered in Berni (2010). For this reason, it was only possible to make a partial comparison between the results obtained through the two different methods. Nevertheless, the Pareto front approach offers the possibility of using additional graphical tools (Lu et al., 2017), which enable multi-response optimization of more than three response variables.

Moreover, through the analytical approach, the optimization was carried out considering both non-standardized and standardized data, where the latter gave the best optimization results.

5. GENERAL COMPARISON AND FINAL REMARKS

The results obtained through the case study allows us to perform an empirical comparison between the two approaches, where some specific differentiations could be viewed in a theoretical perspective, as outlined in the following scheme (Table 3). Both methods use the same experimental plan, data and analysis, but then differ in how choose to optimize the settings of inputs.

Tab. 3: Theoretical step comparison between the Pareto front approach and the analytical method

Step	***Method***	
	Pareto front	**Analytical**
1	DoE: planning and trials	DoE: planning and trials
2	Statistical modelling	Statistical modelling
3	Optimization: A) objective phase - identification of Pareto-optimal set; B) subjective phase - choice of the optimal solution among the points belonging to the Pareto-optimal set, taking the quantitative results and the decision-makers' priorities into account; C) validation of the results obtained at step (B), intrinsic in the subjective phase.	Optimization: a) definition of objective function (formula (4)); b) minimization (or maximization) of the objective function, and identification of the optimal solution (optimal process variable levels); c) validation of the obtained results at step (b) by: 1. the objective function value, (results also checked through: convergency, gradient estimates, determinant of the Hessian matrix); 2. application of the optimal solution (obtained through step (b)) in the real (actual) production process, by involving the stakeholders (engineers).

Undoubtedly, the Pareto front approach offers the advantage of using graphical tools in a simple and intuitive way, enabling straightforward identification of leading solutions with discussion allowing for consensus of the optimal solution among the various company teams involved. The elimination of non-competitive choices streamlines where to focus further discussion. Moreover, a subjective evaluation (Table 3, step B) can also be performed, with the possible achievement of a unanimous decision among different stakeholders, and considering different weightings of how important the performance on each response is to overall results. It is possible to compare different identified solutions, and see their relative strengths and weaknesses for each of the responses of interest. Indeed, it allows for accurate comparison among several input combinations of interest. A further advantage is the flexibility in response weighting to handle multiple combinations of business priorities and to examine the impact of these choices on the identified results. The transparent nature of the Pareto front presents the experimenter with different alternatives that can be explored and compared. Nevertheless, this is also possible by performing analytical optimization methods (see Lin and Tu, 1995). In addition, response weighting and analytical methods assign relative importance to each response according to the estimated corresponding weight (Berni, 2010). This is particularly helpful for solving technological issues and constraints, that can be measured and evaluated in a wide and general context.

An advantage of the analytical method is the ability to include random effects, within both the modelling and the optimization steps. Therefore, the fixed as well as random effects are wholly involved, and as a result a robust process optimization can be carried out, and the final validation (Table 3, step c.2) specifically verified in the firm, allows for checking the validity in the actual context. It is straightforward to use the same optimization function based on the inclusion of random effects for each of the responses as the basis for constructing the Pareto front.

The aforementioned advantages and disadvantages highlight the significant relevance of both methods, as each has specific strengths and weaknesses that would be relevant for a wide range of empirical situations (real industrial processes, technological contexts) where they can be effectively applied.

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CIRCULAR ECONOMY IN SMALL AND MEDIUM-SIZED ENTERPRISES IN THE EUROPEAN UNION: HETEROGENEITY BETWEEN AND WITHIN COUNTRIES

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Abstract. *In this paper, we analyze the different behavior of small and medium-sized enterprises (SMEs) with reference to eight specific Circular Economy (CE) actions. Data come from a Flash Eurobarometer survey that investigates efficiency in use of resources. We estimated classification trees (CART) in order to identify homogeneous groups of European countries with regard to the adoption of CE practices by SMEs and multilevel regression models to measure differences among SMEs in adopting sustainability management, considering firms' characteristics. Results of the analyses revealed heterogeneity between and within European countries. Five groups of countries are identified, with SMEs having a similar attitude towards CE. Within each group of factors, however, specific firms' characteristics have a non-negligible effect on firms' decision to adhere to sustainability.*

Keywords: *Efficiency of resources, Circular Economy, SMEs, CART, multilevel analysis.*

1. INTRODUCTION

In this paper, we analyze the different behavior of small and medium-sized enterprises (SMEs) with reference to eight specific Circular Economy (CE) actions. The transition from a linear economic context to a circular one implies for products and services a change from a production system with the phases of conception, construction, use and disposal, to a system committed to having less waste and to environmental issues. The market is giving way to a circular idea of the value chain, which means that the environmental impact, that the materials that compose it will have, is assessed from the very beginning of the production phase, from its conceptualization and design (Suárez-Eiroa et al., 2019). Therefore, in the last few decades, the major companies begun to consider as a new resource the opportunity of processing the materials released by production and the products themselves, once their use is finished. Reuse, and recycling are among the Rs on which the Circular Economy is based (Vermeulen et al., 2019).

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In order to understand how SMEs are dealing with CE and specifically to evaluate heterogeneity of behavior in European countries, we analyzed the data collected with a Eurobarometer survey, precisely with Flash Eurobarometer 456, conducted from 11th to 26th September 2017 on sample of European firms. These data refer to eight green actions to be implemented in the production process: saving water, saving energy, using renewable energy, saving materials, minimizing waste, recycling, designing products that are easy to maintain or repair, selling scrap material to another company.

In this paper, we will use classification trees (CART, Breiman et al. 1984) in order to identify homogeneous groups of European countries with regard to the adoption of CE practices by SMEs and multilevel regression models (Hox, 2002) to measure differences among SMEs in adopting sustainability management, considering firms' characteristics.

The paper is organized as follows: section 2 reviews the concept of CE and the recent reference literature, with a specific attention to SMEs; section 3 describes the data; section 4 presents the results of the analyses and section 5 concludes.

2. CIRCULAR ECONOMY: ORIGINS, DEVELPOMENT AND IMPLEMENTATIONI IN SEMS

The origin of the modern idea of industry started at the end of the eighteenth century with the Industrial Revolution, this era was characterized by the overproduction of goods and the extensive use of fossil energy sources. Only during the World Wars, companies were forced to reconsider a really different method of using raw materials, due to the enormous costs to support the war front. The dynamics of the production system of the time consists in proceeding from virgin raw materials to transformation, consumption and final conferment in landfill; this production model can be defined as linear. The linear model can be improved and optimized, but still what remains is waste, pollutants and scraps of industrial production and consumption with negative environmental and social implications (Sharma et al., 2021). The introduction of the concept of Circular Economy dates back to the end of the twentieth century, when several publications arouse the attention of scholars (Lieder and Rashid, 2016). Several authors, such as Andersen (2007), Ghisellini et al. (2016), and Su et al. (2013) attributed the introduction of the concept to Pearce and Turner (1989) in their work "Economics of Natural Resources and the Environment". These authors wrote how natural resources sustain the economy by providing inputs for production and consumption, but, at the same time, natural resources produce outputs, which are represented almost entirely from waste. From these considerations, the idea of Circular Economy was formulated. Pearce and Turner were influenced by the work of Boulding (1966), who described the Earth as a circular and closed system with limited assimilation capacity, deducing that the economy and the environment should coexist in equilibrium. Stahel and Reday (1976) introduced some features to this economic approach, with a particular focus on the industrial sector; they devised a continuous cycle economy to write industrial strategies on waste prevention, job creation, resource efficiency and dematerialization. Later, Stahel (1982) further stressed that granting use, instead of relinquishing ownership of goods, is the most relevant sustainable business model for a closed economy, thus allowing companies to profit from waste without having costs and risks deriving from them. The term Circular Economy was coined in China in 2002, when the government approved the first CE Promotion Law of the People's Republic of China, which became effective in January 2009 (The Standing Committee of the National People's Congress China, 2008). The main goal was to reduce pollution and protect the planet by making important public decisions. After this turning point, institutions from all over the world, including the European Union, had to inevitably adapt to addressing these problems. The first European countries to adopt CE practices were Sweden, the United Kingdom and Spain (Lieder and Rashid, 2016).

The use of the term CE has evolved in the business world in an attempt to find a compromise between economic growth and environmental protection. This idea of economy wants to be in contrast with the linear one. The most renowned definition of CE was given by the Ellen MacArthur Foundation (2015), introducing the Circular Economy as "a restorative industrial economy or regenerative in intention and design", from then, many different ways to describe the process were proposed. Thinking about the eco-environmental industry, the CE can also be defined as a closed flow of materials within a well-structured economic system (Geng and Doberstein, 2008). Kirchherr et al. (2017) analyzed over one hundred definitions of Circular Economy and concluded that all are in line with 3Rs (Reduction, Reuse and Recycling) paradigm, which purpose is to make the flow of materials closed or circular (Yuan et al., 2006). The fact that the present economic development model has taken a dead-end way, it is recognized not only by those who work in the sectors directly concerned, but by the majority of the people. It is evident that it is necessary to rearrange the bases of the production system in order to guarantee adequate well-being to future generations.

The European Union is encouraging the business activities to seriously face ethical problems, which concern the economic cycle in an active way. (European Commission, 2008; Dalhammar 2015). The rules to guide the cycle of a product can be summarized as it follows: prohibition of dangerous substances, products energy-efficient and correct disposal of materials after their use. The European Union presented in 2015 an executive plan for CE, which includes legislative proposals and measures for the management of the production, consumption and waste (Dalhammar, 2016). The plan is divided into two parts: the first part explains how CE measures can be introduced into the product life cycle and the second one, instead, is devoted to the care and the specific treatment of scraps (European Commission, 2014).

One of the objectives of the recommendations is to inform and address not only the behavior of companies, but also that of consumers. Therefore, the goal is making everyone more aware that the cycle of a product involves the whole of society and that the gain following a correct behavior is for everyone's life, not only for the economic benefit. The action plan seeks to put industries in a sustainable but competitive context, stimulate economic growth and create new types of jobs. From this, it arises the need for companies to have a qualified workforce with new and specific green skills (Bassi and Guidolin, 2021, ⁄beda-García et al. 2021). The professions that fall into this category can be defined in many ways, Burger et al. (2019), for example, did an in-depth exploration of the US market.

This transition, however, has a very high cost. The European Commission is moving in this direction, with measures to encourage the adoption of CE practices and employment growth. The first action plan (European Commission, 2014) was designed for the entire life cycle of a product: from production to consumption, from repair to regeneration, to waste management. The intent was to direct it to all the administrations involved, starting from the member States of the European Union, then passing through the regions, cities, businesses and finally citizens. The European Commission attributes a very important role to the production phase in the chain, encouraging companies to replace harmful chemicals and/or to have innovative technologies for production processes. For this reason, the European Resource Efficiency Excellence Center was created, helping companies to improve their production efficiency. The devised action plan takes into account also the contribution and the responsible choices that consumers will make in the purchasing phase, this in fact is an element that will directly affect the functioning of the CE. An example regards the fact the price of a product that has been conceived and put on the market using sustainable production techniques with a good environmental impact, will be higher. It is important that customers appreciate this effort and are willing to pay the additional cost. The cost of a product with these characteristics will be proportional to the attention it has for the environmental effects, the companies in this will be supported through incentives from the European Union but the consumer will have a great responsibility in considering environmental protection as a quality during the purchase (European Commission, 2018a). In the European Union the CE regards almost exclusively small and medium-sized enterprises (SMEs), which represent over 99% of all European companies and around two thirds of total employment. SMEs have been defined by the European Commission as companies that have less than 250 employees and whose turnover does not exceed 50 million euros and/or whose total balance sheet does not exceed 43 million (European Commission, 2003). In detail, micro enterprises are those with less than 10 workers and an annual balance sheet lower than 2 million euros; small businesses are those with less than 50 workers and a budget of less than 10 million; businesses are defined medium-sized if they have between 50 and 250 workers and a budget between 10 and 43 million euros. From the annual report of the European Commission on SMEs 2018/2019 (European Commission, 2020b), it emerged that in the European Union about 25.1 million SMEs are operating: 23.3 million micro-enterprises, 1.47 million small ones and about 236 thousand medium-sized enterprises. It is estimated that SMEs create between 60 and 70% of total air pollution (Hoogendoorn et al., 2015). The European Union considers the contribution of SMEs to be fundamental to the CE also because they should be more active and predisposed to changes in the sectors of recycling, repair and product innovation. The distribution of SMEs in the EU is not homogeneous, compared to an average of 92% on all active companies, this figure can vary considerably from state to state. For example, in Germany, SMEs represent 82% of all businesses, unlike countries like Greece, Poland or the Czech Republic where they are over 96%.

The circular chain is a model based on the supply of renewable, recyclable and biodegradable products. With the recovery of resources, at the end of a production process, waste continues to have an intrinsic value and can be used in further transformation processes. The sharing model promotes collaboration between users of goods and services in order to exploit overcapacity and underutilization. To implement the transition to sustainable and Circular Economy models, the European action plan defines 54 measures to close the loop life of products, identifying five priority areas to accelerate the transition along their value chain (plastics, food waste, essential raw materials, construction and demolition, biomass and materials biological, European Commission, 2015). The plan places a strong emphasis on creating a solid foundation on which investment and innovation can thrive. The transition is financially supported by the European Structural and Investment Funds, from Horizon 2020, from the European Fund for Strategic Investments (EFSI) and the LIFE program, founded in 1992 to promote protection strategies of the environment. A recent step taken by the European Union was to implement the second action plan for the Circular Economy on 11th March 2020 (European Commission, 2020a). This initiative is one of the main measures of the European Green Deal, defined as the roadmap to make the EU economy as sustainable. The new plan describes the way to progress towards a climate-neutral and competitive economy, in which consumers are empowered. The objectives are: making sustainable products as the standard within the Union. The Commission proposed a legislative action on the strategy for sustainable products to ensure that they are designed to last longer, easy to reuse, repair and recycle, and contain as much recycled materials as possible rather than primary raw materials. The measures will also limit single-use products, they will deal with premature obsolescence and ban the destruction of unsold durable goods. Secondly, the empowerment of consumers who will have access to reliable information on issues such as reparability and durability of products so they can make better informed choices. As Najami et al. (2020) noted, sustainability cannot be fulfilled without the collaboration of end consumers.

Finally, it is important to recognized that the Circular Economy will produce net assets in terms of GDP growth and job creation; it is estimated that the application of ambitious Circular Economy measures in Europe will be able to increase GDP by a further 0.5% between now and 2030, creating around 700.000 new jobs (European Commission 2020a).

3. THE DATA

Our data were collected within the Flash Eurobarometer 456 survey, conceived and proposed by the European Commission. The data collection period is included between 11th September 2017 and 26th September 2017; questions were answered by 13,117 SMEs belonging to the 28 countries of the European Union (before the Brexit)[2]. The intent was to understand how many efficiency measures were developed by firms. With reference to the single SME, the following "demographic" information was collected: country, economic activity sector, number of workers, year of foundation, if turnover changed or remained stable in the past two years, turnover in 2016, type of output, whether products or services were sold.

Eight specific CE actions were investigated: paying attention to the waste and reuse of water; minimize energy use while maximizing performance; using mainly renewable energy (including own production through solar panels or other); saving

[2] Quota sampling was used with quotas applied to company size and sector, adjusted according to country's universe. Interviews were conducted by CATI mode.2 For the analyses the software R was used.

of raw materials; waste minimization; the permission to other companies of the use of waste; recycling, reusing materials or waste from the company itself; creation of products that are easier to maintain, repair or reuse. With reference to these eight actions, SMEs had to declare if they were implemented in the preceding two years and/or if there was the intention to consider them for the future two years. Additional information with reference to these actions was collected, regarding costs, percentage of turnover invested, eventual financial support received and from which source, workers employed in green jobs, difficulties and needs related to the implementation of sustainability practices.

We expected that the size of the company had direct effects on the choice to undertake activities related to the CE (Bianchi and Noci, 1998). Larger companies have access to more resources to invest, while smaller ones can suffer from the absence of a strong economic structure that supports them for investments and measures that have a targeted production scheme to recycling (Hogg et al., 2011). From the point of view of sustainability, all companies have the goal of creating a type of environmental economics. It is noted that companies that generate one low portion of waste in relation to what they produce are less motivated to think about recycling methods (Reike et al., 2018). On the other hand, in large companies, ethics plays a central role in their behavior as they are more importantly exposed to criticism and it is therefore a necessity to preserve their reputation (Inigo and Blok, 2019).

The age of an SME has a direct effect on the willingness to undertake Circular Economy practices (Hoogendoorn et al., 2015). The competence and social responsibility of a company can derive precisely from the experience that has been accumulated in the area (Trencansky and Tsaparlidis, 2014). Social responsibility derives from an economic and corporate stability. When business procedures for the environment are put in place although costs might increase, it is in all respects a way to please stakeholders. The same concept also applies to new companies, who, having to set up new working strategies, can gain in considering the idea of the Circular Economy as a new perspective model both for the environment and from the business point of view. Older and newer SMEs have more interest in undertaking a business model that follows the CE, more than companies with an intermediate age.

The sector in which an SME operates influences its willingness to undertake sustainable activities or to follow green economy policies (Bradford and Fraster, 2008). SMEs operating in sectors with production processes are more tangible and producing greater quantities of waste are the keenest to follow CE expedients. The sectors that are most inclined to suggest sustainable activities are manufacturing, construction, agriculture and waste management. In these sectors, the production process disperses a lot of waste and this leads to requesting and having large quantities of raw materials. Furthermore, strict environmental and corporate parameters have been devised by nations and by institutions to stem waste and give a common direction to SMEs (European Commission, 2018b)). The need for greater quantities of materials for the sectors with the most organic value chain composed of tangible materials is an element that makes the sustainable choice of SMEs a priority. In fact, in the EU action plan, the plastics, food and raw materials sectors, constructions and demolitions, biomasses and products biologicals have priority for the implementation of efficiency measures.

SMEs that participated in the survey employ on average 18 workers: 80.4% of them have between 1 and 9 employees, 15.5% between 10 and 49, 3.0% between 50 and 249, and 1.1%, large companies, have more than 250 employees. 57.4% of SMEs have no employees engaged in a green job. The average age of SMEs is 25.7 years: 76.9% were founded before to 2010, 9.3% between 2010 and 2012, 23.3% between 2013 and 2016, and only 1.5% were founded in 2017. For what regards economic activity sector, 10.1% of SMEs belong to the manufacturing sector, 15.9% to the industrial one, 30.1% are active in retail, and 43.9% in services. Another relevant aspect to consider to assess the propensity of a company to undertake CE actions is its annual turnover. In the two years preceding the questionnaire, the turnover of SMEs grew for 42.5% of them, decreased for 21.2% while it remained almost the same for the other 20.1%. 19.6% of SMEs have a turnover of less than 100,000 euro in the reference year, 23.3% a turnover between 100 and 500 thousand, 22.8% between 500 thousand and 2 million, 18.8% between 2 and 10 million, 10.4% between 10 and 50 million and only 5.1% had a turnover that is greater than 50 million euros.

As already introduced, the survey aimed at measuring the adoption of specific CE practices by European SMEs. The most adopted efficiency action was the minimization of waste, undertaken by 65.5% of SMEs; minimizing energy use by keeping stable or increasing performance was adopted by 63.2% of them, saving materials regards 56.8% of SMEs, and minimization of water waste is adopted by 47.3%. Recycling inside company through reuse and use of waste was undertaken by 41.8% of companies; designing ad hoc of products that are easier to maintain, repair or reuse them is applied by 25.4% of firms. The sale of waste to other companies is done by 21.1% European SMEs, while the least adopted sustainability practice is the choice to use mainly renewable energy (14.0%).

Table 1 shows the relationship between the adoption of sustainability practices and the characteristics of the firms by number of employees, economic activity sector, age, turnover in 2016; all relationships are statistically significant according to the Chi-squared test.

Tab. 1: Percentage of European SMEs adopting CE practices by characteristics.

	Minim. waste	Saving energy	Saving materials	Saving water	Recycling	Design products	Selling scrap	Renewable energy
EU 28	65.5	63.2	56.8	47.3	41.8	25.4	21.1	14.0
Size								
1-9	64.7	62.3	55.4	46.9	40.1	24.3	18.0	12.6
10-49	66.3	64.1	62.3	46.1	45.9	28.2	31.5	17.4
50-249	77.2	75.9	64.7	56.3	58.6	38.1	47.7	30.2
250+	80.3	81.9	62.0	69.6	59.1	26.8	29.7	26.8
Turnover								
-100,000	57.0	58.1	54.2	43.4	38.0	21.2	17.2	11.6
100,00-500,000	66.7	63.3	57.0	48.3	39.0	26.5	18.8	14.6
500,000-2mil	68.8	67.1	59.7	46.4	46.1	28.9	26.6	15.5
2-10mil	71.3	69.5	63.6	46.5	47.4	22.3	30.0	17.7
10-50mil	78.4	77.9	72.4	58.0	56.9	42.9	53.0	43.3
+50mil	84.7	80.9	64.5	68.5	50.5	17.3	23.4	21.6
Sector								
Manufacturing	71.3	64.6	64.2	43.4	41.9	33.2	31.5	12.7
Retail	65.1	66.9	56.9	48.3	44.1	24.3	21.6	11.7
Services	62.7	61.3	54.2	46.4	38.5	23.2	15.1	14.1
Industry	70.4	60.4	59.1	46.5	46.4	28.1	30.0	18.7
Age								
-31 Dec 2010	66.7	64.4	57.2	47.9	41.7	25.3	22.4	14.4
1 Jan 2010-31 Dec 2012	62.2	59.3	55.8	42.0	41.9	24.5	16.3	13.3
1 Jan 2013-31 Dec 2017	61.0	58.5	55.1	46.7	40.2	26.5	17.5	13.0
1 Jan 2017+	66.8	63.8	52.0	47.4	53.1	26.0	21.1	5.6

Entrepreneurial sustainability is by definition linked to the social and economic context. In developed countries, both legal framework and financial resources are very solid, favoring sustainable entrepreneurship. In developing countries, transition to Circular Economy is more challenging, especially in terms of infrastructures and new technologies (Abarca Guerrero et al., 2020). The legal context is one of the factors which varies most from state to state also in the European Union; even if our analyses do not directly focus on this aspect, it is an element that must be kept in consideration for appropriate comparisons. Economic indicators at national level are also important to understand the wealth of the country since the economic dimension of sustainability coincides with the large amount of liquidity that can be used to satisfy the needs and requests of stakeholders. In more developed countries, investment policies are directed mostly to the private sector, since it is more inclined to support innovation and competitiveness, which favor a sustainable growth (Cadil et al., 2018). The level of innovation goes hand in hand with new technologies, which can also be considered a prerequisite. Although SMEs do not usually make innovation as the most important aspect of their structure, there is significant financial support by the European Union to increase their performance in terms of sustainability. The reference literature shows that entrepreneurial sustainability is also influenced by factors such as gender, age, education, skills, family context and community background. Therefore, differences between countries with regard to CE practices are the result of the complex mixture of all aspects mentioned above (Spangenberg et al., 2002). Table 2 lists the percentage of firms implementing each sustainability action in the 28 European MSs.

A preliminary exploratory cluster analysis on the data reported in Table 2 classifies the 28 EU MSs in four homogeneous groups for the percentage of SMEs operating in the country and adopting CE practices. The greenest firms are located in France, Ireland, Portugal, Spain, Sweden and Great Britain, countries were the percentage of SMEs adopting CE practices is higher than the average for at least seven among the eight considered actions, except for the efficiency practice of using renewable energy. A second group is formed by Austria, Belgium, Croatia, Czech Republic, Denmark, Finland, Germany, Italy, Luxemburg, Poland, Slovenia, The Netherlands; in these countries the percentage of firms adopting CE practices is higher than the average for many practices, these percentages, however, are lower than those observed for SMEs located in the first group of countries. The percentage of firms in these countries that are saving water and energy is lower than that in the average sample. The third group refers to Greece, Hungary, Latvia and Slovakia whose SMEs implement only in small percentages, lower than those observed at European level, the majority of actions; however, in these countries, firms are involved in selling scrap material to other companies. Finally, in the last group of countries, Bulgaria, Cyprus, Estonia, Lithuania, Malta, and Romania only a very small percentage of SMEs adopts green practices. This first result highlights the presence of a discrete level of heterogeneity in adopting efficiency practices in the 28 European countries, this evidence will be further explored in the next section of the paper.

Tab. 2: Percentage of European SMEs adopting CE practices by country, figures in *italics* indicate a value greater than the average.

	Minim. waste	Saving energy	Saving materials	Saving water	Recycling	Design products	Selling scrap	Renewable energy
EU 28	65.5	63.2	56.8	47.3	41.8	25.4	21.1	14.0
Austria AT	60.0	*71.8*	52.3	44.1	*47.7*	*31.3*	*25.6*	*32.3*
Belgium BE	*75.0*	*69.8*	61.6	46.7	40.5	25.3	*25.6*	*19.9*
Bulgaria BG	27.7	36.4	30.6	29.5	16.9	9.8	16.3	4.4
Cyprus CY	28.6	50.0	28.6	28.6	*46.4*	7.1	14.3	7.1
Czech Republic CZ	64.0	60.9	46.2	42.4	34.7	*32.6*	*29.1*	7.2
Germany DE	61.3	*70.2*	57.1	35.8	38.6	24.1	23.0	*32.0*
Denmark DK	50.0	56.3	52.3	41.4	28.9	*26.6*	*26.4*	9.4
Estonia EE	8.6	20.0	14.3	8.6	11.8	5.7	5.7	2.9
Spain ES	65.5	*72.4*	*69.5*	*54.8*	*56.9*	*31.9*	20.0	7.4
Finland FI	55.2	50.7	53.7	26.9	31.6	23.3	18.7	*14.3*
France FR	*83.1*	*71.2*	*59.4*	*67.8*	*42.5*	*32.7*	18.0	5.5
Great Britain GB	*81.9*	*66.8*	*61.8*	*55.7*	*70.2*	*25.8*	*28.8*	*16.3*
Greece GR	36.8	51.4	45.4	32.8	30.1	18.3	*25.9*	12.3
Croatia HR	64.3	*65.5*	*62.4*	*51.2*	29.8	17.9	*28.2*	8.3
Hungary HU	40.1	57.8	45.0	40.1	18.8	16.3	20.9	7.4
Ireland IE	*84.9*	*68.5*	*57.4*	*59.3*	*70.4*	24.5	*25.9*	*18.5*
Italy IT	*73.6*	57.3	52.5	44.4	37.3	23.0	15.2	*15.0*
Lithuania LT	20.5	42.0	33.0	35.2	6.8	6.8	15.9	3.4
Luxemburg LU	60.0	50.0	52.4	33.3	*45.0*	*28.6*	25.0	*15.0*
Latvia LV	34.5	60.0	54.5	43.6	14.5	16.4	10.9	3.6
Malta MT	64.3	*71.4*	35.7	28.6	*50.0*	14.3	21.4	*14.3*
Netherlands NL	65.2	*64.7*	*61.3*	32.1	36.9	20.6	*25.7*	*26.7*
Poland PO	55.1	57.3	*59.9*	*49.5*	23.6	16.7	21.1	4.1
Portugal PT	55.1	*75.6*	*74.8*	*63.1*	*65.9*	*42.2*	*23.7*	9.2
Romania RO	31.0	32.9	29.5	23.4	21.5	6.3	12.0	4.4
Sweden SE	*76.3*	57.9	*66.1*	36.1	*61.1*	*32.4*	*26.3*	*35.3*
Slovenia SI	50.7	47.9	52.1	35.6	32.9	*26.0*	21.9	*16.4*
Slovakia SK	44.1	57.7	43.6	44.9	35.7	14.5	15.9	5.7

4. STATISTICAL ANALYSIS[3]: METHODS AND RESULTS

4.1 CLASSIFICATION TREE

In order to identify homogeneous groups of countries with reference to the number of CE practices, among the eight considered in the survey, adopted by SMEs, we

[3] For the analyses the software R was used.

estimated a classification tree (CART) (Breiman et al., 1984). CART is a statistical method of a-priori segmentation, i.e, segments are identified on the basis of a criterion variable *Y*. In our application, this variable quantifies the adherence of a generic SME to the efficiency measures proposed in the questionnaire with the following three categories: 5 or more measures adopted (class 1), between 1 and 4 CE practices (class 2), no sustainable measures (class 3). From the dataset, it emerged that 36.4% of SMEs in the sample belong to the first class, 52.3% to the second one and 11.3% had not carried out any efficiency action in the reference period. As independent variable for the classification tree, we considered: the countries where the SME operates (28 levels). Considering these values for all SMEs operating in the 28 European countries, the CART algorithm identifies the best partition of countries through an iterative algorithm, which is reported in Table 3. These groups will be the starting point to analyze and quantify the heterogeneity between EU member states (MSs), in terms of adopted resource efficiency variable *Y* for a generic SME in each of the five groups of countries identified by the CART algorithm. The CART procedure can be divided into two distinct parts: tree growing and tree pruning. In the first part of the model, the response variable is repeatedly split, starting with the variable that has the highest association with it. The splitting continues till a predetermined stopping criteria (Zhang, 2016). In the pruning phase of the algorithm, which is performed on another subsample of data in order to avoid overfitting, the best grouping is identified on a basis of a measure of fit; we used total deviance.

Tab. 3: Groups of homogeneous countries: CART best partition.

Group of countries	
A	Austria, Belgium, France, Great Britain, Ireland, Portugal, Sweden Spain
B	Croatia, Germany, Italy, Malta, Slovakia, The Netherlands
C	Czech Republic, Denmark, Luxemburg, Poland
D	Cyprus, Finland, Greece, Hungary, Latvia, Slovenia
E	Bulgaria, Estonia, Lithuania, Romania

Tab. 4: Probabilities (%) of belonging to the three classes of variable *Y* in the five groups of countries

Group of countries	Class 1 5+ actions	Class 2 1-4 actions	Class 3 No actions
A	42.63	51.95	5.42
B	30.98	60.76	8.26
C	28.89	56.45	14.66
D	20.60	57.77	21.63
E	8.68	58.32	33.01

Groups of countries in the Tables 3 and 4 are ordered by decreasing probabilities of adopting CE practices by SMEs operating in their territories. There is a big difference of behavior between firms in groups A and E; for example, the percentage of SMEs that do not implement efficiency actions increases from 5.42% to 33.01%. In group A we find the European countries with the greenest businesses; in group E, the least green ones. Group B includes countries belonging to Western and Southern Europe; the proportion of SMEs not activating sustainability practices is a bit higher than that of group A, 8.26%. Group C is composed of only four countries, where a high percentage of SMEs is adopting at least one CE practice. Countries in group D are the most different for what concerns location in Europe and with one fifth of them not implementing CE practices. Finally, countries in group E are all located in Eastern Europe.

4.2 MULTILEVEL ANALYSIS

The CART analysis identified homogeneous groups of European Union MSs, confirming heterogeneity of behavior between countries. In each group, however, it is important to explore further differences among SMEs, especially in relation to their characteristics that might affect their decision to adopt CE. The identification of homogeneity and heterogeneity among European countries must be followed by an appropriate analysis of heterogeneity within each MS. As written in the introduction, there is a rich literature on the factors affecting companies' decision to comply with sustainability; some of these evidences are confirmed also by the descriptive analyses of our data as reported in section 1. In order to face this problem, it is necessary to use statistical methods for hierarchical data (Hox, 2002). In our specific sample, SMEs are nested into countries and this originates a multilevel dataset. In this section of the paper, we will explore how decisions towards CE actions are related to factors as size, turnover, number of workers, etc., i.e., we aim to quantify how the probability of adopting CE actions is determined by SMEs characteristics. A second goal of the analyses is to understand how economic investment affects environmental measures and if this aspect varies among the groups of countries. And finally, we will look at the eight specific CE actions considered in the survey to evaluate which factors are specifically determinant in their adoption. We now indicate with Y_{ij} the number of resource efficiency actions undertaken by the *i*-th SME belonging to the *j*-th group with *j=1,..,28*, as we are considering the 28 EU MSs; Y_{ij} will assume values from 1 to 8. Our multilevel model is given by equation (1):

$$\ln\left(\mu_{ij}\right) = \beta_{0j} + \beta_{1j}\, x_{ij} + R_{ij}$$

where Y_{ij} is assumed to follow a Poisson distribution with mean μ_{ij}. In the random intercept model, β_{0j} are random variables representing differences among groups:

$$\beta_{0j} = \gamma_{00} + U_{0j}$$

and U_{0j} is a random effect, at state level, following a Normal distribution with 0 mean and variance equal to σ_U^2. As independent variables (vector $\boldsymbol{X}$), we consider: SME dimension, the year of foundation, average turnover in the reference year, the sector of economic activity; the number of full-time workers employed in green jobs. Tables 5 and 6 list the result of the estimation of this multilevel random intercept model with our dataset, the estimates refer to the best fitting model assessed with the lowest values of AIC and BIC indexes.

Tab. 5: Estimated parameters: random intercept model

	Estimate	Standard deviation	p-value
Intercept	0.966	0.059	<0.001
# workers			
-9 ref. category			
10-49	0.097	0.019	<0.001
50-249	0.058	0.046	0.209
250+	0.119	0.067	0.041
Age			
-31 Dec 2010 ref. category			
1 Jan 2010-31 Dec 2012	-0.026	0.017	0.128
1 Jan 2013-31 Dec 2017	-0.007	0.015	0.620
1 Jan 2017+	-0.037	0.041	0.042
Turnover			
-100,000 ref- category			
100,00-500,000	0.048	0.013	<0.001
500,000-2 million	0.077	0.015	<0.001
2-10 million	0.086	0.022	<0.001
+10 million	0.265	0.030	<0.001
Sector			
Manufacturing ref. category			
Retail	-0.068	0.017	<0.001
Services	-0.166	0.016	<0.001
Industry	-0.062	0.018	0.002
# workers in green jobs			
0 ref. category			
1-5	0.320	0.010	<0.001
6-9	0.283	0.026	<0.001
10-50	0.512	0.025	<0.001
51-99	0.504	0.084	<0.001
100+	0.713	0.115	0.003
var(μ_j)	0.086	0.021	<0.001

Tab 6. Countries' effects: random intercept model

AT	3.261	EE	1.145	HU	2.398	NL	3.108
BE	3.348	ES	3.416	IE	3.668	PL	2.624
BG	1.730	FI	2.442	IT	2.734	PT	3.656
CY	2.172	FR	3.587	LT	1.718	RO	1.532
CZ	2.875	GB	3.954	LU	2.724	SE	3.350
DE	3.023	GR	2.247	LV	2.109	SI	2.721
DK	2.693	HR	2.770	MT	3.015	SK	2.337

The magnitudes of country intercepts mirror the groups obtained with the regression tree analysis. In general, from Table 5 we see which are the factors significantly affecting the decision to implement resource efficiency practices and how they might act. For example, yearly turnover and the number of workers employed in green jobs have a direct effect on the number of implemented actions, while the manufacturing is the sector where SMEs are more prone to sustainability activities. There is also a non-negligible effect of dimension and age, in the sense that bigger and older firms are more inclined to resource efficiency practices. For what regards dimension, small and large firms adopt a greater number of CE practices, while medium businesses do not.

Starting from the above evidences, we consider important to explore another aspect related to the effect of economic investments on sustainability. The question is "do equal investments for sustainable measures led to a proportional total adhesion to CE in the homogeneous groups of countries obtained with the CART segmentation procedure?". The dataset contains the information on the amount invested on average per year by each SME in order to become more resource efficient. This information gives rise to a categorical variable with the following classes: no investment, less than 1% of yearly turnover, between 1 and 5%, between 6 and 10% and more than 10%. Le Y_i the number of CE practices adopted by SME i, that is assumed to follow a Poisson distribution with mean μ_i, we estimate the model in equation (2) separately for the SMEs in the five groups of countries in Table 3.

$$ln(\mu_i) = \eta_i + x_{ik}\beta_k + z_i y \qquad (2)$$

where $k=1,..,5$, x_k are the covariates used in the multilevel regression model and z is the categorical variable indicating the amount of yearly turnover invested to improve the sustainability of the business by SME i. Table 7 lists the results of the estimation of the generalized linear model (GLM) in equation (2) for the SMEs operating in the five groups of countries described in Table 3; i.e., 5 GLMs are estimated.

Tab. 7: GLMs: estimation results

Group A	Estimate of γ	Standard error	p-value
0% ref. category			
<1%	0.335	0.019	<0.001
1-5%	0.419	0.018	<0.001
6-10%	0.516	0.030	<0.001
>10%	0.610	0.045	0.002
Group B			
0% ref. category			
<1%	0.407	0.025	<0.001
1-5%	0.575	0.024	<0.001
6-10%	0.598	0.033	<0.001
>10%	0.726	0.056	<0.001
Group C			
0% ref. category			
<1%	0.700	0.039	<0.001
1-5%	0.743	0.040	<0.001
6-10%	0.746	0.059	<0.001
>10%	0.410	0.099	<0.001
Group D			
0% ref. category			
<1%	1.030	0.061	<0.001
1-5%	1.019	0.058	<0.001
6-10%	0,976	0.082	<0.001
>10%	1.016	0.099	<0.001
Group E			
0% ref. category			
<1%	1.311	0.095	<0.001
1-5%	1.347	0.105	<0.001
6-10%	1.208	0.153	0.003
>10%	1.506	0.144	<0.001

Values of estimated parameters clearly show that the higher the percentage of turnover invested, the higher the number of CE practice adopted by SMEs in all five groups of countries. However, this relationship has a different magnitude in the five groups, increasing from SMEs operating in countries classified in group A to SME operating in European countries classified in group E. In countries of group A, SMEs implement the highest number of sustainability practices, for this reason the result that in this group investments have the lowest impact deserves attention. In our opinion, this evidence shows that the transition from a linear economic system to a circular one in these countries, once started, does not require high extra investments to be maintained, we can briefly say that a Circular Economy system, once implemented, continues to increase business sustainability, somehow self-expanding.

As a further analysis, we want to obtain a measure of adhesion for each state to the single actions studied; to answer this question, again we must apply a statistical method that takes into account the hierarchical nature of the data.

For this scope, we define a new variable Y_{ij} that takes value 1 if SME *i*, operating in European country *j*, adopted the specific considered efficiency action, while it takes value 0, otherwise; the following multilevel logit model in equation (3) is estimated for the eight surveyed actions:

$$\log\left[P\left(Y_{ij}=1\middle|\mu_j\right)\right]=x_{1ij}\beta_1+x_{2ij}\beta_2+x_{3ij}\beta_3+x_{4ij}\beta_4+x_{5ij}\beta_5+\mu_j \tag{3}$$

x_1 represents the number of workers, x_2 the age of the SME, x_3 average yearly turnover, x_4 the sector of economic activity and x_5 the number of workers employed in green jobs; μ_j is the random intercept with Normal distribution with mean 0 and variance σ_μ^2. Table 8 lists the values of the random intercepts for the eight models, estimated for the corresponding efficiency actions, obtained for each European country and refer to micro-enterprises with a number of employees between 1 and 9, founded before 1st January 2010, belonging to the sector manufacturing, with an average yearly turnover of less than 100 thousand euros and without any workers in green jobs. The eight actions are: minimize waste of water, minimize energy use, use of renewable energy, attention to raw materials, waste minimization, selling of waste to other companies, recycling of waste or others materials and designing of sustainable products ready for reuse, reuse or with minimal environmental impacts. Figures in the table show that preferences in adopting specific CE actions are different in the 28 MSs; these evidences emerged also from descriptive statistics in Table 2; they are confirmed taken into account the multilevel structure of our data.

Tab. 8: Random intercepts

	Minimizing waste	Saving energy	Saving materials	Saving water	Recycling	Design products	Selling scrap	Renewable energy
AT	0.35	0.63	0.23	0.51	0.56	0.26	0.38	0.25
BE	0.39	0.64	0.14	0.62	0.73	0.26	0.33	0.24
BG	0.26	0.33	0.04	0.34	0.30	0.22	0.14	0.12
CY	0.27	0.47	0.07	0.39	0.63	0.21	0.37	0.14
CZ	0.38	0.58	0.06	0.49	0.65	0.32	0.30	0.33
DE	0.28	0.62	0.23	0.56	0.57	0.22	0.29	0.22
DK	0.36	0.50	0.06	0.52	0.47	0.25	0.22	0.25
EE	0.17	0.29	0.04	0.28	0.17	0.19	0.15	0.08
ES	0.45	0.64	0.05	0.68	0.61	0.21	0.47	0.29
FI	0.21	0.42	0.09	0.51	0.50	0.20	0.24	0.21
FR	0.64	0.67	0.04	0.62	0.83	0.19	0.36	0.33
GB	0.50	0.63	0.13	0.65	0.84	0.34	0.66	0.26
GR	0.25	0.41	0.08	0.43	0.32	0.27	0.22	0.17
HR	0.38	0.53	0.05	0.58	0.57	0.25	0.22	0.15
HU	0.36	0.54	0.07	0.48	0.40	0.24	0.16	0.17
IE	0.47	0.60	0.12	0.57	0.81	0.25	0.60	0.22
IT	0.33	0.45	0.10	0.49	0.69	0.15	0.19	0.27
LT	0.33	0.41	0.04	0.38	0.23	0.21	0.08	0.11
LU	0.28	0.45	0.09	0.51	0.53	0.24	0.34	0.22
LV	0.32	0.48	0.03	0.51	0.31	0.18	0.12	0.15
MT	0.32	0.61	0.10	0.46	0.62	0.23	0.42	0.19
NL	0.26	0.58	0.20	0.62	0.64	0.29	0.30	0.20
PO	0.41	0.49	0.03	0.60	0.53	0.23	0.18	0.16
PT	0.54	0.67	0.06	0.73	0.51	0.27	0.58	0.40
RO	0.19	0.27	0.03	0.30	0.29	0.16	0.17	0.07
SE	0.27	0.47	0.24	0.62	0.73	0.25	0-32	0.28
SI	0.47	0.44	0.11	0.54	0.50	0.18	0.29	0.25
SK	0.36	0.49	0.04	0.41	0.39	0.42	0.27	0.13

The sector of economic activity and the dimension of the firm have a different effect on the different actions. For example, actions as 2 (minimize energy use), 3 (use of renewable energy) and 6 (sale of waste to other companies), which require large investments, are more chosen by larger SMEs.

5. CONCLUDING REMARKS

The scope of this paper is to investigate differences in behavior towards sustainability practices of European SMEs. Heterogeneity emerges both between and within

European countries.

Segmentation analysis identified five groups of European countries, homogeneous for the attitude of SMEs to CE actions. In eight states, Austria, Belgium, Spain, France, Great Britain, Ireland, Portugal and Sweden, (group A), firms show the highest level of innovation in the field of sustainability, only a very small percentage of businesses (5.4%) do not adopt any efficiency measure. In this group of countries, the average number of green actions implemented by each SME is 3.9, out of the eight investigated by the Flash Eurobarometer survey. The estimation of a multilevel regression model shows a similar behavior among the eight nations, i.e., low level of within group heterogeneity. On the opposite side we find SMEs that operate in countries classified in group E, Latvia, Lithuania, Romania and Estonia, where we found the lowest attention to Circular Economy practices; SMEs adopt on average only 1.4 CE actions.

For what concerns firms' characteristics, the yearly turnover and the sector of economic activity proved to be significant in determining an efficient business management; SMEs in the manufacturing sector are the most inclined to perform green actions. The presence or absence of employees involved in green jobs is another important factor. The proportion of yearly turnover invested in sustainability directly affects the number of resource efficiency actions implemented by European SMEs, i.e, as investment increases, more actions are implemented; however, this effect is not the same in its magnitude in the five groups of homogenous countries, it is lower in the group of greenest countries. This result shows that investment in sustainability has decreasing marginal returns on implementation of resource efficiency actions.

As a general consideration, results from our analyses show that, for what regards CE attitudes in European SMEs, there is a lot of between and within country heterogeneity. Policies that aim to increase CE practices adoption must take these differences into account and therefore should be tailored for specific SMEs within each country. For what concerns countries, differences are related to geographical location, SMEs in Western-European countries exhibit more attention to green matters that SMEs in Eastern-European countries. However, there are some exceptions. Moreover, the geographical location is strictly correlated to economic and social conditions in the European MSs. A limitation of this study is that we did not insert in our models covariates collected at country level; this is a topic that deserves further attention. Further attention has to be paid also to the specific CE actions; also in this case there are difference between and within countries. These differences are related to SMEs' characteristics and to costs of implementation. Incentives to favor green economy should consider these elements as well.

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JOB SATISFACTION AND TELEWORKING: A STUDY ON PUBLIC ADMINISTRATION WORKERS IN ITALY

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Abstract. This paper presents the results of one of the first surveys carried out in Italy on the living and working conditions of public administration employees who were engaged in compulsory telework during the first stages of the COVID-19 pandemic (March–May 2020). Although this study examines a small sample of public workers in Campania region, interesting results emerge in a modelling implementation. In fact, by means of a heteroskedastic Ordered Probit model, some findings are presented with job satisfaction being the response variable. Considering the workers' need to adjust to a completely novel situation, our results reveal a significant role played by a potential lack of concentration and by the satisfaction of using their own home as a workplace as well as by the differences experienced in work efforts. The presence of children in the household turns out to be slightly significant, whereas childcare duties do seem to exert some impacts on job satisfaction, implying relevant effects on work-life balance. Workers' concern regarding a possible lack of recognition of their job by supervisors or managers is also highlighted.

Keywords: Job Satisfaction, Teleworking, Covid-19, Ordered Probit Model

1. INTRODUCTION

In 2020, the global COVID-19 pandemic crucially altered global economies and people's ordinary social and working lives. To contain the spread of the virus, governments imposed various social-distancing measures and, as a result, private and public companies began experimenting with strategies to reduce the number of people in contact with each other, thus making it possible for employees to work at their homes. Consequently, all over the world an unprecedented number of workers

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were asked to or allowed to work from home, after decades of often ineffective attempts to develop the use of telework (Ogbonna and Harris, 2006, Welz and Wolf, 2010; Eurofound, 2010 and 2012; Pyöriä, 2011).

In Italy, teleworking in public administration (*"lavoro agile"* in Italian or "smart working" in everyday language) was introduced by Law No. 124/2015 and is presently regulated by Law No. 81 of 2017. Until the outbreak of the COVID-19 pandemic, such modality of work was not common. In fact, with the arrival of the restrictive measures due to the pandemic, in combination with the *low uptake* of teleworking in the past decades, Italy displayed one of the largest increases in the figures of employees working from home among European Union (EU) member states: an upsurge of 39.9% as compared to an average EU27 growth close to 36.5% (Eurofound, 2021; EU-OSHA, 2021b). According to data from the National Observatory on Smart Working, an agency of the Ministry of Public Administration (Osservatorio Nazionale del Lavoro Agile, 2020), at the beginning of February 2020 only 2.5% of public employees were classified as teleworkers. Within just a few weeks, this figure had risen to almost 65%. In such a short period, about 86% of public administration offices activated forms of "smart working" for at least part of their staff, and this percentage rose to 99% when considering administration offices with more than 50 employees.

With specific reference to such circumstances, this paper presents the results of one of the first studies of the living and working conditions of public administration personnel in Italy who began teleworking during the first lockdown period, from March to May 2020. The survey was conducted with our scientific support on behalf of the *Confederazione Generale Italiana del Lavoro, Funzione Pubblica* (CGIL for Public Sector), a largely representative Italian trade union. More specifically, the employed data stem from an observational study aimed at analysing the conditions of public administration workers in the Campania region and in the province of Naples during the lockdown periods, to investigate the unexpected large-scale application of emergency "smart working" arrangements. The survey was designed to determine, on the one hand, the employees' satisfaction with work conducted under these unprecedented conditions and, on the other hand, the material and environmental conditions under which the telework was carried out. Finally, a further focus of the investigation was the complex balance, sometimes resulting in disruption, between private and working life as compared to the pre-existing circumstances. The fieldwork of the survey was conducted by CGIL for Public Sector, Naples and Campania section, which administered the questionnaire directly through its social media channels.

By means of a heteroskedastic Ordered Probit model, some results are presented with job satisfaction being the response variable. The paper is organised as follows. After a brief review of the recent literature on teleworking conditions in Section 2, data of interest and results of the estimated model are presented in Section 3, while Section 4 discusses the main findings and presents some concluding remarks.

2. LITERATURE REVIEW AND MOTIVATION

During the COVID-19 pandemic, teleworking has been regarded as the most effective and cost-efficient approach to preserve and restore the functioning of the entire economy (among others: ILO, 2021 and 2022). Apart from "native teleworkers", those employed generally as telemarketers and customer care staff, home-based work assisted by information and communication technology (ICT) was regarded with some degree of scepticism by both employers and workers themselves. On the employers' side, teleworking was often considered as likely to lead to low productivity because of the lack of direct control (Harker Martin and MacDonnell, 2012; Hilbrecht et al., 2013; Putnam et al., 2014; Messenger, 2019). On the workers' side, two different attitudes can be distinguished. First, employees' concerns about career dynamics were heightened by the physical distance from the company premises, due to the perceived difficulty of recognition by managers or supervisors of their work performance. Second, blurred feelings of interest and aversion have arisen towards a condition often perceived as a "privilege" experienced especially by public sector employees in the perspective of reducing their difficulties in balancing work and non-work duties, and mostly in the case of working women (Chung and Van der Horst, 2018; Kaduk et al., 2019).

However, despite media interest and both corporate and academic debates on the potentials of teleworking, only a comparatively low number of establishments and organisations had adopted some home-based teleworking practices in the past decades. Until March 2020, primarily because of the inadequacy of legal and welfare frameworks, working from home essentially remained a seductive proposition in highly developed countries (Baruch, 2001). Even though the advances in ICT have undoubtedly triggered improvements at both business and societal levels, home-based teleworking benefits have long been regarded as a preferential treatment (Parry et al., 2021).

Additionally, for some scholars, teleworkers seem to be exposed to greater levels of stress than their office worker counterparts, even presenting additional physical health symptoms. Mann and Holdsworth (2003) underline some practical benefits of teleworking, such as increased flexibility, less commuting time, and a better work-life balance in general, while clearly highlighting the potentially unfavourable consequences of telework on workers' mental health, such as perceived loneliness, social isolation, blurring of boundaries, and presenteeism (i.e. the lost efficiency which occurs when employees are not fully functioning in the workplace because of an illness, injury, or other condition) (see also: Steidelmüller et al., 2020).

Wide-ranging practices of flexible working settings have appeared only with the outbreak of COVID-19, and their effects are compared using "before" and "after" benchmarks (Parry et al., 2021; Dunatchik et al., 2021). Furthermore, a new digital divide based on teleworkability is now discussed in literature as a possible driver of increased disparities (among others, Fana et al. 2020; Sostero et al., 2020). Teleworkability indicates the degree to which an activity can be performed remotely thanks to ICT devices, thus implying that job tasks requiring physical handling or duties must necessarily be performed on-site, at the employers' premises (ILO, 2021). Such a concept is essential for properly exploring the impacts of the 2020–2021 actions to develop telework practices in the coming years.

As teleworking remained a marginal issue in the past, mostly confined to private companies and adopted in a few countries, its implementations were rarely the subject of detailed statistical surveys in Western developed countries. With reference to EU countries, the scant statistical evidence on teleworking across member states has been obtained by extrapolating relevant information from surveys focusing on other related topics, such as the European Working Conditions Survey, the European Survey of Enterprises on New and Emerging Risks, and the European Labour Force Survey itself (EU-OSHA, 2021a and 2021b). Although not up to date, these official statistics are currently the only ones that can be consulted to obtain representative information.

During the first months of the 2020 pandemic, Eurofound conducted a non-statistically representative survey across European countries. Moreover, in 2021 a special wave of the European Working Conditions Survey was implemented to provide comparable and representative data on working conditions during the pandemic across EU 27 member states and other European countries, but those micro-data are not available yet. For the specific Italian context, the situation is similar, since most of the studies conducted in the past two years are qualitative or do not meet the requirements of reliable sample surveys (Eurofound, 2021). The same can be said for the public sector across Europe and in Italy as well. Consequently, we have chosen to employ information stemming from an observational study developed in collaboration with CGIL Campania, which is long established[3] in the public sector, to examine the response patterns of a small sample of workers towards job satisfaction during the first lockdown period in the Campania region.

3. DATA AND METHODS

The research targeted the five provinces of Campania, with the aim of assessing organisational aspects and impacts on both working life and perceived job quality during the pandemic, as perceived by public employees.

To set the scene, it should be mentioned that, according to the Ministry of Economy and Finance (2020), in 2019 the total number of public employees[4] in Italy was 3,186,014. In the Campania region, 279,077 people were employed in the public sector, thus representing about 8% of the national aggregate. Actually, in the city of Naples, belonging to a large metropolitan area (province), the absolute value is 45,947. Our respondents come mainly from local functions based in the area of Naples. In particular, most of the interviewees (78.5%) live in the province of Naples, with 7.2% in the province of Salerno, 6.1% in both Avellino and Caserta, and only 2.15% in the province of Benevento.

This disproportion is related to the fact that the responses were collected by a trade union, which traditionally has a stronger presence in more sizeable public offices, therefore helping to explain the larger ratio of respondents from Naples. The fieldwork, in fact, was carried out directly by CGIL Campania, which disseminated 320 questionnaires through its online social media channels between October 2020 and January 2021.

The administered questionnaire focuses on the analysis of workers' conditions following the emergency imposition of remote work practices, with particular reference to: i) assessed job satisfaction with respect to the tasks completed under

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3 According to the data provided by ARAN (Agency for the Negotiation Representation of Public Administrations), in the three-year period 2019-2021, when distinguishing public employment by sector, for the local functions the percentage distribution of union membership saw CGIL covering 34.3% of unionised workers, CISL 27.4% and UIL 18%. Hence, the CGIL is considered the most representative trade union in the labour sector investigated (see: https://www.aranagenzia.it/rappresentativita-sindacale-loader/rappresentativita/triennio-2019-2021-provvisorio.html).

4 The contingent of public employees (excluding those with flexible, temporary, or other non-standard contracts) in Italy is 3,186,014. Of these, 7.1% of the employed people belong to the Central Functions sector, while 38.3% of the employees belong to the Education and Research sector. Three sectors register a number of employees close to each other: about 20% are employed in the public Health sector, while those with public law contracts are about 17.8%; the amount of employees in the local government sector is 15.5% of the total. A marginal quota, out of these sectors, accounts for 1.5% of the total.

novel and unexpected circumstances; ii) physical and environmental conditions in which their work was carried out; and iii) suitability or disruption of the work-life balance in comparison to the previous period.

In addition to the usual demographic variables (gender, marital status, education, composition of the household, type of work), information[5] was collected on the type of public institution to which respondents belonged, as well as on their work organisation, such as workspace at home, working time and procedures. Perceptions and assessments regarding job satisfaction, work-life balance, and relationships with colleagues and supervisors were also considered. Overall, 279 individuals answered the survey, resulting in a response rate of approximately 87%, thus confirming the effective interest of respondents towards the topics of the questionnaire.

The sample, of course, is small; nevertheless, the positive response rate is quite consistent with such types of investigations. The main descriptive statistics to understand the composition of the sample of respondents are presented below.

Our sample of interest is equally distributed by gender; 72.8% of the respondents are married or declare to have a partner, while 10% are single. As far as age is concerned, 50.2% of the sample is in the 35–54 age group, while 43% of the sample is between 55 and 67 years old, and only 7% are younger than 34 years. Because of this age composition, the presence of young children of primary school age is extremely limited, which means that parental care duties may not influence the satisfaction of working from home in our sample. However, 72% of the respondents state that they do have children, and 36.2% of the entire sample report that their partner has a job. When considering only the married respondents, almost 41% affirm that their partner is employed.

Regarding the composition of the household, 8.5% of the sample declare that they live alone (regardless of their marital status), 54.7% of the sample say they live in a household of two or three people, and 36.8% report living in households of more than three people.

With respect to the size of the respondents' employer, as indicated in Table 1, more than 56.6% of the workers belong to an administration office with more than 1,000 employees.

The distribution by workers' reported net income is presented in Table 2 and includes four income classes. Most of the sample report an annual income from employment ranging from 20,000 to 30,000 euros per year.

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[5] Data are available from Authors on request.

Tab. 1: Respondents by Administration Size

Administration Size	Freq.	Percent	Cum.
< 15	10	3.58	3.58
15–50	13	4.66	8.24
51–100	32	11.47	19.71
101–250	38	13.62	33.33
251–500	18	6.45	39.78
501–1,000	10	3.58	43.37
> 1,000	158	56.63	100.00
Total	279	100.00	

Participants were also asked to respond to questions about various aspects of family and work life, using a Likert-type scale to assess their degree of agreement or disagreement with the statements. The results are depicted in Figure 1.

Our variable of interest is the satisfaction with telework. The original variable is expressed on an 11-point scale from 0 to 10 (with 0=totally disagree and 19=totally agree) and presents a substantial dispersion, with a considerable number of responses assigned to the "balance" modality of the scale (rating=5), and quite high ratings assigned to both the low modalities and the high ones, as seen in Figure 1.

Tab. 2: Respondents by Income Classes

Income classes (Euros)	Freq.	Percent	Cum.
< 20,000	56	20.07	20.07
20,001–30,000	154	55.20	75.27
30,001–40,000	55	19.71	94.98
> 40,000	14	5.02	100.00
Total	279	100.00	

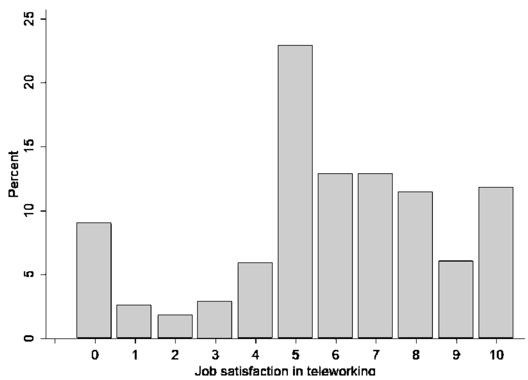

Fig. 1: Job Satisfaction in Teleworking, Original Likert Scale (percentage)

We also explore interviewees' satisfaction with their own "home as a place of work". Furthermore, the perceived "lack of recognition" from supervisors or managers regarding work performed in teleworking mode is investigated, as well as the employees' perception of a "never-ending" working day. All of the considered variables are expressed on the same 11-point scale.

As indicated in Table 3, nearly 6% of the sample declare to be totally dissatisfied (rating=0) with their home as a place of work, while more than 43% reported a high or very high level of satisfaction (ratings between 7 and 9). Additionally, 20.43% affirm that they are more than satisfied (rating=10). Conversely, it is remarkable that the concern that one's work may not be fully acknowledged due to teleworking is diversely distributed. In fact, while more than 16% of respondents do not rate this as a prominent concern, approximately 22% assign a medium-high rating (between 7 and 9) and as many as 17% claim they fear a significant lack of appreciation of their work (rating=10). With respect to the long working days which "do not seem to finish", responses indicate that 17% totally disagree, 19% totally agree, and 10% express an "intermediate" answer, leaving the remaining categories equally distributed.

Tab. 3: Respondents' Self-Assessments (percentages)

Level of proposed scale	Satisfaction towards home as a place of work	Lack of recognition of work done in teleworking	Never-ending working days
0	6.1	16.1	17.6
1	2.2	4.7	3.9
2	2.2	4.3	3.9
3	2.2	4.3	3.6
4	3.9	6.8	2.9
5	8.2	14.7	10.4
6	11.8	10.4	9.3
7	15.4	7.5	7.2
8	19.0	9.0	14.7
9	8.6	5.0	7.5
10	20.4	17.2	19.0
Total	100.0	100.0	100.0

Similar quite diverse response patterns are registered for other self-reported assessments, such as the level of concentration experienced during teleworking. In fact, approximately 58% of respondents assert that their work effort has increased overall while teleworking, whereas 38.8% do not report any change. With respect to housework and other unpaid duties, 61% of respondents state they share childrearing tasks with their partners, 23% report caring for their offspring alone, and only 10% said they received some help with parental duties from people outside the family. Finally, approximately 61% of interviewees report incurring some additional expenses for useful ICT devices to enable them to telework from home.

3.1 ESTIMATED MODEL RESULTS

Various modelling approaches can be applied in the case of ordinal responses. Agresti (2010), Tutz (2012), and Piccolo and Simone (2019) are the main references in this field. Taking into account the small sample size and the nature of variables, in our opinion, a simple Ordered Probit model is the most suitable methodology. However, due to the dispersion of responses to the job satisfaction question on the original 11-point scale, the response variable was conveniently recoded on a three-level scale (see Table 4), and the probability of being "dissatisfied", "indifferent", or "satisfied" (*job satisfaction*) is studied using an Ordered Probit model.

Tab. 4: Recoded Dependent Variable

Telework satisfaction (original modalities)	Freq.	Percent
0 dissatisfied (0–4)	61	21.86
1 indifferent (5–7)	136	48.75
2 satisfied (8–10)	82	29.39
Total	279	100.00

Given the available information, the model takes into account a number of basic demographics: *gender* (dummy variable, 1=woman), a dummy variable for presence of children in the household (*children*), and *marital status* (categorical variable, 1=single; 2=married; 3=other). Moreover, *age* classes, dimension of public administration office (*size*), *income*, and *expenses* for buying ICT devices to work at home are inserted. Finally, some ordinal variables are considered: the expressed level of satisfaction with home as workplace (*home as wp*), perceived differences in efforts pursued at work (*work effort change*), lack of concentration (*concentration*), endless working days (*neverending*), perceived lack of recognition of work done (*lack of recog*), and activities devoted to care for children (*carechildren*).

In the Ordered Probit model, the probability of an outcome *j* is given by the probability that the estimated linear function, plus random error, lies within the range of the estimated cut-points for the outcome. Formally, the model is:

$$Pr(Y_i = j) = Pr(k_{j-1} < \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots + \beta_m x_{mi} + u_i \leq k_{J-1}) \quad (1)$$

where $u_i \sim N(0, \sigma^2)$, coefficients ($\beta_1 \ldots \beta_m$), and cut-points ($k_1 \ldots k_{J-1}$) are the parameters to be estimated, J is the number of possible outcomes; and $i = 1 \ldots n$, k_0

is taken as $-\infty$ and k_J is taken as $+\infty$. When in binary or an ordinal regression model the homoskedastic error hypothesis is incorrectly assumed, the standard errors are wrong, and the parameter estimates are biased (Yatchew and Griliches, 1985). Therefore, the inferential conclusions based on the usual z-test statistics can be misleading. To address the potential heteroskedasticity within the data, Williams (2009 and 2011) proposed the heteroskedastic ordered models, in which the factors affecting the heteroskedasticity are explicitly specified.

In particular, in heteroskedastic ordered models, the log-variances are specified by:

$$\log(\sigma_i^2) = \sum_{j=1,h} z_{ij} y_j \qquad j = 1 \ldots n \tag{2}$$

where z_{ij} is the value assumed by variable Z_j for the i-th observation. The vector $Z = (Z_1, Z_2, \ldots, Z_h)$ may include dummy or continuous variables and define groups with different error variances.

The estimated coefficients for the model are presented in Table 5 as obtained by maximising the likelihood function with the ordinal generalised linear models (OGLM) package in STATA14 (Williams, 2011). Given the results, it is possible to assume that, since the survey refers to the beginning of a strict lockdown period, response patterns appear to be mainly affected by a potential lack of concentration and by the availability of a comfortable home, suitable as a workplace. Considering workers' necessity to adjust to a completely new situation, the impacts of such variables are somehow expected, since they are, of course, strongly interconnected.

The presence of children is significant at 10%, since it should be considered that, as mentioned, children in the households are almost all in their late teens, and, therefore, substantially autonomous. The variable *carechildren* is significant in the variance equation, thus indicating some impact of the overall amount of usual family caregiving duties.

No statistical significance is attached to age, gender, and marital status (80% of the sample were married), consistent with the respondents' status of public employees, therefore presumably sharing similar overall conditions. Income class, instead, is slightly significant.

To consider the different effects of determinants, the model was estimated with the variance taking into account factors such as age, caring for children as a parental duty, and a variable referred to the lack of acknowledgement of the work carried out (*lack of recognition*). The latter driver turns out to be significant only in the variance equation but not as a general explanatory variable in the model: In fact, it was deleted from the model main equation, so as not to overload it with non-significant explanatory variables.

Tab. 5: Heteroskedastic Ordinal Probit for Teleworking Job Satisfaction, Coefficient Estimates, Variance Equation Coefficients, and Cut Points Estimates

TW job satisfaction	Coef.	Std. Err.	Z	P > z	
Gender	0.009	0.136	0.060	0.948	
Children	0.354	0.211	1.680	0.093	*
Marital status	-0.174	0.143	-1.210	0.225	
Age	-0.098	0.074	-1.320	0.185	
Size	0.045	0.036	1.250	0.211	
Income	-0.189	0.111	-1.700	0.090	*
Home as wp	0.157	0.066	2.370	0.018	**
Work effort change	0.351	0.166	2.110	0.035	**
Concentration	0.368	0.141	2.610	0.009	***
Neverending	0.008	0.023	0.340	0.735	
Expenses	0.307	0.168	1.820	0.068	**
Log(sigma) equation					
Children0.350	0.225	1.550	0.120		
Age class	-0.070	0.097	-0.730	0.468	
Lack of recognition	0.041	0.023	1.790	0.073	*
Carechildren	-0.165	0.083	-1.970	0.048	**
Cut point1	1.534	0.794	1.930	0.053	
Cut point2	3.142	1.241	2.530	0.011	
Pseudo R^2= 0.21			LR test $\chi^2(15)$=119.83		

***: significant at 1%; **: significant at 5%; *: significant at 10%

The discussion of the results from the estimated model must take into account that in the Ordinal Probit model the magnitude and sign of the coefficients cannot be interpreted by themselves, so it could be worth examining specific response profiles. In particular, we analyse the probability to be “very satisfied” and “not satisfied” as a function of the level of satisfaction with home as a workplace and the perceived variation in work effort, assigning to all the remaining variables in the model their median value, considering a female individual with children who has encountered some expenses to be able to work from home.

In general, as it may be observed in Figure 2, the probability of being more satisfied with telework clearly grows as the degree of satisfaction with home as a place of work increases and the work efforts varies. This circumstance is more evident in case of greater work effort, meaning that home conditions do play a prominent role. On the contrary, the probability of being less satisfied is undoubtedly higher for the same conditions, when respondents’ satisfaction for home as a workplace declines (Figure 3), even in case of a lower work effort. It should be noted that since gender is not statistically significant, the corresponding estimated probabilities for a male with the same characteristics are almost identical.

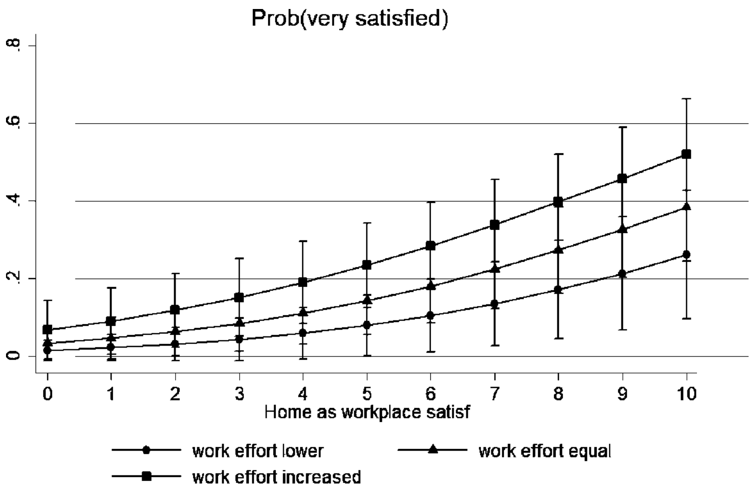

Fig. 2: Marginal effects of being "very satisfied" with telework for a female respondent with children, by varying work effort

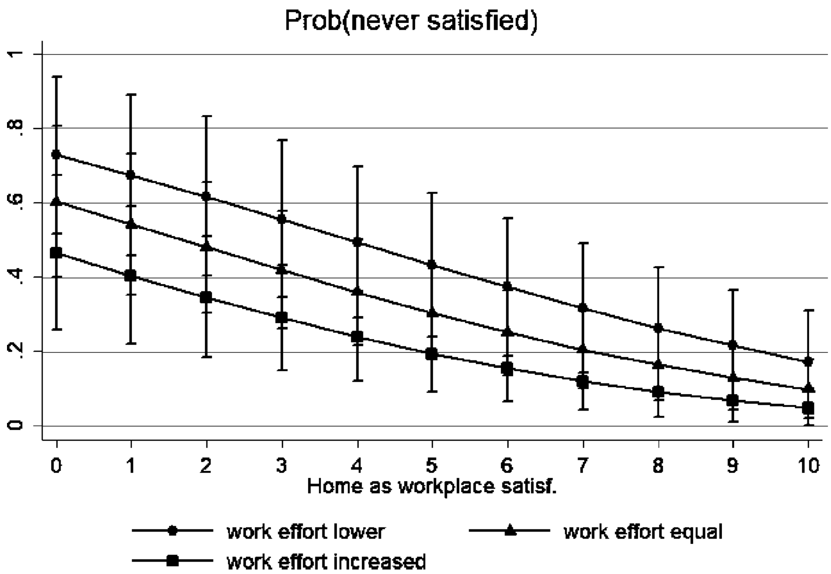

Fig. 3: Marginal effects of being "not satisfied" with telework for a female respondent with children, by varying work effort

4. DISCUSSION AND CONCLUDING REMARKS

The probability of being satisfied with telework, as well as with using their own home as a place of work, is rather high for the surveyed public employees. This first observation might seem to contrast with some findings of several research studies on the level of satisfaction with this specific job arrangement. The widespread consensus found in this study was rarely seen in previous transformation processes of work organisation, therefore representing a resource not to be disregarded as a basis for future improvements (among others: Messenger, 2019).

The respondents clearly perceived the unusual circumstances they experienced in the first phase of the COVID-19 pandemic to be potential advantages, envisaging the benefits in terms of less commuting, greater productivity, and increased self-management of workload. This outcome could not have been predicted, especially in light of the upheavals to daily life caused by the pandemic as well as of the lack of an established culture of telework in Italy.

Beyond a general good reception of compulsory teleworking in the early stages of containment and social distancing measures, some essential aspects and limitations of the study should be underlined. First and foremost, our research refers to a small sample of interviewees with respect to conditions experienced in the period between March and May 2020, a time in which the workers were basically forced to telework. We may assume that the novelty of working from home exerted an initially strong positive effect because of the possibility of staying “safe”, not commuting to workplaces, and, at the same time, remaining connected to the world.

Additionally, respondents’ positive perceptions may have benefitted from other effects, such as the awareness of being observed and studied as a sub-group of interest. This could also be a manifestation of the well-known Hawthorne effect, which refers to the set of modifications in a phenomenon or a behaviour which occur as a result of the presence of observers, but which is not likely to last over time (for a statistical interpretation of the Hawthorne effect, see Franke and Kaul, 1978).

Negative impacts, as underlined in the literature (Fana et al., 2020; EU-OSHA, 2021a; Eurofound, 2021) seem to take place only at a subsequent stage, when the problems and inconveniences of teleworking have begun to become more palpable in everyday life. In fact, the detrimental effects of such a new working arrangement likely would arise only when employees encountered an increase in their workload, more pressure regarding their work performance, and, in the long run, a failed opportunity to settle work-life balance. The situation was entirely new in the Italian context, since the country’s teleworking implementation figures before the pandemic were extremely low in comparison to other similar European economies. Then, the continuation of the pandemic and protracted periods of involuntary work from home began to negatively affect the perceived quality of life of teleworkers, also in terms of technostress[6]. These occurrences were higher for teleworkers (28% compared to 22% of other employees) and even stronger for women (29% compared to 22% of male colleagues). Moreover, teleworkers have been considerably affected by the reduction or absorption of social contacts and by the blurring of boundaries between working and non-working time (INPS, 2021).

In general, although with some intrinsic limits due to the small sample size, our results reveal that the probability of being satisfied with teleworking increases as satisfaction with home as a place of work rises, even in the case of work effort intensification. These circumstances lead us to surmise that workers in our sample are deeply engaged and can express their own ability to control their work processes.

It seems remarkable that many respondents in middle- and low-income classes have undertaken expenses to enable them to work from home. This observation is apparently at odds only with the fact that our sample consists of workers employed in the public sector: Italian public employees have seen many of their advantages eroded over the past 30 years. To date, figures demonstrate that, in comparison with the rest of Europe, the Italian public sector workers are in the lowest positions[7] with respect to almost all the available indicators.

With respect to a better balance of living and working time, our results – consistent with evidence at a national and international level (among others, Del Boca et al.; 2020; Dunatchik et al., 2021; EU-OSHA, 2021b) – have demonstrated that teleworking may be considered an effective contributor to a better work-life balance only if it is properly managed. In fact, research on the impacts of telework has begun to disclose that telework activities, when not properly managed, could lead to a non-sustainable overlapping of care and professional roles, with more severe consequences for women, especially with regard to their career prospects (Rodríguez-Modroño and López-Igual, 2021).

These results call for further research on larger datasets and deep investigation of the impacts of telework on the quality of working life, aiming to provide valuable information to both policy makers addressing specific regulatory measures and to managers in charge of implementing companies' welfare.

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6 Some possible negative effects of the so called "technostress" are deterioration of the work-life balance and overworking. Overall, overworking (i.e. dedicating a large amount of time to work and neglecting moments of rest) involved 13% of workers and to a greater extent teleworkers than other workers (17% compared to 9%), women than men (19% compared to 11%) and managers than collaborators (19% compared to 9%) (Osservatori.net, 2021).

7 As an instance, the percentage of public workers out of the total number of workers in Italy in 2017 (13.4%) is lower than it is in France (19.6%), Spain (15.9%), and in the United Kingdom (16%), and higher only as compared to Germany (10.8%) (Eurofound and ILO, 2017).

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