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Logib – the federal government's equal pay self-test tool to verify wage equality between women and men

The Confederation's standard analysis model

Methodological approach of Logib Modules 1 and 2

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1 Contents

2 Preface

Logib, the Confederation's standard analysis tool for analysing equal pay between women and men, consists of two modules. Both are designed as self-assessments that can be performed by users with the aid of the documents made available and without requiring any specialist knowledge. They are available to all employers free of charge as modern online applications[1].

This document describes in detail the methodological principles that underpin the two modules (1 and 2) of the Confederation's standard analysis model.

Logib Module 1 was developed by the Federal Office for Gender Equality (FOGE) with the support of private specialist institutions in the early 2000s (Strub, 2004). The Excel version of Logib Module 1 has been freely accessible since 2004. Logib Module 1 was validated by various evaluations (INFRAS, 2013, Felfe, Trageser & Iten, 2015) and developed into the online application, which went live on 1 July 2020. Logib Module 1's theoretical approach is based on human capital theory (Becker, 1993). A statistical method (multiple regression analysis) is used to check to what extent objective and non-discriminatory personal and workplace (i.e. job-related) characteristics determine wages and to what extent, if any, gender influences wages (see *section 3*). For statistical reasons, this module is particularly suitable for larger companies.

Logib Module 2 was developed with scientific assistance from the University of Bern and widely trialled in field tests between 2011 and 2019 in order to make the Confederation's standard analysis tool equally accessible to smaller companies (see Hirschi & Ghetta, 2020). Once developed, the methodology was validated by means of a scientific peer review involving outside experts from a variety of disciplines (economics, work science, law) and the International Labour Organization ILO. The result confirmed its scientific rigour and conformity with legal requirements. Module 2 is based on the scientific method of job evaluation and can be used to check to what extent the requirements and demands of a function, along with personal experience and education and training, determine wages and whether there are any differences between women and men (see *section 4*). Module 2 is especially recommended for small companies.

Both modules of the standard analysis model use the same personal and pay data. The function-related data is recorded differently in each of the two modules, as required by the respective methodological approach. Both the OLS regression analysis on which Module 1 is based and the job evaluation method used in Module 2 have been approved by the Swiss Federal Supreme Court as viable approaches to substantiating whether wage discrimination exists[2].

This description of the methodological approaches used serves to create transparency and make the two modules easier to understand.

3 The standard analysis model in Logib Module 1

3.1 Overview

Logib Module 1 is designed for medium-sized and large enterprises and can technically be used from starting at 50 or more valid data sets. It consists of four components:

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[1] https://logib.admin.ch

[2] For Module 1 see BGE 130 III 145, for Module 2 BGE 117 Ia 262, since regularly confirmed. For more information on the scientific rigour and legal conformity of Logib and its two modules, see the FOGE's declaration of conformity. declaration of conformity.

a. one dependent variable: standardised gross wage based on a wage specification;

b. multiple independent variables: factors to justify wage differences between men and women (education, seniority, potential work experience, occupational skill level and professional position) as well as the gender variable;

c. a statistical analysis method: semi-logarithmic OLS regression analysis;

d. a limit value of $\pm 5\%$ for the gender factor that must be statistically significantly different to zero[3].

The *standard analysis* model used for evaluating compliance with wage equality consists in explaining the wages of employees by their personal characteristics (education, seniority, potential work experience), job related factors (level of requirements and professional position) as well as their gender. All other things being equal, this method allows isolation of the effect on the wage that is due solely to an employee's gender. In other words, it makes it possible to determine the unexplained wage difference between men and women under otherwise equal circumstances within a company.

In the context of controls of the FOGE in federal procurement processes a limit value of 5% is applied. [4] For equal pay analyses with Logib outside the context of public procurement, a target value of 2.5% is issued. The target value is a voluntary guideline, to be distinguished from the binding limit value that is used in the context of public procurement and which can lead to sanctions if exceeded.

3.2 Methodology

The Confederation's standard analysis tool for equal pay analysis is based on the approach of the *multiple linear regression*[5], a statistical procedure which is used to study the relationship between a dependent variable (e.g. the logarithm of the wage) and independent variables (e.g. potential work experience, training, professional position, …). Alternatively, the dependent variable is also called the explained variable and the independent variables are called the explanatory variables.

3.2.1 Multiple linear regression model

The general form of the multiple linear regression model[6] with *n* observations and *p* independent variables is given by:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \ldots + \beta_p x_{ip} + \epsilon_i,$$

for $i = 1,2, \ldots, n$.

y_i	dependent variable for the i^{th} individual (e.g. the logarithm of the monthly gross wage of person i)
$x_{i1}, \ldots, x_{ip}$	independent variables for the i^{th} individual (e.g. age, potential work experience, education, professional position, etc. of employee i)
β_0	the constant or intercept
$\beta_1, \ldots, \beta_p$	coefficients to be estimated. The value of a coefficient β_j indicates the marginal effect of an increase in one unit of the variable x_{ij} on the dependent variable (ceteris paribus)

[3] This limit value of $\pm 5\%$ is not to be confused with the significance level $\alpha = 5\%$ of the hypothesis test which is also 5% in this approach.
[4] If the control shows that the limit value is exceeded, the participation requirements with regard to the provisions on gender equality in terms of equal pay in government procurement is considered as not fulfilled.
[5] The basics of this approach are described in this section, for a more thorough treatment of regression analysis; refer to J.M. Wooldridge (2006).
[6] See decision BGE 130 III 145 of the Swiss Federal Supreme Court.

ϵ_i random error term for the i^{th} individual with zero mean and constant variance

The regression coefficients $\beta_0, \ldots, \beta_p$ are estimated as $\hat{\beta}_0, \ldots, \hat{\beta}_p$ by the method of ordinary least squares (OLS). That is, the coefficient estimates are obtained by minimizing the sum of squared residuals[7]: $\sum_{i=1}^{n} \hat{\epsilon}_i^2 = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$, where $\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_{i1} + \cdots + \hat{\beta}_p x_{ip}$.

3.2.2 Data basis

The standard analysis model is applied at company-level and thus, the following data is required for the reference month for each employee[8] of the company:

- *gender*, the gender of the employee, female or male
- *age*, the bygone age of the employee
- *training*, the effective highest completed level of training of the employee, a code from 1 to 8 which is then used to compute the years spent in education for each employee
    1. University (codes 1 and 2)
        - Option 1, by type of institution
            1. Universities and institutes of technology (UNI, ETH) : 17 years
            2. University of applied sciences (FH), university of teacher education (PH) or equivalent : 15 years
        - Option 2, by type of degree
            1. Master's degree : 17 years
            2. Bachelor's degree : 15 years
    2. Higher vocational training with Federal PET diploma, advanced or master craftsman diploma, diploma from a technical college (TS), PET/engineering/business administration/art and design college or equivalent : 14 years
    3. Teaching certificate at various levels : 15 years
    4. Academic baccalaureate, vocational baccalaureate, specialized baccalaureate or equivalent : 13 years
    5. Completed vocational education and training (Federal VET Certificate), full-time vocational school, upper secondary specialized school, VET programme (Federal VET diploma – EBA) or equivalent : 12 years
    6. Purely in-house vocational training : 11 years
    7. Compulsory schooling without professional qualification : 7 years
- *years of service*, the number (in decimal) of years spent by the employee in the current company
- *function*, the name of the job or function carried out by the employee

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[7] The error term represents the difference between the dependent variable and the population regression, while the residual represents the difference between the dependent variable and the sample regression. Thus, an error term is not observable while a residual is observable and quantifiable.

[8] Employees with special employment contracts are excluded from the analysis. For a definition of special employment contracts, refer to the guideline for the standard analysis tool logib.

- *level of requirement*, is used to enter, for each function, the requirements for the work or function being performed by the employee, a code from 1 to 4 defined as:
    1. Extremely demanding and difficult tasks
    2. Independent and skilled work
    3. Work requiring professional/technical skills
    4. Simple and/or repetitive tasks
- *professional position* is used to enter the responsibility associated with each function (management responsibility, specialist responsibility or responsibility for human life, etc.), a code from 1 to 5 defined as:
    1. Senior management / Functions with highest responsibility
    2. Middle management
    3. Lower management
    4. Lowest management
    5. Employees with no management function / Functions without added responsibility
- *work-time percentage*
    - Employees paid monthly: *activity rate*, a (decimal) number corresponding to the contractual activity rate in percentage points
    - Employees paid hourly: *paid hours in the reference month*, a (decimal) number corresponding to the number of hours paid by the company in the reference month (without compensation for holidays and public holidays)
- *gross wage*[9], the wage earned by the employee in the month of reference, consisting of
    - *basic wage*, wage components that are paid regularly with the ordinary wage
    - *statutory allowances*, extra pay for difficult working conditions and any other hardship allowances
    - *13th monthly wage*, proportion of the 13th monthly wage
    - *special payments*, part of the regular or irregular special payments such as performance bonuses and other bonuses, pro rata amount for the reference period
- *usual weekly working hours*, the usual working hours in hours per week for an activity rate of 100%

3.2.3 Wage standardisation

For each employee, the sum of wage components is standardised to correspond to a full-time job at the company. If there are different usual weekly working hours, the *modal* usual weekly working hours (i.e. the most frequent usual weekly working hours within the company) is used. The standardised wage is computed as:

- for employees paid monthly:

[9] For a precise description of the pay specification see PricewaterhouseCoopers AG (2020)

$$standardised\ wage \equiv gross\ wage \cdot \frac{100}{activity\ rate} \cdot \frac{company's\ modal\ usual\ weekly\ working\ hours}{usual\ weekly\ working\ hours\ of\ the\ employee}$$

- for employees paid hourly:

$$standardised\ wage \equiv gross\ wage \cdot \frac{52 \cdot company's\ modal\ usual\ weekly\ working\ hours}{12 \cdot paid\ hours}$$

3.2.4 Specification of the standard analysis model Logib Module 1

The particular formula[10] used in the Confederation's standard analysis model Module 1 reads as:

$$\ln(Wage_i) = \beta_0 + \beta_{Train} \cdot Train_i + \beta_{Exp} \cdot Exp_i + \beta_{Exp^2} \cdot Exp_i^2 + \beta_{Tnr} \cdot Tnr_i \\ + \beta_{Skl} \cdot Skl_i + \beta_{Pos} \cdot Pos_i + \beta_{Gender} \cdot Gender_i + \epsilon_i$$

where

$\ln(Wage_i)$	Logarithm of the gross wage standardised to a full-time job for employee i at the company's modal usual weekly working hours (see subsection 2.3).
$Train_i$	Years of training of employee i, converted from the training code as explained in subsection 2.2.
Exp_i	Years of potential experience for employee i, calculated as $\max\{Age_i - Train_i - 6, 0\}$. This variable also enters the equation in its squared form as the effect of professional experience on wages is generally non-linear according to economic theory.
Tnr_i	Years of service in the current company for employee i.
Skl_i	Level of requirement for the function of employee i. This variable enters the regression model as a categorical variable with up to four levels (i.e. 3 dummy variables, see subsection 2.2 for a description of the levels).
Pos_i	Professional position for the job performed by the employee i. This variable enters the regression model as a categorical variable with up to five levels (i.e. 4 dummy variables, see subsection 2.2 for a description of the levels).
$Gender_i$	Gender dummy variable for the employee i, 1 for women and 0 for men.

The model uses the logarithmic form of the dependent variable, i.e. $\ln(Wage_i)$ in this case. It is common to logarithmize the wage as a dependent variable, as empirically, wages approximately follow a log-normal distribution, thus the logarithm of the wage follows a normal distribution[11]. Furthermore, this log-transformation reduces the impact of outliers (extremely high or low wages), rendering the estimates more robust and provides a better interpretation of the results. When the logarithm of the dependent variable is used, the regression equation is said to be *semi-logarithmic* or *log-level*. In a semi-logarithmic regression, the interpretation of the estimates $\hat{\beta}_1, \ldots, \hat{\beta}_p$ changes slightly: under this form, $\hat{\beta}_j$ can be interpreted as an approximation of the percentage increase of the wage if the variable x_{ij} is increased

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[10] For employees paid hourly, the gross wage is indicated without compensation for holidays and public holidays. Furthermore, in order to alleviate the notation, the categorical dummies are represented by a single variable each. Categorical variables such as Skl_i or Pos_i enter the model as multiple dummy variables. Consider for instance a company with all four skill levels in the data, in that case, $\beta_{Skl} \cdot Skl_i$ in the equation above is truly $\beta_{Skl1} \cdot Skl1_i + \beta_{Skl2} \cdot Skl2_i + \beta_{Skl3} \cdot Skl3_i$, where $Skl1_i, Skl2_i, Skl3_i$ are 0-1 dummy variables representing the skill level of employee i.

[11] The lognormal distribution is used in particular when the dependent variable only takes on positive values and the frequencies in the left-hand side of the distribution are greater than in the right-hand side of the distribution, i.e. when there is a right-skewed distribution. This is typically the case in the distribution of wages, with many small wages on the left-hand side and a few very high wages on the right-hand side of the scale.

by one unit. For instance, if $\hat{\beta}_{Train} = 0.02$, the model indicates that an additional year of training will increase the gross standardised wage by $100 \cdot (\exp(\hat{\beta}_{Train}) - 1)\% = 2.02\%$ which can be approximated by $(100 \cdot \hat{\beta}_{Train})\% = 2\%$. The approximation error occurs since, as the change in the logarithm becomes larger and larger, the approximation becomes more and more inaccurate.

3.2.5 Estimation of the gender effect

To estimate the impact of the gender on the wage, we use the estimator due to Kennedy (1981), which yields a consistent and almost unbiased estimator (assuming normal errors) and is formulated as:

$$\hat{\tau}_K \equiv \exp\left(\hat{\beta}_{Gender} - \frac{\widehat{\mathbb{V}}[\hat{\beta}_{Gender}]}{2}\right) - 1,$$

with $\exp(\cdot)$ being the exponential function and $\widehat{\mathbb{V}}[\hat{\beta}_{Gender}]$ being the square of the estimated standard error of the estimated discrimination coefficient.

For instance, if $\hat{\beta}_{Gender} = -0.061$ and $\widehat{\mathbb{V}}[\hat{\beta}_{Gender}] = 0.041$, then $\hat{\tau}_K = \exp\left(-0.061 - \frac{0.041}{2}\right) - 1 = -0.0783$, which implies that, under otherwise equal circumstances, women earn 7.83% less than men.

3.2.6 Significance of the gender effect

Estimating a parameter such as the discrimination coefficient always entails an element of uncertainty, as the true value of the parameter β_{Gender} will remain unknown. Nevertheless, one can hypothesise about the value of β_{Gender} and use statistical inference to test this hypothesis. Given a hypothesis, a result is said to be statistically significant if it is very unlikely to have occurred by chance. Therefore, the estimate of the discrimination coefficient must be interpreted jointly with its *statistical significance*.

Consider the *null hypothesis*

$$H_0: \beta_{Gender} = 0,$$

which corresponds to the hypothesis of the gender having no effect on the wage once the other explanatory variables have been controlled for. If this hypothesis was true, it would imply that the gender has no effect on the wage once the other variables have been accounted for. If it was false on the other hand, a gender effect would be identified.

We cannot know for sure whether H_0 is true or false, but we can determine a data-driven rule on whether to reject it or not. Consider the following *test statistic*:

$$t_{\beta_{Gender}} = \frac{\hat{\beta}_{Gender} - \beta_{Gender}}{se(\hat{\beta}_{Gender})},$$

where $se(\hat{\beta}_{Gender})$ is the standard error of the estimated gender coefficient. Further consider a *significance level*, denoted by α, which is the probability of rejecting the null hypothesis when it is in fact true. The choice of $\alpha = 5\%$ is very common and the value used in the Confederation's standard analysis model, also.

Given this significance level α, we can calculate a critical t_{crit} such that we are able to reject H_0 in favor of its alternative hypothesis H_A whenever $t_{\beta_{Gender}} > t_{crit}$.

The Confederation's standard analysis model tests the null hypothesis that the discrimination coefficient is zero. The null hypothesis and alternative hypothesis can be formulated as follows:

- $H_0: \beta_{Gender} = 0$, the gender effect is equal to zero
- $H_A: \beta_{Gender} \neq 0$, the gender effect is not equal to zero

This null hypothesis states that women and men are paid the same on average for work of equal value. The alternative hypothesis, on the other hand, is the logical negation of the null hypothesis and it implies that women and men are not paid the same for work of equal value.

If the null hypothesis of no gender effect is rejected in favour of its alternative hypothesis, the second step then assesses whether the gender effect exceeds the specified threshold of 5%. This gives the following hypotheses:

- $H_0: \beta_{Gender} \leq 0.05$, the gender effect is smaller or equal to 5%
- $H_A: \beta_{Gender} > 0.05$, the gender effect is greater than 5%

If the null hypothesis is rejected and $\hat{\tau}_K$ is higher than 5% in absolute terms, the limit value is exceeded. If the null hypothesis is rejected and $\hat{\tau}_K$ is higher than 2.5% in absolute terms, the target value is exceeded.

3.2.7 Module 1 open source code

When using Logib Module 1 online, the statistical calculations are performed in the R programming language. A package containing the open-source version of the code is freely available at CRAN[12]. Instructions on how to use the R package can be found in its README[13].

4 The standard analysis model in Logib Module 2

4.1 Overview

Logib Module 2 is based on the scientific method of job evaluation (Schär Moser, 2019; Chicha, 2016, Katz & Baitsch, 1996) that enables the value of each function in a company to be determined in comparison with the other functions by measuring the requirements and demands in relation to a variety of relatively abstract factors. Requirements are skills which are absolutely essential for the performance of the tasks of a function (e.g. specific expertise and methodological skills, communication skills, organisational skills, etc.). Demands are elements related to carrying out a task that may be harmful to the person (e.g. confrontation with human suffering, working in extreme heat or cold, etc.). The requirements and demands are established solely in relation to the function, i.e. with no regard to who is carrying out the function or other aspects such as the activity rate. Logib Module 2 records the requirements and demands in four areas – intellectual, responsibility-related, psycho-social and physical – by means of six factors (see subsection 4.2.1). The result is a function value. Functions with a higher function value (i.e. those with higher requirements and demands) are accorded higher function-related pay. This approach thus permits users to check whether pay inequalities exist between women and men on the basis of the value of the function performed.

The function values arrived at in this way are combined with data on the personal experience and educational level attained by the person occupying the function. According to human capital theory, this information helps predict an individual's marginal productivity and enables us to make further differentiations within respective functions at the individual level. Experience is approximated here by age and years of service. Combining these elements allows each employee to be given their own individual ranking value that unites the value of the function they occupy with their personal characteristics. All employees can then be ranked by their function value (see subsection 4.2.4),

[12] https://cran.r-project.org/web/packages/logib
[13] https://cran.r-project.org/web/packages/logib/readme/README.html

experience and actual educational level attained, and compared with one another. This theoretical ranking of employees is then compared with their actual ranking by amount of pay (see section 4.2.5). Constellations in which a person earns at least 5% less in comparison with a person of the opposite gender than would be expected on the basis of function, personal experience and education and training are identified as risk pairs. Subsequently comparing risk constellations that disadvantage women and those that disadvantage men determines the risk of non-compliance with the equal pay requirement at company level (see section 4.2.6).

Details of the standard analysis model for Logib Module 2 are presented below. Detailed explanations of the background and development of Module 2 can be found in the development report (Hirschi & Ghetta, 2020).

4.2 Methodology

4.2.1 Determination and evaluation of functions

The first step in establishing the requirements and demands by means of an analytical job evaluation is for the company to define its existing functions.

Functions are specific work activities that can generally be separated from the people who perform them ("jobs"). Jobs which essentially contain similar tasks and responsibilities are generally combined to form one function. This deliberately ignores the fact that people within functions created in this way may differ in terms of varying additional or ancillary tasks. The definition of a function bears no relation to the person occupying that function or to other aspects such as activity rate. As a rule, there are far fewer functions within a company than employees. The function list is complete when all employees have been allocated a suitable function.

The functions defined in this way are then evaluated by the company in relation to the associated requirements and demands with reference to six pre-determined factors. These factors were chosen on the basis of the latest research findings on scientific job evaluation and have been shown to be both relevant and gender-neutral. The factors are:

1. Education/training requirements
2. Requirements regarding ability to work independently
3. Requirements in terms of specific expertise and methodological skills
4. Responsibility-related requirements and demands
5. Psychological and social requirements and demands
6. Physical requirements and demands

The first three factors fall into the intellectual category, the other three each constitute a separate area in their own right. In other words, the four areas of characteristics confirmed as relevant in theory and practice (intellectual, responsibility-related, psycho-social and physical) are taken into account (see Humphrey, Nahrgang & Morgeson, 2007; Krell & Winter, 2011, International Labour Office, 2008, Chicha, 2016).

Each function is evaluated by the company in relation to all the factors using a standardised five-point scale. For the “education and training” factor, this scale corresponds to the level of education typically required for the respective function and ranges from 1 = “No special education and training” via clearly defined steps to 5 = “Master’s degree”. For the other five factors, 1 stands for low and 5 for high requirements and demands. The comparative evaluation is carried out on a factor-by-factor basis for all functions, i.e. one factor after the other is evaluated for all functions and not one function after another for all factors. Thanks to this standardised process and the explanations available for each factor, known distortions in the evaluation of functions (e.g. influence of existing ideas about the function as a whole) can be effectively reduced and the quality of the function evaluations increased (International Labour Office, 2008).

4.2.2 Data required for the analysis

The personal data, pay data, activity rate and usual weekly working hours in company required for the analysis using Logib Module 2 are identical to that for Module 1 (see subsection 3.2.2).

And as in Module 1, the *function* carried out is entered for all employees (for further details see subsection 4.2.1).

4.2.3 Wage standardisation

Wage standardisation for Logib Module 2 is performed in the exact same way as for Module 1 (see subsection 3.2.3).

4.2.4 Calculation of function values and comparison of rankings

The function values are standardised by Logib Module 2 to figures between a minimum of 10 and a maximum of 50; the higher the function value, the higher the associated requirements and demands. The function values are calculated by taking the points assigned by the company to the six factors in its evaluation of the requirements and demands (see subsection 4.2.1), multiplying them by a weighting factor and then adding them together. The weightings of the individual factors automatically vary within pre-defined bandwidths (see below) in such a way as to optimally reflect the actual relationship within the respective company between function value and personal characteristics on the one hand and standardised wage on the other, regardless of gender. The procedure is as follows:

1) A seven-digit personal ranking value[14] is established for all employees on the basis of their function value and the data measuring their personal characteristics. It is defined as follows:

- *Function value of 10 to 50* (based on the evaluation of the function, rounded to the nearest whole number); first two digits of the ranking value.
- *Value for age or years of service*: An algorithm decides whether age or years of service are more relevant for determining pay (see below). The value for age therefore comes *before* that for years of service or vice versa (digits three and four and five and six respectively of the ranking value). Specifically, the age value is calculated using the age minus 15 years' pre-school and schooling. The age value arrived at in this way and years of service are both capped at 30 years. This ceiling reflects the non-linear relationship between experience and pay, thus taking into consideration a fact that can also be observed in figures concerning the economy as a whole: namely, that pay initially tends to increase with age before stagnating after several decades. (Age value = min(max(age-15, 0), 30), years of service value = min(years of service, 30))
- *Highest educational level*: In accordance with code 1-8 (see subsection 3.2.2; for practical reasons these are recoded, i.e. 1 becomes 8, 2 becomes 7, etc.); final digit of the ranking value.

> *Example*: The ranking value of person A in a function with a function value of 21, a capped age of 25 (age 40 minus 15 years' pre-school and schooling), 2 years of service and completed vocational education and training is 2125023. That of person B in a function with a function value of 27, a capped age of 20, 1 year of service and a Bachelor's degree is 2720017.

2) The ranking values thus arrived at and the wages standardised to full-time (see section 3.2.3) are now ranked in order. This serves as the basis for calculating the weighting of the six factors in the evaluation of functions. Bandwidths have been set for each factor, within which the respective weightings may vary in increments of 0.25 points[15]. These bandwidths have been defined as follows on the basis of theoretical and methodological considerations and empirical evidence agreed upon by experts in the field (see Hirschi & Ghetta, 2020, p. 50ff.):

- Education/training requirements: 2.0–3.0
- Requirements regarding ability to work independently 1.5–2.5

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[14] Ranking value refers to the defined combination of numbers that forms the basis for establishing a ranking.

[15] As all possible combinations of weightings are tried out, when conducting analyses with more than 500 employees the Module 2 webtool optimises the figures using increments of 0.5 instead of 0.25 for practical reasons (calculation time required).

- Requirements in terms of specific expertise or methodological skills: 1.5–2.5
- Responsibility-related requirements and demands 1.5–2.5
- Psychological and social requirements and demands: 1.5–2.5
- Physical requirements and demands: 0.0–1.0

These weighting bandwidths ensure that the highest weighting of all is assigned to the intellectual category (first three factors) as it has repeatedly been shown to have the highest relevance to wages. Within the intellectual category, the first factor has the highest weighting bandwidth because the education and training required to carry out a function has established itself as an objective and comparatively reliable rateable factor. Responsibility-related and psychological and social requirements and demands have the same weighting bandwidth. It corresponds to the lower bandwidth of the remaining two factors in the intellectual category. This serves to ensure that appropriate consideration is given to the areas considered relevant on the basis of theoretical deliberations. The physical requirements and demands have the lowest weighting bandwidth and constitute the only factor that can achieve a value of 0 (i.e. non-consideration). This reflects the fact that physical requirements and demands have hardly any influence on pay in many companies. In reality, analyses have frequently found a negative relationship with pay here, which can be attributed to the fact that those functions with the greatest physical requirements and demands are often the poorest paid (e.g. cleaners).

A combination of two employees is designated as concordant if the person with the higher theoretical rank receives a higher salary. A discordant combination exists if person A has a lower (higher) theoretical rank than person B and yet is still paid higher (lower) wages: the formula is *N0 = N(N-1)/2*, where N is the total number of employees in the company included in the analysis and *N1, N2* enable ties to be taken into account[16]. A combination of two employees that is neither "concordant" nor "discordant" is referred to as a "tie" or "tied pair". Tied pairs are thus pairs of employees who either receive the same wage and/or have the same ranking value.

> *Example:* Person A with the ranking value 2125023 earns CHF 5,200, Person B with the ranking value 2720017 CHF 6,200. The comparison yields a concordant combination. Were Person A to earn CHF 6,800, this would result in a discordant combination.

The optimised weighting of factors is achieved when Kendall's tau-b coefficient (Kendall, 1938) is maximised:

$$\frac{(\#\text{concordant combinations} - \#\text{discordant combinations})}{\sqrt{(N_0 - N_1) \cdot (N_0 - N_2)}}$$

The optimisation is performed once with the priority of age over years of service and once with the priority of years of service over age. For further analysis, the optimised weights and priority with the highest Kendall's tau-b coefficient are selected.

If several weighting combinations reach the maximum according to Kendall's tau-b coefficient, the next step is to determine one of these optimum weighting combinations on the basis of the highest linear correlation (Pearson's correlation coefficient) between the ranking values and the actual standardised wages.

For the purpose of optimisation, the function value is recalculated on each change of data and does not represent an absolute value. Instead, it should be viewed relative to the other functions and their

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[16] $N_1 = \sum_i t_i(t_i - 1)/2$, where t_i is the number of tied values in the i^{th} group of ties for the ranking values. A similar formula is $N_2 = \sum_j u_j(u_j - 1)/2$, where u_j is the number of tied values in the jth group of ties for wages.

evaluations within a certain company and at a certain time. It is not possible to compare the function values for a certain function with those of other companies.

4.2.5 Identification of risk pairs

To verify compliance with the equal pay requirement, risk pairs are identified by comparing the rankings based on individual ranking values and the rankings based on wages and applying three tests. Risk pairs are constellations in which a person earns at least 5% less in comparison with a person of the opposite gender than would be expected on the basis of their function, personal experience and education and training. They are identified by means of three tests which complement one another.

Test 1: Comparison of theoretically expected and actual wage rank

This test identifies women and men who, compared with a person of the opposite gender, occupy a lower wage rank than would be expected from their ranking value, and where the wage difference is at least 5%. Specifically, this means that each person is compared with every person of the opposite gender on the basis of their ranking value and actual standardised wage. Each constellation in which a person with the same or a higher ranking value receives a wage (in terms of their own actual standardised wage) that is at least 5% lower than a person of the opposite gender is identified as a risk pair.

The negative wage difference threshold of at least 5% in identifying risk pairs was agreed upon and considered suitable by the experts: the threshold is neither too low (so that non-relevant cases would be identified) nor too high (so that relevant cases would be overlooked).

> *Example:* Mr M works in a function with a function value of 39 and Ms S in a function with a function value of 36; Mr M is older than Ms S and has been with the company for longer. Mr M's ranking value places him in 12th rank within the company. His standardised wage is CHF 5,800. Based on her ranking value, Ms S occupies 14th rank. Her standardised wage is CHF 6,500. Mr M thus earns more than 5% less and is paid a lower wage than Ms S, against expectations. The pair is identified as a risk pair by Test 1.

Test 2: Estimating the wage rank using regression analysis

Linear regression, taking into account the function value and capped value for age and years of service, is used to estimate the predicted or "fitted" wage for all employees, which will serve as the basis for an alternative, theoretically expected ranking. The formula is:

$$\ln(wage_i) = b_0 + b_1 \cdot function\ value_i + b_2 \cdot age\ value_i + b_3 \cdot years\ of\ service\ value_i + \epsilon_i$$

The fitted wage rank is calculated using the wages estimated by the model and compared with the actual wage rank. Constellations in which a woman or man occupies a lower actual wage rank in comparison with a person of the opposite gender than estimated by the model, and where the wage is at least 5% lower (in terms of that person's actual standardised wage) are identified as risk pairs. Comparisons are made only between persons carrying out functions with the same function value or where the comparator with higher earnings occupies a function that is no more than two points higher[17]. Test 2 thus complements Test 1 and can also recognise additional risk pairs that were not identified by Test 1. The focus here is on the specific interplay of (potentially contradictory) differences in function value and experience within the respective company and how they impact wages. For example, if a person with a slightly lower function value earns less than a person of the opposite gender with a slightly higher function value, Test 1 will not identify them as a risk pair, even if the lower-paid person is considerably more experienced. Such risk pairs will be identified by Test 2.

> *Example:* Based on the general level of pay within the company and the individual values for functions, age and years of service, the wage of Ms Z (function value 30, 10 years of service,

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[17] Equivalent functions are compared. This definition of equivalent value of work was agreed by expert consensus, taking into account theoretical and empirical considerations which are set out in the development report (see Hirschi & Ghetta, 2020).

age 45) is estimated at CHF 4,812 and that of Mr D (function value 32, 3 years of service, age 33) at CHF 4,344. The wage rank arrived at through regression is 16 for Ms Z and 17 for Mr D. The standardised actual wages come to CHF 4,200 for Ms Z and CHF 4,500 for Mr D. Ms Z's wage is ranked 15th and Mr D's 14th within the company. Mr D thus occupies an unexpectedly higher ranking than Ms Z. As the function values are identical and the negative wage difference exceeds 5%, this difference represents a risk of non-compliance with the equal pay requirement and the pair is identified by Test 2 as a risk pair.

Test 3: Checking major wage differences

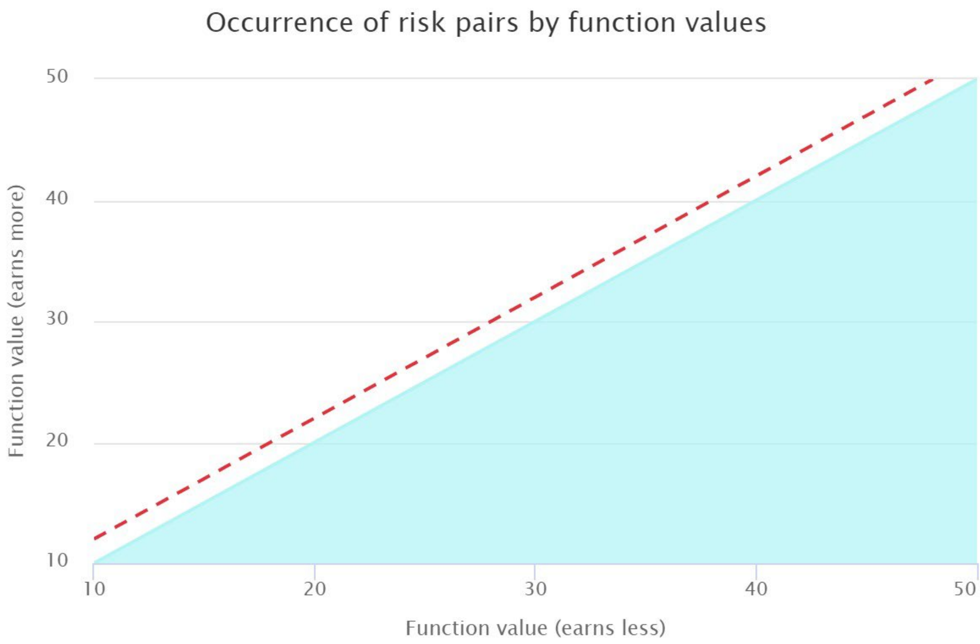
This test checks the size of the pay gap between all pairs in which one person's function value is no more than 2 points lower than that of a higher-paid person of the opposite gender (see footnote 17). Where persons of the opposite gender occupy an equivalent function and there is a wage difference of 20-35%[18], additional differences in the values for age and years of service are taken into account. If the difference in the values for age *and* years of service is less than five years, the wage differences cannot plausibly be explained by differences in the length of experience. In the case of a wage difference of 35% or above in an equivalent function, a differently gendered pair is always identified as a risk pair regardless of differences in the values for age or years of service. Test 3 thus focuses on constellations in which there are large differences in wages between women and men in equivalent functions. Test 3 therefore complements tests 1 and 2 as it also identifies risk pairs in which the ranking is as expected, but where there is a very large difference in wages for equivalent functions that is disproportionate and lacks objective justification, indicating that there may nevertheless be a potential risk of non-compliance with the equal pay requirement.

Example: Ms T performs a function with a function value of 42 and has standardised total earnings of CHF 6,400. Mr O also performs a function with a function value of 42 and is paid standardised earnings of CHF 8,300. The wage difference is thus almost 30% within an equivalent function. Both are aged 42 and Ms T has 11 years of service, while Mr O has 14. The major wage difference therefore cannot be plausibly explained by a difference in age or years of service and the pair is identified as a risk pair by Test 3.

Figure 1 below illustrates how the three tests identify risk pairs. The x-axis shows the function values of the people with lower wages and the y-axis those of the comparators. Constellations in which a person with a higher ranking value earns at least 5% less than the comparator of the opposite gender all lie within the light blue area. Test 3 recognises situations in which particularly large wage differences exist in equivalent functions and thus also covers the area from the upper demarcation of the light blue area (same function value) to the red line (comparator's function evaluated a maximum of 2 points higher). The same applies to Test 2, which uses the company's general wage structure to identify situations in which risk constellations exist in respect of equivalent functions, taking the individual values for age and years of service into account. Depending on the specific situation, a constellation may be identified as a risk pair by one, two or all three tests; each constellation is taken into consideration once.

[18] The lower-paid person is the reference point for calculating the percentage value, i.e. the share of their actual standardised wage constituted by the negative difference.

Figure 2: Identification of risk pairs in various constellations



4.2.6 Determination of the risk of non-compliance with the equal pay requirement

Logib Module 2 shows the risk of non-compliance with the principle of equal pay for women and men on the basis of the risk pairs identified by the three tests. It does so on three levels. This enables companies to make a more nuanced analysis of potential problems in respect of gender-specific wage gaps.

Result at overall company level

At company level[19], a total score is calculated based on the number of risk pairs where men are lower paid and the number of risk pairs where women are lower paid and their average wage differences. This enables the company to assess whether and to what extent there is a risk of its failing to comply with the gender-based equal pay requirement.

The total score is calculated in two steps. In the first step, the risk weighting for women respectively for men is calculated. The risk weighting of gender $g \in \{women, men\}$ is given as $w_g = n_g(1 + \delta_g)$. n_g is the number of risk pairs to the disadvantage of the gender g. δ_g is the mean percentual pay difference of the risk pairs to the disadvantage of the gender g.

In the second step, the total sore can be calculated as follows:

$$total\ score = \frac{\max\,(w_{women}, w_{men})}{\min\,(w_{women}, w_{men})}$$

If for one gender the risk weighting w_g has the value 0, the total score is equal to the risk weighting of the other gender. If both risk weightings have the value 0, the total score is equal to 1. The total score is rounded up or down to the nearest 0.5.

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[19] "Company" here refers to all kinds of private and public sector enterprises and organisations.

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This method of calculating the total score using the two risk weightings for men and women is based on the Bayes factor from Bayesian statistics (Kass & Raftery, 1995). It takes informal rather than formal probabilities. This means that the hypothesis that the risk of non-compliance with the equal pay requirement will be to the disadvantage of one or the other gender does not necessarily have to apply or be rejected. It is also possible for unexplained wage differences to exist that disadvantage both genders or neither. In other words, calculating a total score in this way takes into account the fact that a high number of risk pairs to the disadvantage of both genders tends to indicate an incoherent wage system rather than a systematic, gender-specific distortion of wage practices. However, as the risk of gender-specific wage differences in individual cases increases the more incoherent wage practices are, companies are additionally shown the percentage number of risk pairs from all theoretically possible pair combinations as further information.

> *Example:* If a company employs 6 women and 4 men, there are 6 * 4 = 24 possible pairs. If 11 risk pairs are identified to the disadvantage of men and 11 to the disadvantage of women, these 22 pairs mean that more than 90% of all possible pairs represent risk pairs.

The risk of non-compliance with the equal pay requirement is considered as "very high" if the total score is higher than 5.

Module 1 and Module 2 are aligned in such a way that, empirically, a "very high" risk of non-compliance with the equal pay requirement in Module 2 should occur as frequently as the limit value being exceeded in Module 1 ("Significant gender effect: limit value exceeded").

Robustness measurement / "Leave-one-out"-Score

The total score can be influenced by individual cases. In order to estimate their influence on the total score, a "Leave-one-out"-Score (LOO-Score) is calculated as a robustness measurement.

Let $i \in \{1, 2, 3, \ldots, N\}$ be a person involved in at least one risk pair (either as a person with lower-than-expected wage or as a comparator). N is the number of persons involved in a risk pair. The risk weighting of gender g excluding person i is given as $w_{g_{-i}} = n_{g_{-i}}(1 + \delta_{g_{-i}})$. $n_{g_{-i}}$ is the number of risk pairs to the disadvantage of gender g if all risk pairs are excluded in where person i is involved. $\delta_{g_{-i}}$ is the mean percentual pay difference of the risk pairs to the disadvantage of gender g, if all risk pairs are excluded in where person i is involved[20].

The LOO-Score excluding person i, $Score_{-i}^{LOO}$, is given as

$$Score_{-i}^{LOO} = \frac{\max\left(w_{women_{-i}}, w_{men_{-i}}\right)}{\min\left(w_{women_{-i}}, w_{men_{-i}}\right)}$$

$Score_{-i}^{LOO}$ is calculated for all i. The robustness measurement, $Score^{LOO}$, is then given as $Score^{LOO} = \min\left(total\ score, \min_{\mathrm{i}}\left(Score_{-i}^{LOO}\right)\right)$. $\min_{\mathrm{i}}\left(Score_{-i}^{LOO}\right)$ is the lowest value across all i which $Score_{-i}^{LOO}$ takes[21].

If both the total score and the robustness measurement are higher than 5, the limit value is considered to have been exceeded.

Result at function level and personal level

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[20] In order to calculate $w_{g_{-i}}$ person i is excluded as person with lower-than-expected wage or as a comparator. $w_{women_{-i}}$ ($w_{men_{-i}}$) can therefore be influenced as well if person i is a man (women).

[21] If all risk pairs are attributable to a single person (either as person with lower-than-expected wage or as a comparator), $Score^{LOO} = 1$ is applied.

In addition to the result at whole company level, detailed results are also presented at function and personal level. This gives companies a deeper *insight into their wage practices* from an equal pay perspective and helps them identify potential courses of action.

The result at *function level* shows in which functions how many risk pairs occur for each gender, how many people these relate to and how high the average pay differences are to the disadvantage of women or men, respectively. It also shows how the total score for the company as a whole will change if the risk pairs for the respective function held by the person(s) with a lower-than-expected wage are left out of the equation. The more the total score changes, the greater the influence of the function in question on the total score.

> *Example*: The total score at company level stands at 1.5; this includes 6 risk pairs to the disadvantage of men with an average wage difference of 18.9% and 8 risk pairs to the disadvantage of women with an average wage difference of 18.6%. The “draughtsman/draughtswoman” function has 4 risk pairs to the disadvantage of men with an average wage difference of 20.9% and no risk pair to the disadvantage of women. If the “draughtsman/draughtswoman” function were to be removed from the analysis, the total score at company level would rise to a value of 4 to the disadvantage of women.

The identified risk pairs are presented in detail at *personal level*. The list of risk pairs shows which persons are concerned, the relationship between the personal characteristics and function-related data of the person with the lower-than-expected wage and those of the comparator, and how high the individual wage differences are.

> *Example*: Mr M carries out the “Project Manager” function, which scores 30 points, has an age value of 10 (age 25 minus 15 years’ pre-school and schooling) and 1 year of service. His actual standardised wage is CHF 6,675. Ms O (age value capped at 30, 12 years of service) in the function of “Draughtswoman”, which scores 4 points less at 26 points, has an actual standardised wage of CHF 7,542. The negative wage difference to the disadvantage of Mr M in this risk pair comes to 13%.

Appendix

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