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Diversity of human capital attributes and diversity of remunerations

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Introduction

The purpose is to provide some empirical evidence for promoting new insights into the economics of education. Particular attention is paid to the concept of competence and its influence on employee reward. The paper aims at comparing the impact on fixed earnings and flexible pay of the traditional human capital theory variables (education and experience) on the one hand and of specifically identified and assessed competences, on the other hand. The objective is to test if the HCV (years of schooling, years of labour market experience) and competences substitute or complement each other in the definition of earnings. If they are substitutes, competences may constitute a more explicit vision of what HCV concretely represent. If they are complements, one can assume that they refer to two different dimensions:

- HCV are used in an "anonymous" way to determine the average level of earnings corresponding to given levels of education and experience, in accordance with social rules;
- competences indicate the effective use of different knowledge and skills acquired and are used when individual and contingent criteria are required.

This paper is made up of four parts. First of all, basic considerations will be presented in order to relate our approach to other researches and to expose some limits of human capital theory (HCT). Section 2 describes how the data have been collected. In a third part, methodological considerations are discussed. The fourth part presents the main results of the empirical analysis.

1. Basic considerations on limits of the traditional human capital approach

Our approach is close to the one developed by Green (1998), by Allen and Van der Velden (2000), by Paul (2002) and by Heijke, Meng and Ramaerkers (2002) in trying to find the "value of skills" through hedonic earnings equations. The aforementioned research works represent new approaches of HCT, which propose the use of a checklist of competences to define the individual level of competence.

Our research offers two original features:

- a) the use of competences assessed by direct supervisors, this is to say an hetero evaluation, and not a self evaluation, as used by the abovementioned authors;
- b) the use of profit shares benefited by employees and in addition to the earnings, to assess the impact of human capital variables and competences.

1.1. Traditional human capital variables and competences

Arguing from the point of view of the emerging "economics of competences", one could enforce the claim that the HCV are not sufficient for defining the level of individual competence and its reward in the labour market (Suleman, 2004). Following this line of reasoning, we can formulate the main restrictions of HCT for defining this level of competence.

Firstly, according to the HCT, years of schooling and experience are a proxy for individual competence. The theory has paid little attention to the specific knowledge and skills acquired. Usually, the HCT assumes the stock of human capital homogeneous for a given amount of years of study, or a given degree. New approaches of HCT suggest that the portfolio of competences could differ for a same level of traditional human capital variable.

A limit left by HCT is the confusion between the process and the product. That is to say, when the number of years of schooling is considered, there is confusion between the source of acquisition of the competence and the competence itself. In addition to this, the HCT does not specify the kinds of knowledge and skills acquired through the investments in schooling and experience.

Thus it is assumed that the individual competence refers to qualification or the resources acquired through HC investments. However, the importance of the contextual use of knowledge and skills play an important role. The job matching theory explicitly takes into account this effective use of individual knowledge and skills.

According to Heijke and Ramaekers (1998), the job matching theory differs from HCT because it does not presuppose that individual knowledge and skills are productive in all

available jobs. The main premise of the job matching theory is that jobs and individuals are both heterogeneous. Consequently, if there are differences between jobs, individuals can have comparative advantages in accessing and performing particular activities (Heijke and Ramaekers, 1998).

For the sake of clarity, this paper puts forward a definition of individual competence, which takes into account the following: the qualification acquired through investments in human capital; the effective use of the knowledge and skills; and the assessment of the knowledge and skills acquired and used (Suleman, 2004).

1.2. The diversity of human capital rewards

HCT usually does not take into account the whole reward system. The theory studies how individuals are rewarded through fixed salary or wage. Nevertheless, someone as Armstrong refers to fixed salary as the base pay and suggests that there may also be additional payments related to performance, competence, contribution, skills (Armstrong, 1999). These represent the contingent component of the pay. In his book "Employee Reward", Armstrong (1999) defines competence-related remuneration as a method of remunerating individuals according to their ability to perform: "competence-related pay does not confine itself to the acquisition of competence. It is about the effective use of competence to generate added value" (Armstrong, 1999: 294).

However, Armstrong maintains that pay is in fact "*related*" to competences rather than "*based*" upon them. Indeed, according to Armstrong, it would seem impossible to base remuneration directly upon competences, since the evaluation of competences remains extremely difficult. Other factors, such as those linked to the market, can also influence remuneration.

In accordance with this concept, we will introduce the human resource management concept of "remuneration" to refer to all cash payments and benefits received by employees. The remuneration includes the fixed salary and any additional pay, as well the contingent or flexible pay, such as profit shares.

Our main objective is to underline the heterogeneity of human capital reward, which is, to some extent, the result of employer wage policies. The moral hazard problem employers face calls for some reward rules, which can contribute to leading the employees to cooperate. The question is how firms can configure their wage policies to guarantee the effective use of convenient competences, as well as to face institutional constraints.

2. The data

The data were supplied by an original survey of five large banking companies in Portugal. Six hundred clerks (not in a supervising position) were interviewed regarding their individual characteristics (age, gender, education, experience in the labour market, experience in the company). Their respective supervisors were asked to assess their competences using a list of thirty competences. The list of competences had been previously checked with the help of human resources managers of the main banking companies and some branch managers. In this paper, because of some missing values, only 443 employees will be considered, located in a total of 77 agencies.

There are four main reasons why the banking sector was chosen for the survey:

- a) it is a sector in which the concept of competence finds widespread use in human resources management;
- b) following the restructuring process in the sector, there is a need for competences to carry out commercial functions;
- c) the organisational structure of companies based on branches with small teams and direct supervision by the branch manager;
- d) the geographical distribution of branches throughout the Portuguese territory.

Their average number of school years is 12.7, the number of years of total experience is 17.4 and the number of years of experience within the bank is 11.3.

A proportion of 61% of the population gets a flexible pay, which represents on average about one month pay.

Size	Ν	%
<5%	55	20.7
5%-10%	146	54.5
10%-15%	51	19.2
15%-20%	13	4.9
>20%	2	.8
Total	267	100.0

Profit sharing as a proportion of the total annual earnings

The records of the assessment by supervisors for each of the thirty competences were synthesised using a principal component analysis. Four main factors were produced,

making it possible to define four groups of competences: cognitive competences, strategic competences, behaviour towards the organisation, general knowledge.

	Specific technical knowledge
	Autonomy
	Responsibility
	Adaptability
	Innovation
	Planning and organising
Cognitive competences	Ability to organise
	Ability to selection and to process information
	Ability to solve problems
	Ability to learn
	Ability to transfer knowledge and experiences
	Capacity to understand the specificities of the banking
	activity
	Negotiation
	Persuasion
	Perseverance and orientation towards results
Strategic competences	Orientation towards the client
	Understanding of the strategy of the bank
	Readiness to learn
	Effort to learn
	Following the rules and procedures
Behaviour towards the organisation	Cooperation
	Adaptation to the working hours
	Punctuality
	General technical knowledge
General knowledge	Knowledge of foreign languages
	Computer literacy
NB: the loadings are presented in anne	x

The four clusters of competences built on the principal components

3. Methodological considerations

The objective is to compare to what extent the structure of remuneration differs when either basic pay or profit sharing are considered.

Since only part of the workers receive a flexible salary, we need to test if they differ from the others and if any difference can affect the value of the regression coefficients. The earnings models have to take potential selectivity biases into account.

The second question arises from the hierarchical structure of the data, since workers are grouped under the responsibility of one supervisor, who has been asked to assess their skills and competences. Several problems can arise when such phenomenon and variables are studied: first, since the evaluation is a subjective appreciation of workers by their supervisor, it can be supposed there is some endogeneity. Two factors may cause such an endogeneity: the supervisor may anticipate the consequence of his/her judgement in sub-estimating or super-estimating the mark, if this mark has an impact on the employee's reward. In our survey, the evaluation of skills and competences has been conducted for the specific purpose of the research, without any link with the remuneration strategy. The other factor may be linked to the subjectivity itself of the supervisor. A given worker, with the same level of skill/competences, may be assessed differently by two different supervisors. The method used for building the four dimensions of skills/competences, using a long list of items, may limit this bias, if we consider the supervisors may assess differently the various items. Nevertheless, some supervisors may systematically have high marks, and others low marks. Introducing random effects through multilevel modelling may allow controlling for this endogeneity. An additional method is to consider not the raw values of the competences, but the values centered around the mean of the grades given by each evaluator, as well as the mean of the grades itself.

Let us note the following variables.

HC, for human capital variables: number of schooling years, experience, square of experience and gender (for convenience, gender is considered together with the human capital variables)

CV, for competence variables: cognitive competences, strategic competences, behaviour towards organization, general knowledge.

Let be FW and PS the fixed wage and the profit share of the individual i.

Actually, three families of models will be tested.

Simple OLS models will be tested in order to assess the proportion of variance of the two types of reward explained by the two families of variables

Ln (FW) = f(HC)Ln (PS)= f(HC)Ln (FW) = f(HC, CV)Ln (PS) = f(HC, CV)

Then a Heckman model will be considered to assess to what extent the restriction of the modelling to the workers who get a flexible pay can modify the results. For simplicity, only the human capital variables will be considered.

Ln (FW) = f(HC, λ) Ln (PS) = f(HC, λ) Where λ is the inverse of the Mills ratio, estimated with the following selection equation: Proba (PS>0)= f(HC, type of contract) And finally a multilevel approach is used to take into account the multilevel structure of the data. Two different expressions are considered, one with the individual ratings and one with the ratings centred around the evaluator mean and the evaluator mean itself.

$$Y_{ij} = \beta_{0j} + \sum_{l=1}^{4} \beta_{lj} x_{ij} + \sum_{m=1}^{4} \delta_{mj} z_{ij}$$
 with Y_{ij} either the fixed part or the flexible part of the wages of

the individual i assessed by the supervisor of the branch j, x_{ij} the HC variables and z_{ij} the competence variables

$$Y_{ij} = \beta_{0j} + \sum_{l=1}^{4} \beta_{lj} x_{ij} + \sum_{m=1}^{4} [\delta_{mj} (z_{ij} - \overline{z}_{.j}) + \gamma_{mj} \overline{z}_{.j}]$$

The inverse of Mills ratio will also be included in the multilevel models, together with the individuals variables.

4. Results

In order to get a first sight on the respective influence of the two groups of variables on the two types of remuneration, simple OLS regressions may be run. These regressions allow to undertake a variance analysis and to estimate the significance of the regression coefficient of the different variables taken into account. They consider the individuals who get a flexible income, on top of their fixed income (267 workers).

Regression: logarithm (fixed earnings) = fn (number of school years, experience, experience square, gender/male=1)

Source	SS	df	MS		Number of obs $F(4, 262)$	= 267 = 48.80
Model Residual	5.20352953 6.98426929		1.30088238 .026657516		Prob > F R-squared Adj R-squared	= 0.0000 = 0.4269
Total	12.1877988	266 .04	5818793		Root MSE	= .16327
Lg (fixed)	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
Sch.years	.0244576	.0057371	4.26	0.000	.0131609	.0357542
Exp	.0297862	.0041649	7.15	0.000	.0215854	.0379871
Exp ²	0003294	.000085	-3.88	0.000	0004966	0001621
Gender	.0189675	.0203765	0.93	0.353	021155	.05909
Intercept	11.5448	.103725	111.30	0.000	11.34056	11.74904

Regression: logarithm (fixed earnings) = fn (number of school years, experience, experience square, gender/male=1, cognitive, strategic, behaviour towards organization, general knowledge)

Source	SS	df		MS		Number of obs F(8, 258)	
Model Residual	5.95326424 6.23453457	8 258		58031 64863		Prob > F R-squared Adj R-squared	= 0.0000 = 0.4885
Total	12.1877988	266	.0458	18793		Root MSE	= .15545
Lg (fixed)	Coef.	Std. 1	Err.	t	P> t	[95% Conf.	Interval]
Sch.years Exp Exp2 Cognitiv Strategi Organiza Gen. know Gender Intercept	.0220692 .0304333 0003099 .0338933 .034207 .016866 .0132104 .0177514 11.55543	.00569 .0039 .00009 .00919 .00930 .00974 .01122 .01950 .10055	997 814 985 696 443 723 033	3.87 7.61 -3.81 3.68 3.65 1.73 1.17 0.91 114.94	0.000 0.000 0.000 0.000 0.085 0.242 0.364 0.000	.0108494 .0225623 0004702 .0157797 .0157564 0023225 008987 0206544 11.35747	.0332889 .0383042 -0001496 .052007 .0526577 .0360544 .0354078 .0561572 11.7534

Regression: logarithm (flexible income) = fn (number of school years, experience, experience square, gender/male=1)

Source	SS	df		MS		Number of obs $F(4, 262)$		267 4.20
Model Residual	4.33416229 67.6171437	4 262		354057 8080701		Prob > F R-squared Adj R-squared	= =	0.0026 0.0602 0.0459
Total	71.951306	266	.270	493632		Root MSE	=	.50802
Lg (flex)	Coef.	Std.	Err.	t	P> t	[95% Conf.	In	terval]
Sch.years Exp Exp2 Gender Intercept	.0407481 .0061882 0000921 .2006493 11.58785	.0178 .0129 .0002 .0634 .3227	589 643 011	2.28 0.48 -0.35 3.16 35.90	0.023 0.633 0.728 0.002 0.000	.0055988 0193286 0006126 .0758088 10.95236	•	0758974 .031705 0004284 3254899 2.22334

Regression: logarithm (flexible income) = fn (number of school years, experience, experience square, gender/male=1, cognitive, strategic, behaviour towards organization, general knowledge)

Source	SS	df	MS		Number of obs F(8, 258)	
Model Residual	18.9055821 53.0457239		2.36319776 .205603581		Prob > F R-squared	= 0.0000 = 0.2628
+ Total	71.951306	266	.270493632		Adj R-squared Root MSE	= 0.2399 = .45344
Lg(flex)	Coef.	Std. E	rr. t	P> t	[95% Conf.	Interval]
Sch.years	.0307107	.01661	94 1.85	0.066	0020163	.0634376
Exp	.0098855	.0116	59 0.85	0.397	0130734	.0328443
Exp2	0000597	.00023	75 -0.25	0.802	0005274	.000408
Cognitiv	.1651529	.02683	11 6.16	0.000	.112317	.2179889
Strategi	.1065639	.02733	03 3.90	0.000	.052745	.1603829
Organiza	.1049102	.02842	32 3.69	0.000	.0489392	.1608812
Gen.know	.034289	.03288	02 1.04	0.298	0304588	.0990367
Gender	.1963396	.05688	93 3.45	0.001	.0843132	.308366
Intercept	11.63519	.2932	39 39.68	0.000	11.05774	12.21263

Two main conclusions can be drawn from these results: the human capital variables explain better, as expected, the fixed part of the earnings, whereas the competence variables explain better the flexible part of the earnings. This statement can be expressed in a symmetrical way: the human capital variables hardly explain the flexible part of the earnings, whereas the competences are weakly related to the fixed part of the earnings.

In the models with the fixed earnings, the adjusted R square amounts 42% with only the three human capital variables and gender, but increased only to 47% when the four competences are taken into account. When the models with the flexible part of earnings are considered, the human capital variables contribute only to 5% of the total variance, whereas the introduction of the competences increases the proportion of explained variance to 24% (a proportion multiplied by near 5 times).

These first simple results can be challenged since they don't take into account the characteristics of the data. Workers who get a flexible income on top of the fixed part represent a part of the total of workers: the question of a potential selectivity bias has to be considered. On the other hand, the workers are grouped into branches under the responsibility of a supervisor. That means that the residuals at a same level may not be independent and that the competence grades can depend partly on the subjectivity of the supervisors.

In order to test any selection effect on the coefficient, two Heckman selection models have been run, with the fixed earnings and the variable pay respectively. The main equations include the four previous human capital and gender variables, whereas the selection equations consider the three human capital variables and the type of contract (permanent versus short term).

Heckman selection model Main regression: logarithm (fixed earnings) = fn (number of school years, experience, experience square, gender/male=1) Selection: proba(flexible income>0)= fn (number of school years, experience, experience square, permanent/short term contract)

	Coef.	Std. Err.	Z	₽> z	[95% Conf.	Interval]
(fixed)						
Sch.years	.0268937	.005942	4.53	0.000	.0152477	.0385398
Exp	.0313383	.0043062	7.28	0.000	.0228982	.0397783
Exp2	0003565	.000088	-4.05	0.000	0005289	000184
Gender	.0212862	.0201472	1.06	0.291	0182016	.060774
Intercept	11.67	.1062231	109.86	0.000	11.46181	11.8782
flexinc>0)						
Sch.years	0507686	.0336195	-1.51	0.131	1166615	.0151244
Exp	0477653	.0257301	-1.86	0.063	0981954	.0026649
Exp2	.0008196	.0005481	1.50	0.135	0002547	.0018938
Long term	1.538656	.2514613	6.12	0.000	1.045801	2.031511
Intercept	0102041	.6143514	-0.02	0.987	-1.214311	1.193902
/athrho	5487456	.1932891	-2.84	0.005	9275852	169906
/lnsigma	-1.752728	.0646744	-27.10	0.000	-1.879488	-1.625969
++ rho	4995795	.1450481			7294661	1682897
sigma	.1733005	.0112081			.1526683	.196721
lambda	0865774	.0295467			1444878	0286669

Number of obs = 443 (regression model with sample selection) Censored obs = 176

<pre>Heckman selection model Main regression: logarithm (flexible income) = fn (number of school years experience, experience square, gender/male=1) Selection: proba(flexible income>0)= fn (number of school years, experience, experience square, permanent/short term contract)</pre>										
Number of obs (regression mode Uncensored obs Wald chi2(4) Log likelihood =	el with sample s = 267 = 20.33	selection) Pro								
	Coef.		Z	P> z	[95% Conf.	Interval]				
+ Lq (flex)										
	.0541769	.0199931	2.71	0.007	.0149912	.0933627				
Exp	.0151369	.014396	1.05	0.293	.0149912 0130789 0008309	.0433526				
Exp2	- 000249	0002969	-0.84	0.402	0008309	.0003329				
Gender	2051175	.0599438	3.42	0.001	.0876298	.3226052				
Intercept					10.94441					
P(flexinc>0)										
					1208675					
Exp	0244458	.0249331	-0.98	0.327	0733136	.0244221				
Exp2	.0003436	.0005239	0.66	0.512	0006833	.0013705				
Long term	1.132214	.2172395	5.21	0.000	.7064324	1.557995				
Intercept	.2272738	.6014733	0.38	0.706	0006833 .7064324 9515922	1.40614				
/athrho	-1.246145	.1949602	-6.39	0.000	-1.62826	8640298				
/lnsigma	4548512	.0668475	-6.80	0.000	5858698	3238325				
rho	847199	.0550283			9258134	6983281				
sigma	.6345424	.0424176			.5566215	.7233714				
lambda	5375837	.066271			6674725	4076949				
LR test of ind	ep. eqns. (rì	no = 0):	chi2(1) =	12.49	Prob > chi	2 = 0.0004				

In the two models, there appears a clear selection effect, since the correlation between the errors of the two equations is significant as well as the lambdas. To get a permanent contract makes more eligible to the flexible pay regime. But this selection does not affect the significance of the coefficients, which remain highly significant in the fixed earnings equation and poorly significant in the flexible pay equation.

In the following models, the hierarchical structure of the data will be taken into account, using a multilevel approach (the GLLAMM procedure, under STATA, has been used). In order to take care of potential endogeneity issues, two measures of the competences have been considered. In a first stage, the initial grades of the competences have been introduced into the models. In the second one, the competences have been decomposed into two parts, a measure of each respective competence centred around the mean of the branch and the mean of the branch (i.e. the mean for each supervisor). Such a method allows assessing to what extent an influence of the branch (or of the supervisor) has to be considered. But the limit of such an approach relies on the impossibility of estimating the proportion of the variance explained by the variables of a same level. The Mills ratios have been introduced into the models.

Multilevel models with competence ratings

Lg(fixed)	Coef.	Std. Err.	Z	₽> z	[95% Conf.	Interval
Sch.years	.0294777	.0039863	7.39	0.000	.0216648	.0372906
Exp	.0324899	.0026494	12.26	0.000	.0272973	.0376826
Exp2	0003259	.0000565	-5.77	0.000	0004367	0002151
Cognitiv	.0469219	.0069138	6.79	0.000	.0333712	.0604720
Strategi	.0335977	.0072838	4.61	0.000	.0193217	.047873
Organiza Gen.know	.0004173 .0191005	.0073963 .0096405	0.06 1.98	0.955 0.048	0140792 .0002056	.014913
Gender	.0007558	.0142146	0.05	0.048	0271043	.028615
M. ratio	0975894	.0289648	-3.37	0.001	1543593	040819
Intercept	11.51098	.0704144	163.47	0.000	11.37297	11.6489
Variance at l	evel 1					
.01741961 (.	00127149)					
riances and	covariances of	of random ef	fects			
var(1): .	01197069 (.00					
var(1): .	,			 P> z	[95% Conf.	 Interval
var(1): . og likelihood Lg(flex)	01197069 (.00 l = -122.69539 Coef.	9 Std. Err.				
var(1): . og likelihood Lg(flex) Sch.years	01197069 (.00 l = -122.69539 Coef. .0245298	9 Std. Err. .014312	1.71	0.087	0035213	.052580
yar(1): . g likelihood Lg(flex) Sch.years Exp	01197069 (.00 l = -122.6953 Coef. .0245298 .015133	Std. Err. .014312 .0093863	1.71 1.61	0.087 0.107	0035213 0032638	.052580
<pre>var(1): . g likelihood Lg(flex) Sch.years</pre>	01197069 (.00 l = -122.69539 Coef. .0245298	9 Std. Err. .014312	1.71	0.087	0035213	.052580 .033529 .000253
var(1): . g likelihood Lg(flex) Sch.years Exp Exp2	01197069 (.00 l = -122.6953 Coef. .0245298 .015133 0001119	Std. Err. .014312 .0093863 .0001865	1.71 1.61 -0.60	0.087 0.107 0.548	0035213 0032638 0004775	.052580 .033529 .000253 .198521
var(1): . g likelihood Lg(flex) Sch.years Exp Exp2 Cognitiv	01197069 (.00 l = -122.69538 Coef. .0245298 .015133 0001119 .1565578	Std. Err. .014312 .0093863 .0001865 .0214105	1.71 1.61 -0.60 7.31	0.087 0.107 0.548 0.000	0035213 0032638 0004775 .1145939	.052580 .033529 .000253 .198521 .173025
<pre>var(1): . g likelihood Lg(flex) Sch.years Exp Exp2 Cognitiv Strategi Organiza Gen.know</pre>	01197069 (.00 1 = -122.69533 Coef. .0245298 .015133 0001119 .1565578 .1286861	Std. Err. .014312 .0093863 .0001865 .0214105 .0226224	1.71 1.61 -0.60 7.31 5.69 4.96 1.31	0.087 0.107 0.548 0.000 0.000	0035213 0032638 0004775 .1145939 .0843469	.052580 .033529 .000253 .198521 .173025 .166582
var(1): . g likelihood Lg(flex) Sch.years Exp Exp2 Cognitiv Strategi Organiza Gen.know Gender	01197069 (.00 1 = -122.69539 Coef. .0245298 .015133 -0001119 .1565578 .1286861 .1194324 .0373343 .1194597	Std. Err. .014312 .0093863 .0001865 .0214105 .0226224 .0240566 .0285075 .0455114	$ \begin{array}{r} 1.71\\ 1.61\\ -0.60\\ 7.31\\ 5.69\\ 4.96\\ 1.31\\ 2.62\end{array} $	0.087 0.107 0.548 0.000 0.000 0.000 0.190 0.009	0035213 0032638 0004775 .1145939 .0843469 .0722824 0185393 .0302591	.052580 .033529 .000253 .198521 .173025 .166582 .093207 .208660
<pre>var(1): . g likelihood Lg(flex) Sch.years Exp Exp2 Cognitiv Strategi Organiza Gen.know Gender M. ratio</pre>	01197069 (.00 1 = -122.6953 Coef. .0245298 .015133 0001119 .1565578 .1286861 .1194324 .0373343 .1194597 2926602	Std. Err. .014312 .0093863 .001865 .0214105 .0226224 .0240566 .0285075 .0455114 .1724554	1.71 1.61 -0.60 7.31 5.69 4.96 1.31 2.62 -1.70	0.087 0.107 0.548 0.000 0.000 0.000 0.190 0.009 0.090	0035213 0032638 0004775 .1145939 .0843469 .0722824 0185393 .0302591 6306667	.052580 .033529 .000253 .198521 .173025 .166582 .093207 .208660 .045346
<pre>yar(1): . g likelihood Lg(flex) Sch.years Exp Exp2 Cognitiv Strategi Organiza Gen.know Gender</pre>	01197069 (.00 1 = -122.69539 Coef. .0245298 .015133 -0001119 .1565578 .1286861 .1194324 .0373343 .1194597	Std. Err. .014312 .0093863 .0001865 .0214105 .0226224 .0240566 .0285075 .0455114	$ \begin{array}{r} 1.71\\ 1.61\\ -0.60\\ 7.31\\ 5.69\\ 4.96\\ 1.31\\ 2.62\end{array} $	0.087 0.107 0.548 0.000 0.000 0.000 0.190 0.009	0035213 0032638 0004775 .1145939 .0843469 .0722824 0185393 .0302591	.052580 .033529 .000253 .198521 .173025 .166582 .093207 .208660 .045346
var(1): . og likelihood Lg(flex) Sch.years Exp Exp2 Cognitiv Strategi Organiza Gen.know Gender M. ratio Intercept	01197069 (.00 l = -122.6953 Coef. .0245298 .015133 -0001119 .1565578 .1286861 .1194324 .0373343 .1194597 -2926602 11.83707	Std. Err. .014312 .0093863 .001865 .0214105 .0226224 .0240566 .0285075 .0455114 .1724554	1.71 1.61 -0.60 7.31 5.69 4.96 1.31 2.62 -1.70	0.087 0.107 0.548 0.000 0.000 0.000 0.190 0.009 0.090	0035213 0032638 0004775 .1145939 .0843469 .0722824 0185393 .0302591 6306667	
var(1): . g likelihood Lg(flex) Sch.years Exp Exp2 Cognitiv Strategi Organiza Gen.know Gender M. ratio Intercept	01197069 (.00 1 = -122.69533 Coef. .0245298 .015133 0001119 .1565578 .1286861 .1194324 .0373343 .1194324 .0373343 .1194397 2926602 11.83707 	Std. Err. .014312 .0093863 .001865 .0214105 .0226224 .0240566 .0285075 .0455114 .1724554	1.71 1.61 -0.60 7.31 5.69 4.96 1.31 2.62 -1.70	0.087 0.107 0.548 0.000 0.000 0.000 0.190 0.009 0.090	0035213 0032638 0004775 .1145939 .0843469 .0722824 0185393 .0302591 6306667	.052580 .033529 .000253 .198521 .173025 .166582 .093207 .208660 .045346
og likelihood Lg(flex) Sch.years Exp Exp2 Cognitiv Strategi Organiza Gen.know Gender M. ratio Intercept Variance at 1	01197069 (.00 1 = -122.69533 Coef. .0245298 .015133 0001119 .1565578 .1286861 .1194324 .0373343 .1194324 .0373343 .1194397 2926602 11.83707 	Std. Err. .014312 .0093863 .001865 .0214105 .0226224 .0240566 .0285075 .0455114 .1724554	1.71 1.61 -0.60 7.31 5.69 4.96 1.31 2.62 -1.70	0.087 0.107 0.548 0.000 0.000 0.000 0.190 0.009 0.090	0035213 0032638 0004775 .1145939 .0843469 .0722824 0185393 .0302591 6306667	.05258(.03352) .00025 .19852 .17302 .16658 .09320 .20866(.04534(

With the two models, the level 2 (the branch) appears to be significant. In the fixed pay model, the level 2 represents 41% of the total variance, and 42% with the flexible pay model. But the main important result regards the significance of the coefficients which is not affected by the new structure of the models. Human capital variables remain more significant in the fixed pay model, whereas the competence variables remain more significant in the flexible pay model.

A different treatment of the competence variables (centred variables and supervisor means) does not affect neither the significance nor the value of the competence variables.

Multilevel models with competence ratings centred around the supervisor mean and with the supervisor mean

log likelihood = 212.46926

Cognicen .0455654 .0071518 6.37 0.000 .031548 Stratcen .0308722 .0074491 4.14 0.000 .0162723 Organcen .007544 .00778 0.10 0.922 .0144851 Knowcen .0217666 .0098003 2.22 .0026 .0025583 Cognitiv_mn .0651679 .0249293 2.61 0.009 .0163073 Organzamn .0035742 .0249293 0.14 0.886 0454047 Sknow_mn .0072967 .0235097 0.31 0.756 0387816 Bender 0012411 .0140765 03 0.001 1571621 Intercept 11.63496 .0705599 164.89 0.000 11.49667 Variance at level 1							
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	Interval	[95% Conf.	P> z	Z	Std. Err.	Coef.	Lg(fixed)
$\begin{array}{c c c c c c c c c c c c c c c c c c c $.0370302	.0212913	0.000	7.26	.0040151	.0291607	Sch.years
$\begin{array}{ c c c c c c c c c c c c c c c c c c c$.03765			12.26			
Cognicen .0455654 .0071518 6.37 0.000 .031548 Stratcen .0308722 .0074491 4.14 0.000 .0162723 Organcen .007594 .007778 0.10 0.922 .0144851 Knowcen .0217666 .0098003 2.22 0.026 .0025583 Organity_mn .0651679 .0249293 2.61 0.009 .0163073 Organity_mn .0035742 .0249896 0.14 0.886 0454047 Sknow_mn .0072967 .0235097 0.31 0.756 0387816 Gender 012411 .0140765 009 0.930 0288305 I.ratio 099597 .023705 -3.39 0.001 1571621 Intercept 11.63496 .0705599 164.89 0.000 11.49667 Arriance and covariances of random effects	0002117						
Stratcen .0308722 .0074491 4.14 0.000 .0162723 Organcen .0007594 .007778 0.10 0.922 0144851 Knowcen .0217666 .0098003 2.22 0.026 .0025583 tegnitiv_mn .0651679 .0249293 2.61 0.009 .0163073 organiza_mn .0035742 .0249866 0.14 0.886 0454047 .know_mn .0072967 .0235097 0.31 0.756 0387816 ender 0012411 .0140765 -0.09 0.930 0288305 1.ratio 009597 .0293705 -3.39 0.001 1571621 intercept 11.63496 .0705599 164.89 0.000 11.49667 'ariance at level 1 0127457 .01347566 .00322022) .0001 11.49667 'ariances and covariances of random effects	.0595827						-
Knowcen .0217666 .0098003 2.22 0.026 .0025583 lognitiv_mn .0613109 .0314619 1.95 0.051 0003533 trategi_mn .0651679 .0249293 2.61 0.009 .0163073 trganiza_mn .0035742 .0249896 0.14 0.886 0454047 know_mn .0072967 .0235097 0.31 0.756 0387816 lender 0012411 .0140765 -0.09 0.930 0288305 l.ratio 095977 .0293705 -3.39 0.000 11.49667 - 00125411 .01727457 .00125411 .01727457 .0125411 'ariances and covariances of random effects	.0454722	.0162723	0.000	4.14	.0074491	.0308722	-
tognitiv_mn .0613109 .0314619 1.95 0.051 0003533 ttrategi_mn .0651679 .0249293 2.61 0.009 .0163073 organiza_mn .0035742 .0249293 2.61 0.009 .0163073 sknow_mn .0072967 .0235097 0.31 0.756 0387816 tender 0012411 .0140765 -0.09 0.930 0288305 1.ratio 099597 .0293705 -3.39 0.001 1571621 Intercept 11.63496 .0705599 164.89 0.000 11.49667	.0160039	0144851	0.922	0.10	.007778	.0007594	Organcen
strategi_mn .0651679 .0249293 2.61 0.009 .0163073 brganiza_mn .0035742 .0249896 0.14 0.886 0454047 s.know_mn .0072967 .0235097 0.31 0.756 0387816 iender 0012411 .0140765 -0.09 0.930 0288305 1.ratio 099597 .0293705 -3.39 0.001 1571621 ntercept 11.63496 .0705599 164.89 0.000 11.49667	.0409748	.0025583	0.026	2.22	.0098003	.0217666	Knowcen
rganiza_mn .0035742 .0249896 0.14 0.886 0454047 .know_mn .0072967 .0235097 0.31 0.756 0387816 leender 0012411 .0140765 -0.09 0.930 0288305 l.ratio 099597 .0293705 -3.39 0.001 1571621 ntercept 11.63496 .0705599 164.89 0.000 11.49667	.1229751	0003533	0.051	1.95	.0314619	.0613109	ognitiv_mn
k.know_mn .0072967 .0235097 0.31 0.756 0387816 lender 0012411 .0140765 -0.09 0.930 0288305 l.ratio 099597 .0293705 -3.39 0.001 1571621 Intercept 11.63496 .0705599 164.89 0.000 11.49667 ariance at level 1	.1140284	.0163073	0.009	2.61	.0249293	.0651679	trategi_mn
hender 0012411 .0140765 -0.09 0.930 0288305 I.ratio 099597 .0293705 -3.39 0.001 1571621 Intercept 11.63496 .0705599 164.89 0.000 11.49667 //ariance at level 1	.052553	0454047	0.886	0.14	.0249896	.0035742	rganiza_mn
1.ratio 099597 .0293705 -3.39 0.001 1571621 Intercept 11.63496 .0705599 164.89 0.000 11.49667 //ariance at level 1 .01727457 (.00125411) //ariances and covariances of random effects ***level 2 (branch) .var(1): .01347566 (.00322022) .og likelihood = -121.18478 Lg(flex) Coef. Std. Err. z P> z [95% Conf. Sch.years .0280625 .0144724 1.94 0.052 0003028 Exp .01705 .0100796 1.69 0.091 0027057 Exp2 0001438 .001986 -0.72 0.469 000533 Cognicen .1593973 .0222211 7.17 0.000 .1158447 Stratcen .1355739 .023343 5.81 0.000 .088395 Organcen .1175191 .0248877 4.72 0.000 .0687402 Knowcen .0177641 .0307913 0.58 0.564 0425857 Cognitiv_mn .2010293 .0746673 2.69	.0533749	0387816	0.756	0.31	.0235097	.0072967	.know_mn
Intercept 11.63496 .0705599 164.89 0.000 11.49667 Variance at level 1	.0263484	0288305	0.930	-0.09	.0140765	0012411	Sender
<pre>Variance at level 1 .01727457 (.00125411) Variances and covariances of random effects ***level 2 (branch) var(1): .01347566 (.00322022) cog likelihood = -121.18478 Lg(flex) Coef. Std. Err. z P> z [95% Conf. Sch.years .0280625 .0144724 1.94 0.0520003028 Exp .01705 .0100796 1.69 0.0910027057 Exp2 .0001438 .0001986 -0.72 0.469000533 Cognicen .1593973 .0222211 7.17 0.000 .1158447 Stratcen .1355739 .0233343 5.81 0.000 .0898395 Organcen .1175191 .0248877 4.72 0.000 .0687402 Knowcen .0177641 .0307913 0.58 0.5640425857 Cognitiv_mn .2010293 .0746673 2.69 0.007 .0546841 Strategi_mn .060795 .078178 0.78 0.437092431 Organiza_mn .1207897 .0731855 1.65 0.0990226513 S.know_mn .1474563 .084725 1.74 0.0820186017 Gender .125276 .0458549 2.73 0.006 .0354021 1.ratio 2805877 .1710712 -1.64 0.101615881</pre>	0420319	1571621	0.001	-3.39	.0293705	099597	I.ratio
.01727457 (.00125411) Variances and covariances of random effects ***level 2 (branch) var(1): .01347566 (.00322022) .og likelihood = -121.18478 Lg(flex) Coef. Std. Err. z P> z [95% Conf. Sch.years .0280625 .0144724 1.94 0.0520003028 Exp .01705 .0100796 1.69 0.0910027057 Exp2 0001438 .0001986 -0.72 0.469000533 Cognicen .1593973 .022211 7.17 0.000 .1158447 Stratcen .1355739 .023343 5.81 0.000 .0898395 Organcen .1175191 .0248877 4.72 0.000 .0687402 Knowcen .0177641 .0307913 0.58 0.5640425857 Cognitiv_mn .2010293 .0746673 2.69 0.007 .0546841 Strategi_mn .060795 .078178 0.78 0.437092431 Organiza_mn .1207897 .0731855 1.65 0.0990226513 S.know_mn .1474563 .084725 1.74 0.0820186017 iender .125276 .0458549 2.73 0.006 .0354021 1.ratio 2805877 .1710712 -1.64 0.101615881	11.77320	11.49667	0.000	164.89	.0705599	11.63496	ntercept
ariances and covariances of random effects **level 2 (branch) var(1): .01347566 (.00322022) og likelihood = -121.18478 Lg(flex) Coef. Std. Err. z P> z [95% Conf. Sch.years .0280625 .0144724 1.94 0.0520003028 Exp .01705 .0100796 1.69 0.0910027057 Exp2 .0001438 .0001986 -0.72 0.469000533 Cognicen 1.593973 .0222211 7.17 0.000 .1158447 Stratcen .1355739 .023343 5.81 0.000 .0898395 Organcen .1175191 .0248877 4.72 0.000 .0687402 Knowcen .0177641 .0307913 0.58 0.5640425857 ognitiv_mn .2010293 .0746673 2.69 0.007 .0546841 trategi_mn .060795 .078178 0.78 0.437092431 rganiza_mn .1207897 .0731855 1.65 0.0990226513 .know_mn .1474563 .084725 1.74 0.0820186017 ender .125276 .0458549 2.73 0.006 .0354021 .ratio 2805877 .1710712 -1.64 0.101615881						vel 1	ariance at le
<pre>**level 2 (branch) var(1): .01347566 (.00322022) og likelihood = -121.18478 Lg(flex) Coef. Std. Err. z P> z [95% Conf. Sch.years .0280625 .0144724 1.94 0.0520003028 Exp .01705 .0100796 1.69 0.0910027057 Exp2 0001438 .0001986 -0.72 0.469000533 Cognicen .1593973 .0222211 7.17 0.000 .1158447 Stratcen .1355739 .0233343 5.81 0.000 .0898395 Organcen .1175191 .0248877 4.72 0.000 .0687402 Knowcen .0177641 .0307913 0.58 0.5640425857 lognitiv_mn .2010293 .0746673 2.69 0.007 .0546841 trategi_mn .060795 .078178 0.78 0.437092431 irganiza_mn .1207897 .0731855 1.65 0.0990226513 S.know_mn .1474563 .084725 1.74 0.0820186017 tender .125276 .0458549 2.73 0.006 .0354021 I.ratio 2805877 .1710712 -1.64 0.101615881</pre>						00125411)	.01727457 (.
var(1): .01347566 (.00322022) log likelihood = -121.18478 Lg(flex) Coef. Std. Err. z $P> z $ [95% Conf. Sch.years .0280625 .0144724 1.94 0.0520003028 Exp .01705 .0100796 1.69 0.0910027057 Exp2 .0001438 .0001986 -0.72 0.469000533 Cognicen .1593973 .0222211 7.17 0.000 .1158447 Stratcen .1355739 .0233343 5.81 0.000 .0898395 Organcen .1175191 .0248877 4.72 0.000 .0687402 Knowcen .0177641 .0307913 0.58 0.5640425857 Cognitiv_mn .2010293 .0746673 2.69 0.007 .0546841 Strategi_mn .060795 .078178 0.78 0.437092431 Organiza_mn .1207897 .0731855 1.65 0.0990226513 S.know_mn .1474563 .084725 1.74 0.0820186017 Sender .125276 .0458549 2.73 0.006 .0354021 4.ratio .2805877 .1710712 -1.64 0.101615881				fects	of random ef	covariances o	Variances and
log likelihood = -121.18478 Lg(flex) Coef. Std. Err. z P> z [95% Conf. Sch.years .0280625 .0144724 1.94 0.052 0003028 Exp .01705 .0100796 1.69 0.091 0027057 Exp2 0001438 .001986 -0.72 0.469 000533 Cognicen .1593973 .0222211 7.17 0.000 .1158447 Stratcen .1355739 .0233343 5.81 0.000 .0898395 Organcen .1175191 .0248877 4.72 0.000 .0687402 Knowcen .0177641 .0307913 0.58 0.564 0425857 Cognitiv_mn .2010293 .0746673 2.69 0.007 .0546841 Strategi_mn .060795 .078178 0.78 0.437 092431 Organiza_mn .1207897 .0731855 1.65 0.099 0226513 S.know_mn .1474563 .084725 1.74 0.082 0186017 Sender .125276 .0458549 2.73)322022)	,	
Sch.years .0280625 .0144724 1.94 0.052 0003028 Exp .01705 .0100796 1.69 0.091 0027057 Exp2 0001438 .0001986 -0.72 0.469 000533 Cognicen .1593973 .0222211 7.17 0.000 .1158447 Stratcen .1355739 .0233343 5.81 0.000 .0898395 Organcen .1175191 .0248877 4.72 0.000 .0687402 Knowcen .0177641 .0307913 0.58 0.564 0425857 Cognitiv_mn .2010293 .0746673 2.69 0.007 .0546841 Strategi_mn .060795 .078178 0.78 0.437 092431 Organiza_mn .1207897 .0731855 1.65 0.099 0226513 G.know_mn .1474563 .084725 1.74 0.082 0186017 Gender .125276 .0458549 2.73 0.006 .0354021 M.ratio 2805877 .1710712 -1.64 0.101 615881 <th>Interval</th> <th> [95% Conf</th> <th> D> 7 </th> <th></th> <th></th> <th></th> <th></th>	Interval	 [95% Conf	 D> 7				
Exp.01705.01007961.690.0910027057Exp20001438.0001986-0.720.469000533Cognicen.1593973.02222117.170.000.1158447Stratcen.1355739.02333435.810.000.0898395Organcen.1175191.02488774.720.000.0687402Knowcen.0177641.03079130.580.5640425857Orginitv_mn.2010293.07466732.690.007.0546841Organiza_mn.1207897.07318551.650.0990226513Sknow_mn.1474563.0847251.740.0820186017Gender.125276.04585492.730.006.0354021I.ratio2805877.1710712-1.640.101615881							+
Exp20001438.0001986-0.720.469000533Cognicen.1593973.02222117.170.000.1158447Stratcen.1355739.02333435.810.000.0898395Organcen.1175191.02488774.720.000.0687402Knowcen.0177641.03079130.580.5640425857Jognitiv_mn.2010293.07466732.690.007.0546841Strategi_mn.060795.0781780.780.437092431Jorganiza_mn.1207897.07318551.650.0990226513S.know_mn.1474563.0847251.740.0820186017Gender.125276.04585492.730.006.0354021I.ratio2805877.1710712-1.640.101615881	.0564279	0003028	0.052	1.94	.0144724	.0280625	Sch.years
Cognicen.1593973.02222117.170.000.1158447Stratcen.1355739.02333435.810.000.0898395Organcen.1175191.02488774.720.000.0687402Knowcen.0177641.03079130.580.5640425857Jognitiv_mn.2010293.07466732.690.007.0546841Strategi_mn.060795.0781780.780.437092431Jorganiza_mn.1207897.07318551.650.0990226513J.know_mn.1474563.0847251.740.0820186017Gender.125276.04585492.730.006.0354021I.ratio2805877.1710712-1.640.101615881	.036805	0027057	0.091	1.69	.0100796	.01705	Exp
Stratcen.1355739.02333435.810.000.0898395Organcen.1175191.02488774.720.000.0687402Knowcen.0177641.03079130.580.5640425857Cognitiv_mn.2010293.07466732.690.007.0546841Strategi_mn.060795.0781780.780.437092431Organiza_mn.1207897.07318551.650.0990226513Sknow_mn.1474563.0847251.740.0820186017Gender.125276.04585492.730.006.0354021I.ratio2805877.1710712-1.640.101615881	.0002454	000533	0.469	-0.72	.0001986	0001438	Exp2
Organcen.1175191.02488774.720.000.0687402Knowcen.0177641.03079130.580.5640425857Cognitiv_mn.2010293.07466732.690.007.0546841Strategi_mn.060795.0781780.780.437092431Organiza_mn.1207897.07318551.650.0990226513Sknow_mn.1474563.0847251.740.0820186017Gender.125276.04585492.730.006.0354021I.ratio2805877.1710712-1.640.101615881	.2029498	.1158447	0.000	7.17	.0222211	.1593973	Cognicen
Knowcen.0177641.03079130.580.5640425857Bognitiv_mn.2010293.07466732.690.007.0546841Btrategi_mn.060795.0781780.780.437092431Brganiza_mn.1207897.07318551.650.0990226513Btrow_mn.1474563.0847251.740.0820186017Bender.125276.04585492.730.006.0354021Itratio2805877.1710712-1.640.101615881	.1813083	.0898395	0.000	5.81	.0233343	.1355739	Stratcen
Bognitiv_mn.2010293.07466732.690.007.0546841Strategi_mn.060795.0781780.780.437092431Organiza_mn.1207897.07318551.650.0990226513S.know_mn.1474563.0847251.740.0820186017Gender.125276.04585492.730.006.0354021I.ratio2805877.1710712-1.640.101615881	.1662981	.0687402	0.000	4.72	.0248877	.1175191	Organcen
trategi_mn.060795.0781780.780.437092431organiza_mn.1207897.07318551.650.0990226513tknow_mn.1474563.0847251.740.0820186017tender.125276.04585492.730.006.0354021tratio2805877.1710712-1.640.101615881	.078114	0425857	0.564	0.58	.0307913	.0177641	Knowcen
Organiza_mn.1207897.07318551.650.0990226513.know_mn.1474563.0847251.740.0820186017.ender.125276.04585492.730.006.0354021.ratio2805877.1710712-1.640.101615881	.3473746	.0546841	0.007	2.69	.0746673	.2010293	ognitiv_mn
S.know_mn .1474563 .084725 1.74 0.082 0186017 Gender .125276 .0458549 2.73 0.006 .0354021 I.ratio 2805877 .1710712 -1.64 0.101 615881	.2140211	092431	0.437	0.78	.078178	.060795	trategi_mn
ender .125276 .0458549 2.73 0.006 .0354021 I.ratio2805877 .1710712 -1.64 0.101615881	.2642307	0226513	0.099	1.65	.0731855	.1207897	rganiza_mn
I.ratio2805877 .1710712 -1.64 0.101615881	.3135143	0186017	0.082	1.74	.084725	.1474563	.know_mn
	.2151499	.0354021	0.006	2.73	.0458549	.125276	ender
ntergent 11.7264 2517229 46.62 0.000 11.24201	.0547056	615881	0.101	-1.64	.1710712	2805877	I.ratio
incercept 11.7564 .2517526 46.62 0.000 11.24301	12.22978	11.24301	0.000	46.62	.2517328	11.7364	intercept
Variance at level 1						evel 1	Variance at l
.1052111 (.01058723)						1058723)	.1052111 (.0
Variances and covariances of random effects				fects	of random of	covariances	Variances and

***level 2 (branch)

var(1): .08977852 (.01905066)

Conclusion

This paper could use an original database which provided together with traditional human capital variables ratings of individual competencies estimated by the direct supervisors of banking employees. Along with these attributes, the data inform on two different components of the earnings: a fixed part corresponding to the traditional definition of

wage and a flexible part corresponding to the profit sharing. It tried to take into account the complexity of such data, according to selectivity and multilevel issues.

The results, whatever the structure of the model used, confirm that the traditional human capital variables explain better the traditional way of remunerating workers, whereas the competence variables explain better the performance based remuneration. Two different patterns of remuneration are related to such findings. Traditional wages are mainly decided through conventional rules, where education and experience are basic ingredients. On the other hand, when performance based remuneration is considered, the effective engagement of the worker, as assessed by his/her supervisor, becomes pre-eminent. The question which then arises is to know to what extent the second way of remunerating workers will expand or not. If yes, education systems will probably more directly questioned about the competences they developed rather than about the format of the sheepskins they provide.

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Annex: Results of the principal component analysis

	Factor 1	Factor 2	Factor 3	Factor 4
Technical general knowledge	0.443	0.117	8.593E-02	0.647
Technical specific knowledge	0.680	0.106	6.477E-02	0.317
Foreign languages	4.633E-02	0.172	1.617E-02	0.783
Relations with colleagues	0.243	0.196	0.259	0.161
Working in team	0.263	0.370	0.388	0.220
Communication	0.366	0.480	5.847E-02	0.246
Willingness to help others	0.248	0.323	0.457	0.173
Negotiation	0.325	0.794	0.132	0.159
Persuasiveness	0.368	0.751	7.588E-02	0.126
Perseverance and orientation towards	0.452	0.619	0.323	0.112
others				
Orientation towards the client	0.329	0.661	0.267	0.218
Autonomy	0.760	0.309	0.131	-5.625E-02
Responsibility	0.709	0.271	0.200	-6.342E-02
Adaptability	0.528	0.365	0.300	0.368
Innovation	0.587	0.454	0.190	0.290
Readiness to learn	0.381	0.353	0.526	0.434
Effort to learn	0.373	0.385	0.489	0.413
To follow the rules and procedures	0.479	0.244	0.490	7.102E-02
Cooperation	.362	0.522	0.487	0.224
Adaptation to the working hours	0.113	0.245	0.738	0.187
Punctuality	0.155	8.281E-03	0.789	-8.025E-02
Planning and organising	0.609	0.349	0.304	0.207
Ability to use computing systems	0.520	0.168	0.231	0.472
Capacity to analyse	0.743	0.285	0.191	0.273
Ability to select and to process	0.641	0.398	0.185	0.315
information				
Ability to solve problems	0.728	0.324	0.235	0.173
Ability to learn	0.559	0.289	0.333	0.417
Ability to transfer knowledge and	0.690	0.322	0.180	0.253
experiences				
Capacity to understand the	0.589	0.474	0.235	0.253
specificities of the banking activity				
To understand the strategy of the bank	0.458	0.575	0.350	0.280

Note: variance explained by factors: 1^{st} factor = 56.3%; 2^{rd} factor = 5.4%; 3^{rd} factor = 4.0%; 4^{th} factor = 3.5%; KMO = 0.974; Bartlett test= 13715.154; significance = 0.000 Varimax rotation