

ESTIMATING THE PROFESSIONS THAT CONTRIBUTE MOST TO IT INNOVATION IN BRAZIL

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- **ABSTRACT:** *This article aims to examine which groups of the Brazilian classification of occupations (BCO) contribute most to innovation in information technology in Brazilian companies. The paper uses the rank-ordered logit model to model the variables in the form of posts (ranks), based on a set of explanatory variables. In this approach, the estimation is performed using the well-known form of the proportional risk regression model. This model assumes an equivalent format the rank-ordered logit model. The paper presents results through databases such as the Brazilian Annual Register of Social Information (BARSI) and the hundred most-innovative companies for IT in Brazil according to research from Info Week Brazil in consultation with Deloitte.*
- **KEYWORDS:** *Rank-ordered logit model; proportional risk regression model; information technology; innovation.*

1 Introduction

According to Freeman (1905), innovation can be defined as “...the technical, design, manufacturing, management and commercial activities involved in marketing of a new (or improved) product or the first commercial use of a new (or improved) process or equipment.” Another definition is given by Luecke and Katz (2003), who wrote, “Innovation... is generally understood as the successful introduction of a new thing or method... Innovation is the embodiment, combination, or synthesis of knowledge in original, relevant, valued new products, processes, or services.”

A content analysis of the term “innovation” conducted by Baregheh and Sambrook (2009) in an organizational context defines innovation as follows: “Innovation is the multi-stage process whereby organizations transform ideas into new/improved products, service or processes, in order to advance, compete and differentiate themselves successfully in their marketplace”.

There are other definitions of innovation, but they all share a common point: innovation is the art of thinking differently and producing products and services never before available to consumers. Innovation is essential to business strategy, particularly for businesses that plan to compete nationally, internationally, and globally.

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The adoption of information technologies by organizations has been studied extensively and has been an important area since the early days of computers. Information technologies are a tool for managerial innovation, and the study of innovation and its effects is crucial for organizational management. As technological development, innovation and managerial innovation become more directly tied to productivity and profitability, it is important to evaluate the effects of information technologies on these companies.

Many studies have addressed the topic of innovation. Notably, Hippel (1988), Christensen (2002) and Mckeown (2008) discussed how organizations can improve their innovation process. More recently Jensen *et al.* (2012) and Toner (2011) studied the innovation field in the context of longitudinal analysis of innovation data and Workforce Skills in the innovation process, respectively. However, no studies have explored the ability of various professional roles to innovate in organizations. We propose a methodology to measure the effect of different types of professions on the ranking of organizations by degree of innovation.

In the second section, we present the foundation and the rationale for understanding how various professional roles affect the ability of an organization to produce innovations. In the third section, we develop a statistical model based on the rank-ordered logit model proposed by Beggs (1981), which can be used to estimate the effects of professions in a firm. Then, we present an estimation based on data from Brazil that explores how different types of professions affect the ability to innovate. A measure of the impact of these professions is provided. In the last section, a conclusion will be offered, and future projects are discussed.

2 The effect of groups of professions on innovation

The study of professions and their contributions to the process of innovation is relatively unexplored. A question emerges regarding companies with excellence in innovation: Do professionals contribute to the company's innovations? Do different professions have similar effects on innovation? If various professions influence the company's *rank* among innovative organizations, what is the magnitude of this influence?

To answer these questions, we use data from *InformationWeek Brazil's* InformationWeek (2008) research in association with *Deloitte's* consulting company. This research was conducted in 2008 with the participation of active organizations on the information technology market. The research studied the *ranking* of the hundred top innovation companies according to their results in information technology (IT).

The methodology suggested by *Deloitte Consulting* evaluates factors such as the technology used, the destination of the investments in technology, the degree of management maturity and governance for IT, the degree of maturity of the process of innovation, the management of portfolio projects on IT and the role of IT in the organization. Evaluation of these topics showed the top hundred companies that innovate in IT in Brazil. The objective is to use this information to determine how several types of professionals contribute to this ranking and the influence of these professionals on policy formulation in information technology (IT).

In addition to the information by *Deloitte* and *InfoWeek Brazil*, this study also used a set of data from ARSI (Annual Register of Social Information) provided by Brazil's

ministry of labor. This database is composed of all of Brazil's workers with formal contracts. All private companies must register their workers in this annual database during the first quarter of the year. Each company registers all of the characteristics of each worker, such as educational degree, remuneration, profession and other socioeconomic information.

The variable of interest in this study is workers' occupations within companies. Occupation refers to the activity that workers practice in their jobs or other labor relations. Occupations are established by the Brazilian occupation classification (BCO), instituted by ministerial order n°. 397 in October 2002. The BCO has the objective of identifying occupations in the labor market and standardizing professions.

Based on the information in this database, the next section will discuss the factors that contribute to the ranking of these companies, such as the type and magnitude of innovations in IT.

The rank-ordered logit model

The purpose of this study is to measure the effect of professions on the *ranking* of the companies based on innovations suggested by *InfoWeek Brazil's* research. A model is needed that incorporates the *ranking* of organizations in addition to the explicative variables of the process. The standard regression model is not appropriate because the *ranking* is an ordinal categorical variable. This means that the company ranked second is not necessarily twice as lacking in innovations the first.

Therefore, the model will be specific to ordered data. The modeling of rank-ordered data in the form described has been explored in the literature mainly through utility models. These models are intended to estimate the revealed preferences of specific consumers.

Some studies that have used the utility approach were conducted by Ophem *et al.* (1999) and Dijk (2007). In this paper, however, we estimate the effects of professions (or professionals) at a specific company that is *ranked* in terms of innovation in information technology (IT) to estimate the *revealed capacity for innovation*.

The paper will present the *rank-ordered logit model* to estimate these effects. In contrast to *ordinal regression models*, the *rank-ordered logit model* (or *exploded logit model*) can be used for modeling more than one ranked item.

This model was first suggested by Beggs (1981) as the *rank-ordered logit*, but it is sometimes called the *cumulative logit model*. The model can be estimated using the generic model presented by Koop and Poirier (1994) in which N is the number of tests, such that $n = 1, \dots, N$. For the n -th test, there will be $R_n \geq 0$ indexed replications, so $r = 1, 2, \dots, R_n$. For each replication of the n -th test, there will be J_n discrete alternatives, such that $j = 1, 2, \dots, J_n$.

The D most preferable alternatives are observed: d_{nri} for $i = 1, \dots, D$, $1 \leq D \leq J_n$ e $n = 1, 2, \dots, N$. The alternative d_{nr1} is the most preferable alternative for test n and replication r , and d_{nrD} is the less preferable alternative.

Therefore, it is possible to construct the set

$$J_{nr}(i) = \{j | 1 \leq j \leq J_n, j \neq d_{nrk}\}, \quad (1)$$

for $k = 1, 2, \dots, i - 1$ and $i = 2, 3, \dots, D$, which define the remaining alternatives after eliminating the $i - 1$ -th track alternative for the replication r on the test n . In other words, $J_{nr}(i)$ is the set of alternatives that are less preferable than i .

Let $y_{nr ij}$ also be a binary variable that assumes a value equal to 1 if alternative j is the most preferred among the $J_n - i + 1$ alternatives in choice set $J_{nr}(i)$ on the r th replication of trial n ; otherwise, $y_{nr ij} = 0$.

The analysis is conditioned to the vector z_{nj} to $j = 1, 2, \dots, J_n$ and $n = 1, 2, \dots, N$ containing the characteristics of both test and alternative j . Then given the set of covariates, $\tilde{z}_n = [\tilde{z}'_{n1}, \tilde{z}'_{n2}, \dots, \tilde{z}'_{nJ_n}]$ and a vector of unknown parameters $\tilde{\beta} = [\beta_1, \beta_2, \dots, \beta_k]'$. The probability that alternative j in the replication r of test n is the preferred alternative is assumed to follow the *logit-multinomial* distribution:

$$P(d_{nr1} = 1 | \tilde{z}_n, \tilde{\beta}) = P(y_{nr1j} = 1 | \tilde{z}_n, \tilde{\beta}) = \frac{\exp(\tilde{z}'_{nj}\tilde{\beta})}{\sum_{i \in J_{nr}(1)} \exp(\tilde{z}'_{ni}\tilde{\beta})}. \quad (2)$$

Beggs (1981) demonstrates that the probability of observing the ranking $d_{nr i}$ to $i = 1, 2, \dots, D$ is the product of the *logit-multinomial* probabilities presented in Equation 2. Therefore

$$\begin{aligned} P(d_{nr1} = j_1, \dots, d_{nrD} = j_D | \tilde{z}_n, \tilde{\beta}) &= \prod_{i=1}^D P(d_{nr i} = j_i | \tilde{z}_n, \tilde{\beta}) \prod_{i=1}^D \frac{\exp(\tilde{z}'_{nj_i}\tilde{\beta})}{\sum_{m \in J_{nr}(i)} \exp(\tilde{z}'_{nm}\tilde{\beta})} \\ &= \prod_{i=1}^D \left[\frac{\sum_{j \in J_{nr}(i)} \exp(y_{nr ij} \tilde{z}'_{nj}\tilde{\beta})}{\sum_{m \in J_{nr}(i)} \exp(\tilde{z}'_{nm}\tilde{\beta})} \right] = \prod_{i=1}^D \prod_{j \in J_{nr}(i)} [p_{nr ij}(\tilde{\beta})]^{y_{nr ij}}, \end{aligned}$$

where the probability j that is the best between $J_n - i + 1$ alternatives on $J_{nr}(i)$ on r -th replication of test n is

$$p_{nr ij}(\tilde{\beta}) = P(y_{nr ij} = 1 | \tilde{z}_n, \tilde{\beta}) = \frac{\exp(\tilde{z}'_{nj}\tilde{\beta})}{\sum_{m \in J_{nr}(i)} \exp(\tilde{z}'_{nm}\tilde{\beta})}. \quad (3)$$

Ignoring the unnecessary constants, Koop and Poirier (1994) present the following function of likelihood for the data:

$$L(\tilde{\beta}) = \prod_{n=1}^N \prod_{r=1}^{R_n} \prod_{i=1}^D \prod_{j \in J_{nr}(i)} [p_{nr ij}(\tilde{\beta})]^{y_{nr ij}}, \quad (4)$$

where the purpose is to obtain the values for the parameters $\tilde{\beta}$ that maximize the function above.

3 Estimating the effects of the professions on IT ranking

For the estimation of the effects of professions on the ranking of companies based on their innovation in information technology, this paper suggests a model based on a study

by Beggs (1981) and generalized by Koop and Poirier (1994). In this application, using the notation of Koop and Poirier (1994), there is only 1 test ($n = 1$), one replication for the test ($R_n = 1$) and $J_n = 100$ alternatives, such that $j = 1, 2, \dots, 100 = j_1$.

Suppose that d_1 is the company that innovates more in IT, and d_{100} is the company that innovates less for this set of data. Thus, the set is

$$J(i) = \{j | 1 \leq j \leq J_1 = 100 \text{ } j \neq d_k \text{ for } k = 1, 2, \dots, i - 1\},$$

with $i = 2, \dots, 100$. As presented in the last section, $J(i)$ is the set of alternatives that are less preferable than i . In the paper's approach, j can be seen as the set of companies that innovate less. Based on this information, the probability that alternative j is the favorite in Equation 2 is given by

$$P(d_1 = 1 | \tilde{z}, \tilde{\beta}) = P(y_{1j} = 1 | \tilde{z}, \tilde{\beta}) = \frac{\exp(\tilde{z}'_j \tilde{\beta})}{\sum_{i \in J(1)} \exp(\tilde{z}'_i \tilde{\beta})} \quad (5)$$

for $j = 1, 2, \dots, J_1 = 100$ and $J(1) = \{1, 2, \dots, J_1 = 100\}$, by definition. Similarly, the observed probability for the current ranking of innovative companies in IT (d_i for $i = 1, 2, \dots, 100$) is given by the product of logit-multinomial probabilities such that the expression in Equation 3 simplifies as

$$\begin{aligned} P(d_1 = j_1, \dots, d_{100} = j_{100} | \tilde{z}, \tilde{\beta}) &= \prod_{i=1}^{100} P(d_i = j_i | \tilde{z}, \tilde{\beta}) \prod_{i=1}^{100} \frac{\exp(\tilde{z}'_{j_i} \tilde{\beta})}{\sum_{m \in J(i)} \exp(\tilde{z}'_m \tilde{\beta})} \\ &= \prod_{i=1}^{100} \left[\frac{\sum_{j \in J(i)} \exp(y_{ij} \tilde{z}'_j \tilde{\beta})}{\sum_{m \in J(i)} \exp(\tilde{z}'_m \tilde{\beta})} \right] = \prod_{i=1}^{100} \prod_{j \in J(i)} [p_{ij}(\tilde{\beta})]^{y_{ij}}, \end{aligned}$$

where y_{ij} is a binary variable that assumes a value equal to 1 if alternative j is the most preferred among the $J_1 - i + 1$ alternatives in choice set $J(i)$; otherwise, $y_{ij} = 0$. It was axiomatized that the relative preferences for company i over company j do not depend on which establishments are in the set of current choices, even with other companies already chosen, or the number of items already determined, or the sequence in which this trades were selected, among other variables.

This invariance is a manifestation of independence known as *irrelevant alternatives* (IIA - *Independence from Irrelevant Alternatives*), which features the usual *multinomial logit* model. This assumption is also known as the axiom of *Luce's choice* (Luce, 1977).

The probability that organization j is more innovative in IT among $J_1 - i + 1$ alternatives at $J(i)$ is given by

$$p_{ij}(\tilde{\beta}) = P(y_{ij} = 1 | \tilde{z}, \tilde{\beta}) = \frac{\exp(\tilde{z}'_j \tilde{\beta})}{\sum_{m \in J(i)} \exp(\tilde{z}'_m \tilde{\beta})} \quad (6)$$

Ignoring the unneeded constants, the likelihood is given by

$$L(\tilde{\beta}) = \sum_{i=1}^{100} \prod_{j \in J(i)} [p_{ij}(\tilde{\beta})]^{y_{ij}} \quad (7)$$

Applying the logarithm, the result is the log-likelihood

$$l(\tilde{\beta}) = \sum_{i=1}^{100} \log \left\{ \sum_{j \in J(i)} [p_{ij}(\tilde{\beta})]^{y_{ij}} \right\} = \sum_{i=1}^{100} \sum_{j \in J(i)} y_{ij} \log [p_{ij}(\tilde{\beta})]$$

where

$$p_{ij}(\tilde{\beta}) = P(y_{ij} = 1 | \tilde{z}_j, \tilde{\beta}) = \frac{\exp(\tilde{z}_j' \tilde{\beta})}{\sum_{m \in J(i)} \exp(\tilde{z}_m' \tilde{\beta})}. \quad (8)$$

Thus, the log-likelihood becomes

$$l(\tilde{\beta}) = \sum_{i=1}^{100} \sum_{j \in J(i)} y_{ij} \tilde{z}_j' \tilde{\beta} - \sum_{i=1}^{100} \sum_{j \in J(i)} y_{ij} \log \left[\sum_{m \in J(i)} \exp(\tilde{z}_m' \tilde{\beta}) \right]. \quad (9)$$

Note that the likelihood presented previously is a *partial likelihood* of proportional hazards models for event-history data (Allison and Christakis, 1994). In addition to the standard proportional hazards models, it assumes that censoring is uninformative. It is interesting that the numerator of the likelihood depends only on information from the individual who experiences the event, whereas the denominator utilizes information about all individuals who have not yet experienced the event.

The (partial) maximum likelihood estimates are found by maximizing Equation 7 or, equivalently, Equation 9. The efficient score equations are found by taking a partial derivative of Equation 9 with respect to the $\tilde{\beta}$'s.

More details on the estimation process can be found in Klein and Moeschberger (2003).

4 Results

For each company in the *ranking* of the hundred most innovative companies, we added the covariates of the 43 BCO subgroups. The Brazilian Classification of Occupation (BCO) has the goal of identifying the occupations in the labor market for classification purposes in administrative and residential records. The BCO presents a coding structure that can be aggregated for professionals' large groups and disaggregated into professions.

In this study, we use the first two digits of the BCO code, which refer to the 47 professional subgroups. The BCO professional subgroups are characterized by the aggregation of similar professions in the same code, as shown in Table 7 in the Appendix.

In the model, for each professional subgroup, a dummy variable was generated that assumes the value 1 if the establishment has at least one professional in that subgroup, and zero otherwise. The method used for selecting the model's variables was the *backward*

selection method, with significance equal to 15%. This method begins by calculating the F statistic for the method under the *null hypothesis*, which includes all independent variables. Then the variables are deleted from the model one by one until all remaining variables produce a significant F statistic at a determined level. In this paper, this value is 15%.

In each step of the method, the variable that presents a lower contribution to the model (i.e., has the smallest F statistic or, equivalently, the highest critical level) is withdrawn. Variables deleted from the model are no longer included. For the final adjusted model, after 26 iterations of the *backward* selection model, the result is shown in Table 1.

Table 1 - Testing the global null hypothesis

Test	Chi-Squared	Degrees of Freedom	P-value
Likelihood Ratio	19.8392	8	0.011
Score	21.2299	8	0.0066
Wald Ratio	20.3398	8	0.0091

Source: Prepared by the authors.

Therefore, the resulting model is significant for at least one of the explanatory variables, once the null hypothesis related to the parameter's nullity is rejected. Specifically, the alternatives for the parameters,³ their standard errors and their critical values are given in Table 2:

Table 2 - Maximum likelihood estimates

Parameter	Parameter Estimate	Standard Error	Chi-Squared	P-value	Hazard Ratio
F20	0.55396	0.25533	47.070	0.0300	1.740
F23	0.38402	0.23887	25.846	0.1079	1.468
F34	-0.39796	0.24783	25.785	0.1083	0.672
F63	-0.84684	0.52131	26.388	0.1043	0.429
F64	0.87974	0.51405	29.288	0.0870	2.410
F78	-127.500	0.42350	90.636	0.0026	0.279
F84	0.54380	0.27381	39.442	0.0470	1.723
F95	0.42322	0.25384	27.799	0.0955	1.527

Source: Prepared by the authors.

³Some professional subgroups are listed in all companies (subgroups 21, 35 and 41). To analyze likelihood, it is necessary for these cases to examine the percentage of professionals in a specified subgroup independent of the dichotomous variables previously defined.

It is interesting to note that there are professional subgroups that contribute positively to innovation in IT and subgroups that contribute negatively. In other words, there are professional groups that are associated with the “top” companies that innovate more in IT, and other professional groups below this level.

The results show that the larger contribution is due to professional subgroup 74, assemblers of musical equipment and precision instruments. Thus, it is expected that, with the presence of at least one professional from this subgroup in the organization, an organization will be 4.389 times more innovative than a company that does not have professionals from subgroup 74.

Subgroup 74, according to the Brazilian Classification of Occupations,⁴ is composed of professionals who assemble, disassemble, adjust, test and calibrate precision instruments for measurement and control or musical instruments. These professionals install precision mechanical systems and perform maintenance on industrial production lines and laboratories, record information and technical events.

Innovative companies - or at least those classified this way - include specialized professionals in precision mechanical systems whose expected measured effect on business innovation is 4.389. However, note that there are subgroups of professionals that contribute negatively to the process of innovation, such as professional subgroup 75: jewelers, glassblowers, potters and related occupations. In this case, based on data and estimations, companies that include professionals in subgroup 75 are 88.7% (100% - 11.3%) less innovative than organizations that do not have workers in this subgroup.

Other subgroups of professionals, such as 61, 81, 84 and 91, were not significant at a critical level of 5%. Therefore, for this model, the participation of these subgroups in business innovation in IT is inconclusive.

Estimations by type of establishment

It would be very simplistic and misleading to assume a single model for the various types of business organizations because market diversity produces specialized establishments in distinct markets. Thus, to reduce the noise produced by the heterogeneity of the organizations and, consequently, to obtain more credible estimations for the participation of subgroups of professionals, this analysis was stratified into four large groups: commerce, finance, industry and services.

Again, using the *backward* selection method with input significance equal to 15%, the following values (Table 3) for the adjusted models were obtained:

The 3 tests are asymptotically equivalent. However, due to the small sample size within the class, the *Wald* test diverges from the other 2 tests, the *likelihood ratio* and *score*. We will consider only the likelihood ratio test because this test is preferable to the *Wald* test (Collet, 2003, and Harrell, 2006) and Collett (2003)). Therefore, all models are significant at a threshold of 5%, except the model related to the commercial companies.

⁴For more information, see <http://www.mtecbo.gov.br/cbosite/pages/saibaMais.jsf>.

Table 3 - Testing the global null hypothesis

Class	Test	Chi-Squared	Degrees of Freedom	P-value
Commerce	Likelihood Ratio	3,4463	1	0,0634
	Score	2,9585	1	0,0854
	Wald	2,4113	1	0,1205
Finance	Likelihood Ratio	18,5244	5	0,0024
	Score	20,6490	5	0,0009
	Wald	10,8683	5	0,0541
Industry	Likelihood Ratio	134,1592	38	<0,0001
	Score	120,7882	38	<0,0001
	Wald	40,3807	38	0,3655
Services	Likelihood Ratio	55,6356	25	0,0004
	Score	68,2021	25	<0,0001
	Wald	23,5113	25	0,5477

Source: Prepared by the authors.

For financial institutions, the estimates were as follows (Table 4):

Table 4 - Maximum likelihood estimates – finance

Parameter	Parameter Estimate	Standard Error	Chi-Squared	P-value	Hazard Ratio
F20	-2.3992	1.3928	2.9672	0.0850	0.0910
F26	4.1035	1.5640	6.8844	0.0087	60.5520
F30	2.9535	1.5157	3.7974	0.0513	19.1740
F31	-6.2164	1.9151	10.5367	0.0012	0.0020
F33	4.8198	2.4040	4.0196	0.0450	123.9400

Source: Prepared by the authors.

The highlighted subgroups of professionals were groups 26 (communicators, artists and religious professionals) and 33 (lay teachers and middle level). Communicators are essential in information technology, and financial organizations that employ professionals in these subgroups are expected to be approximately 60 times more innovative than companies that do not have this employee profile. Similarly, with the presence of professional subgroup 33, it is expected that innovation in these companies is 123 times larger than in financial organizations that do not have employees classified in this subgroup.

In industry, the professional profile that contributes to innovation is different from that of the financial sector. For industry, the following model was suggested (table 5):

Table 5 - Maximum likelihood estimates - industry

Parameter	Parameter Estimate	Standard Error	Chi-Squared	P-value	Hazard Ratio
F11	-5.9230	2.7706	4.5701	0.0325	0.003
F12	23.7333	5.8465	16.4791	<0.0001	2.03E+13
F13	-5.3567	3.1641	2.8661	0.0905	0.005
F14	-39.0533	8.6262	20.4963	<0.0001	0.0000
F20	-21.9337	4.1824	27.5029	<0.0001	0.0000
P21	-214.7067	50.0905	18.3730	<0.0001	0.0000
F22	31.2438	6.0151	26.9797	<0.0001	3.71E+16
F23	-25.8557	5.9124	19.1244	<0.0001	0.0000
F24	14.7605	8.5216	3.0002	0.0833	2572688
F25	41.5768	12.6246	10.8459	0.001	1.14E+21
F26	5.1392	1.3854	13.7607	0.0002	170.571
F30	8.2988	2.7002	9.4461	0.0021	4.019.061
F31	29.9822	5.3613	31.2743	<0.0001	1.05E+13
F32	-12.9701	3.3612	14.8900	0.0001	0.0000
F33	16.5062	5.2907	9.7336	0.0018	14741245
F34	-5.4775	1.8751	8.5337	0.0035	0.004
P35	56.6800	11.3273	25.0384	<0.0001	4.13E+27
F37	7.0202	2.3817	8.6883	0.0032	1.118.956
F39	11.2500	2.4495	21.0932	<0.0001	76876.64
P41	25.7591	5.2501	24.0724	<0.0001	1.54E+14
F42	27.2604	4.9654	30.1407	<0.0001	6.90E+14
F51	-21.6480	4.3084	25.2465	<0.0001	0.0000
F52	-19.1092	3.5591	28.8278	<0.0001	0.0000
F61	58.5818	11.4576	26.1419	<0.0001	2.77E+28
F62	-9.8862	3.2850	9.0573	0.0026	0.0000
F63	-7.5877	2.8329	7.1741	0.0074	0.001
F64	-9.2997	4.0947	5.1582	0.0231	0.0000
F72	19.0469	3.8689	24.2362	<0.0001	1.87E+12
F73	8.5492	2.2683	14.2050	0.0002	5.162.714
F76	-20.9177	4.3062	23.5960	<0.0001	0.0000
F77	12.7296	2.6357	23.3250	<0.0001	337585.7
F78	-92.7898	19.5844	22.4482	<0.0001	0.0000
F81	-9.6808	2.4573	15.5207	<0.0001	0.0000

Source: Prepared by the authors.

The subgroup with the largest contribution to innovation is subgroup 61, agricultural producers. In Brazil's industrial sector, the most innovative companies are those with functions related to the exploitation of the farm sector, and the specific professionals in this sector are those that contribute the most toward business innovation.

Finally, for the service sector, the following model was proposed and presented in Table 6.

Table 6 - Maximum likelihood estimates - services

Parameter	Parameter Estimate	Standard Error	Chi-Squared	P-value	Hazard Ratio
F11	-135.5583	51.5229	6.9223	0.0085	0.0000
F12	-34.6313	13.1664	6.9184	0.0085	0.0000
F13	8.1238	3.6255	5.0210	0.0250	3373.748
P21	-110.2421	53.7247	4.2106	0.0402	0.0000
F22	13.0931	4.7945	7.4577	0.0063	485590
F23	-9.8846	3.7180	7.0680	0.0078	0.0000
F26	-20.4371	7.5517	7.3240	0.0068	0.0000
F30	35.2103	13.7581	6.5497	0.0105	1.957E+18
F33	83.0076	36.6909	5.1182	0.0237	1.121E+39
F34	-10.7879	2.7851	15.0032	0.0001	0.0000
P35	31.3875	19.1835	2.6771	0.1018	4.28E+13
F39	-11.8389	6.2757	3.5588	0.0592	0.0000
P41	-85.6069	43.4246	3.8864	0.0487	0.0000
F42	-30.3566	16.2496	3.4899	0.0617	0.0000
F52	35.8756	14.5909	6.0455	0.0139	3.807E+18
F62	-19.5972	5.6456	12.0493	0.0005	0.0000
F63	44.3715	17.6401	6.3271	0.0119	1.863E+22
F64	-59.6666	27.8296	4.5967	0.0320	0.0000
F71	-33.5562	13.4964	6.1817	0.0129	0.0000
F72	13.9726	3.3431	17.4680	<0.0001	1170072
F73	-7.5041	3.6345	4.2629	0.0390	0.001
F75	101.5109	39.0849	6.7454	0.0094	1.218E+47

Source: Prepared by the authors.

The subgroup that contributed the most toward innovation in services was subgroup 75, which has been presented in the global model with every establishment class.

Conclusion

The purpose of this paper was to examine how professional subgroups contribute to Brazil's process of innovation in IT. Therefore, this study measured the degree of professional participation through a *ranking* of innovative companies in information technology (IT).

Analyses based on types of performance were performed with the aim of decreasing the noise induced by the heterogeneity of the establishments in the study. The participation measure of these groups (*hazard ratio*) was presented for each BCO subgroup that was considered in the *rank-ordered logit* model. These variables were added with the *backward* selection method.

Business innovation is a topic that is often discussed, and its consequences can define an organization in the market. Thus, the knowledge profile of innovative companies in terms of their employees and their degree of influence is useful information for management, decision makers and market strategists.

The information presented in this paper can help to define the course that companies must take in positioning themselves as organizations with innovative information technology in Brazil.

ALBUQUERQUE, P. H. M.; LAURETO, C. R. Estimando quais profissões mais contribuem para a inovação tecnológica no Brasil. *Rev. Bras. Biom.*, São Paulo, v.30, n.1, p.136-149, 2012.

- RESUMO: Este artigo tem o objetivo de apresentar quais subgrupos da Classificação Brasileira de Ocupação (CBO) mais contribuem para a inovação em tecnologia da informação nas empresas no Brasil. Para isso, utiliza-se o modelo Rank-Ordered Logit o qual modela variáveis em forma de postos (ranks) com base em um conjunto de variáveis explicativas. Nessa abordagem, a utilização de estimação é realizada o modelo de Regressão de Risco Proporcional, o qual assume forma equivalente (em verossimilhança) ao modelo Rank-Ordered Logit. Ao final do artigo, apresentamos alguns resultados obtidos através das bases de dados Relação Anual de Informações Sociais (RAIS) e das 100 empresas mais inovadoras em TI do Brasil segundo pesquisa da revista InfoWeek Brasil com a consultoria Deloitte, em 2008.
- PALAVRAS-CHAVE: Modelo *Logit* para postos ordenados; modelo de regressão de risco proporcional; tecnologia da informação; inovação.

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Appendix

Table 7: Professional subgroups of the Brazilian classification of occupations

Code	Description
F01	Members of armed forces.
F02	Military police.
F03	Military department.
F11	Premium members and leaders of public service.
F12	Business leaders and organizations (except for public interest).
F13	Directors and managers of company health services or educational, cultural, social or personal services.
F14	Managers.
F20	Researchers and multi-scientific professionals.
F21	Professionals in the exact sciences, physics and engineering.
F22	Professionals in the biological sciences, health and related sciences.
F23	Teaching professionals.
F24	Professionals in legal sciences.
F25	Professionals in social sciences and humanities.
F26	Communicators, artists and religious professionals.
F27	Professionals in gastronomy.
F30	Polyvalent technician.
F31	Middle-level technicians in the physical sciences, chemical engineering and related.
F32	Middle-level technicians in the biological sciences, biochemistry, health and related.
F33	Lay teachers and middle level.
F34	Middle-level technicians in transport services.
F35	Middle-level technicians in the administrative sciences.
F37	Middle-level technicians in cultural services, communications and sports.
F39	Other middle-level technicians.
F41	Clerks.
F42	Workers who attend the public.
F51	Service workers.
F52	Sellers and service trade.
F61	Producers in the farm sector.
F62	Workers in the farm sector.
F63	Fishermen and forest workers.
F64	Workers in agricultural mechanization and forestry.
F71	Workers in the mining industry.
F72	Workers in the processing of metals, composites and building materials.
F73	Workers in electronics manufacturing and installation.
F74	Assemblers of equipment and precision and musical instruments.
F75	Jewelers, glassware, potters and related.
F76	Workers in the textile, tanning, clothing and graphic arts.
F77	Workers in wood and furniture.
F78	Workers with transverse functions.
F81	Workers in continuous process industries and other industries.
F82	Workers at steel plants and with construction materials.
F83	Workers in plants and machinery for manufacturing cellulose and paper.
F84	Workers in the manufacturing of food, beverages and tobacco.
F86	Operators of production, catchment, treatment and distribution (power, water and utilities).
F91	Workers in repair and mechanical maintenance.
F95	Multi-maintenance.
F99	Other workers in conservation, maintenance and repair.

Source: Prepared by the authors.