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Task-Heterogeneity in Human Capital Accumulation

Evidence from Brazilian Employer-Employee Data

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Dissertation presented to the Programa de Pós-Graduação em Economia of the Departamento de Economia, PUC-Rio as partial fulfillment of the requirements for the degree of Mestre em Economia.

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Abstract

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This dissertation studies if there are heterogeneities in the human capital accumulation process while on the job. Using unique Brazilian employer-employee panel data and task description of four-digit occupations, we propose the concept of task experience in log wage equations. We first present a model in which returns to experience are heterogeneous across workers. Then, we estimate the log-wage equations interpreting the returns to experience as the average rate in which workers have their time at past work transformed into productivity in the current job. The results robustly show that the parameter related to analytical experience is greater than the parameters related to routine or other task experiences. Our model helps understanding the importance and limitations of these findings.

Keywords

Human Capital Accumulation; Mincerian Equation; Task Approach; RAIS;

Resumo

Guanziroli, Tomas; Gonzaga, Gustavo Maurício. **Acumulação de capital humano heterogênea por tarefas: Evidências com base na RAIS**. Rio de Janeiro, 2014. 46p. Dissertação de Mestrado — Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

Esta dissertação estuda se existem heterogeneidades no processo de acumulação de capital humano durante o trabalho. Utilizando microdados em painel da RAIS e a descrição de ocupações com base em suas tarefas, nós propomos o conceito de experiência em tarefas em equações de salário. Primeiro, apresentamos um modelo no qual retorno a experiência é heterogêneo entre trabalhadores. Depois, nós estimamos a equação de salário interpretando o retorno a experiência como a taxa média na qual trabalhadores transformam o tempo em trabalhos passados em produtividade no trabalho corrente. Os resultados mostram, de forma robusta, que o parâmetro associado à experiência analítica é maior que os parâmetros associados à experiência rotineira, por exemplo. Nosso modelo ajuda a compreender a importância e limitações deste resultado.

Palavras–chave

Acumulação de Capital Humano; Equação Minceriana; Abordagem de Tarefas; RAIS;

Contents

1
Introduction

Economists have intensively studied the process of post-schooling human capital accumulation and its effect on wages (Becker, 1964; Ben-Porath, 1967; Mincer, 1974). The common approach is the use of a Mincerian equation, which provides an estimate of the average returns to experience. The literature has shown that these parameters are heterogeneous across schooling (Lemieux, 2006; Heckman et al., 2006; Braga, 2013[1]), cohorts (Welch, 1979; Berger, 1985), countries (Menezes-Filho and Muendler, 2005), and more recently, across occupations (Sullivan, 2010). However, none of these studies consider that returns to experience are heterogeneous across the tasks performed by workers.

According to Sanders and Taber (2012), research on human capital has focused on categories such as occupation or industry (Shaw, 1985; Neal, 1995; Parent, 2000; Kambourov and Manoviskii, 2009) only because these measures are readily available in standard data sets. Data on tasks performed by workers in each occupation have recently become available, making room for an emerging literature on tasks. Studies are using tasks to proxy for human capital (Gathmann and Schonberg, 2010; Poletaev and Robinson, 2008), to characterize the skill production function in a Roy Model (Yamaguchi, 2013; Autor and Handel, 2014), and to explain occupational polarization and shifts in the wage structure (Autor et al, 2003; Firpo, Fortin and Lemieux, 2011).

In this context, we use the Mincerian approach to study the role of tasks performed by workers in human capital accumulation. The idea is that some types of tasks performed at the job can provide more skill growth than others More specifically, we develop a specification of the mincerian equation where we divide experience into five task experiences (analytical, interactive, routine cognitive, routine manual and non-routine manual). With a simple model, we see that differences in returns to experience between tasks can be perceived as differences in human capital accumulation. We are only able to do this because we have occupations mapped into tasks and workers job history. Therefore, we estimate how much time a worker spends in each type of task.

We combine a high-quality longitudinal dataset of Brazilian workers with the task performed in occupations. Worker data comes from a unique and

[1] Lemieux and Heckman find that returns to potential experience decreases with schooling, while Braga finds that returns to actual experience increases with schooling. Mincer (1974) finds that returns to potential experience do not change across educational groups.

comprehensive Brazilian administrative dataset (*RAIS - Relação Anual de Informações Sociais*) collected by the Ministry of Employment and Labor. *RAIS* contains all formal employer-employee matches in Brazil. It has information on worker characteristics such as age, gender, and education, and job characteristics including the wage, occupation and dates of hiring and separation. We restrict attention to male young workers past their first entry into the active labor force.

Task data is constructed from the task usage composition of 258 four-digit occupations[2]. Applying a task classification proposed by Spitz-Oener, the descriptions of four-digit occupations conceive the intensity of use of the five types of tasks.

The estimation results of the traditional log wage equation show wage return to experience of 12.4% in our sample[3]. The task approach, however, shows that returns are heterogeneous across tasks. Results show returns to analytical experience of 20.3%, for the same sample. This is almost the double than returns to interactive, routine cognitive, non-routine manual and routine manual experience (12.3%, 11.8%, 10.9% and 10.3%, respectively).

We develop a simple model to better understand how differences between these coefficients should be interpreted. We do not interpret them as return to task, or even as a internal rate of return to some investment. We just interpret the parameters associated to experience measures as a rate at which a population of workers has their time at past jobs be transformed into productivity in the current job. This should take into account the changing price of skills and occupational decisions. Relying on some assumptions and on our results, it can be said that routine tasks allow less human capital accumulation than non-routine tasks. We infer that this should happen due to the repetitive nature of this task, that does not enforce learning.

In order to show that these findings are not reflecting the educational heterogeneity of returns, we separate the sample into schooling groups. First, results for the traditional log wage equation show that returns to experience grow from 5.4% to 12.2% with schooling, which is an interesting result by itself. Then, the task approach shows that returns to analytical experience are the highest among other tasks for almost every schooling group (workers with college appear to have a different wage setting). We also run similar specifications to samples of occupational movers and stayers. Even though coefficients estimations vary, returns to analytical experience are still greater than returns to routine or interactive tasks. The same happens when we split

[2]We thank Bruno Funchal for kindly providing the task data used in this study.
[3]We remember that our sample is constituted of young workers.

workers by their industry sector.

The article proceeds as follows. Section 2 introduces the literature on wage structure and briefly comments the literature of task approach to technological change. Section 3 presents worker and task data, together with descriptive statistics. Section 4 presents a model that justifies this approach. Section 5 outlines the fixed effects empirical strategy. Section 6 presents our main results. Finally, Section 7 concludes.

2
Related Literature

In the traditional human capital model, wages reflect worker productivity, which depends on the human capital stock. Within this framework, the Mincerian equation presents log wages as a function of schooling and experience. One of the assumptions is that time at work is also an investment in human capital, due to on-the-job training and learning-by-doing.

A large number of studies estimate the returns to experience in these equations. In a review of the Mincerian approach, Heckman et al. (2006) bring attention to a more general model formulated by Mincer, where returns to experience can differ across individuals, an assumption that we will keep for this study. One way to characterize this heterogeneity is to observe the average return to experience across different groups. Heckman et al (2006) show that this heterogeneity extends to schooling groups. They demonstrate that log-earnings experience profiles are not parallel across educational groups. Similarly, Lemieux (2006) shows that the college-high-school wage gap declines with experience. [1]

Extending the human capital theory, Becker (1964) analyzes the bargain between firm and worker relative to who pays the costs of human capital investment. He suggested that some knowledge acquired by workers while on the job is specific to the firms they are employed, differently from general human capital. Hence, workers' skills may have low transferability. Subsequent work by Neal (1995) and Parent (2000) find that human capital is industry specific. Shaw (1985) and Kambourov and Manovskii (2009) suggest it is occupation specific.

To illustrate this concept, Kambourov and Manovskii (2009) argue that it is natural to expect that when a truck driver switches industries he loses less human capital than when he switches occupations (for example, to become a cook). Further, Sullivan (2010) claims that human capital can be both industry and occupation specific. All these studies rely on the structure of a simple log wage equation, where wages increase with experience and firm, industry or occupational tenure. These equations are usually estimated with instrumental variables or with worker fixed effects.

[1] Braga (2013) presents opposite results. In his study (as in ours), he uses actual experience instead of potential experience. He suggests that the latter measure creates a larger bias to the returns to experience for more educated workers. This bias occurs if educated workers suffer greater wage losses after out-of-work periods. His results show that returns to actual experience increase with schooling.

Most of this literature does not allow for heterogeneities in the human capital accumulation process. One exception is Sullivan (2010), who estimates the parameters of a log-wage equation separately for each one-digit occupation. He finds that some occupations allow for more accumulation of industry specific skills, while others for more occupational specific skills or simply general skills. The given explanations for these differences are purely pecuniary, that is, some occupations reward more some types of skills.

A more recent development in this field concerns the use of task data to proxy for human capital. Poletaev and Robinson (2008) group jobs based on tasks and skill requirements data from the Dictionary of Occupational Titles (DOT)[2]. They find that human capital is not specific to industry or occupation, but to some basic skills that can be used in various contexts.

Gathmann and Schonberg (2010) use occupation's task information from the German BIBB data source to create a unidimensional measure of task tenure. Task tenure increases if there is occupational stability or close occupational movements[3]. Thus, they propose the concept of task specific human capital, and include task tenure in the log wage equation similarly to other types of tenure. Their finding is that more than 50% of the wage growth is explained by this measure.

Yamaguchi (2012) contributes to this discussion with the distinction of worker's skills from job‘s tasks. He summarizes the task data from the DOT into two tasks, motor and cognitive. He also defines occupations as a bundle of tasks and characterizes them by complexity in a two-dimensional vector of tasks. Then, he estimates a structural model of heterogeneous human capital using a Kalman Filter. The estimation results indicate that workers employed in occupations with more complex tasks have faster skill growth. Moreover, the results also show that cognitive skills have a central role in wage growth.

Subsequently, Yamaguchi (2013) presents a task-based Roy model. He differentiates skills between those that are task specific and those that are general. Returns to skills are heterogeneous across occupations because tasks define skill use and characterize occupations. In addition, low skill workers have higher costs to perform complex tasks. Together with heterogeneous workers' endowments and educational attainment, these features generate a self-selection into occupations, configuring the Roy model. They conclude that high skill workers would be more suitable to occupations with more complex tasks, while low skill workers would prefer simpler tasks.

[2]The DOT is an American data base that describes occupations based on the tasks performed, skill requirements and work context. It was replaced by the O-NET.

[3]Occupations with similar task composition have a small distance between them.

Autor and Handel (2013) argue that an OLS regression of log wages on workers task input does not recover the average returns to tasks. They present a task-based Roy model, where workers self-select into jobs according to their task inputs. Those with higher efficiency in a given task will sort towards jobs more intensive at this task. Therefore, the cross-sectional estimation of the log wage model would recover biased estimates due to these unobserved abilities. They also argue that the logic of "returns to task" is not applicable, since tasks are not durable investments. Tasks performed would be application of workers skills. In their words, "*tasks are a high-dimensional bundle of activities, the elements of which must be performed jointly to produce output.*". Our longitudinal analysis considers this. We do not interpret the returns to task experience as returns to task. We see tasks as the vehicle through which workers employ their skills to produce output. In addition, we allow for the possibility that working in some types of tasks generate faster accumulation of human capital than in others.

Autor and Handel (2013) also use innovative survey data on tasks at the worker level and find that tasks vary substantially within and between occupations.

The first use of task data was in Autor et al. (2003). The authors divide tasks between routine and non-routine. Routine tasks are those that consist on the repetition of some procedure that can be specified with programmed instructions. Thus, they are replaceable by computer-controlled machinery. On the other hand, non-routine tasks are those that cannot be specified by certain rules.

Their conceptual model predicts that computerization enlarges the task set that machines can perform. Hence, technological improvements and the reduction of computer costs lead to lower labor demand for routine tasks. Another feature is the complementarity of computerization with non-routine tasks, such as analytical.

This leads to the justification of the U-shaped inequality in the United States observed in Acemoglu and Autor (2011). In their view, technological change favors skilled workers, because computer use complements their cognitive tasks. Medium skilled workers are usually those that exert routine tasks, being more substitutable.

3
Data

Our main data source comes from Brazil's administrative records of formal sector workers and their employers. Using the 4-digit occupational codes, we combine this worker information with data on type of tasks performed at work.

3.1
Worker Data

Our worker data comes from the *RAIS (Relação Anual de Informações Sociais)*, a confidential longitudinal dataset of administrative records collected by the Brazilian Ministry of Employment and Labor. By Brazilian law, all tax-registred firms must report the workers employed during the previous year[1]. In this database, relevant worker information includes age, gender, schooling and monthly wages; job information includes occupation and firm tenure; firm information includes industry sector.

Using this data, we are able to construct measures of actual experience, occupational tenure and real wages. Our unit of observation consists of these measures for each worker in each year. If the worker switches firms in the middle of a year, we observe two observations for the same year. In Appendix B.3 we show an example of how the data is organized.

We observe a cohort of male workers who were 18 years old or less in 2003. This cohort is constituted by 2,556,049 workers since they enter the formal job market through all their jobs and occupations. In our analysis, we use information from 2003 to 2010 [2]. We cannot use previous years because occupational codes changed in 2003. As in other similar studies, we do not include workers employed in the agriculture and public sectors. We also do not include workers with simultaneous jobs[3]. We show our sample restrictions more detailed in Appendix B.1.

To prevent reporting errors, we exclude workers with any variation in schooling across years[4]. We only include workers born in 1985 or later (18

[1] The main purpose of RAIS is to administer a federal wage supplement (Abono Salarial) to formal employees. There are incentives for truthful reporting.In principle, an employer's failure to report the information can result in fines proportional to the firm size.

[2] This is the reason why we only observe young workers.

[3] We drop workers that have more than one job in the same month.

[4] Table B.2 in the appendix presents the schooling measure of RAIS and the relative years of experience for each schooling category.

years old or less in 2003). For workers with college, we include those born in 1981 or later (22 years old or less in 2003).

3.2 Task Data

Our task data comes from Funchal and Soares (2013). It constitutes of the task usage composition of 275 four-digit occupations, which represents 87% of workers' observations[5]. The task measure was created using the occupational descriptions of the Brazilian classification of occupations (*Classificação Brasileira de Ocupações - CBO*) also available from the Brazilian Ministry of Employment and Labor. This database describes occupations by their task content.

The *CBO* structure is coded into 9 one-digit *groups* that contain 49 two-digit *main subgroups*, 195 three-digit *subgroups*, 614 four-digit *families*, and 2,529 six-digit *occupations*. In order to simplify data description, hereafter we will refer to all groups as occupations. We use the four-digit code to merge task data with worker data.

The construction of the task measure proceeded as follow. First, the occupations descriptions provide a number of activities for each occupation. Then, using Table 3.1, activities are classified in the five types of task (Analytical, Interactive, Routine Cognitive, Routine Manual and Non-Routine Manual[6]). For example, the activity "analyze the economic environment" in the economist occupation is classified as an analytical task, since it concerns the "Analyzing" activity. Next, the percentage of each task in occupation o is calculated as the ratio between the number of that task's activities and total activities in the occupation. For example, the economist occupation has seven analytical activities out of ten activities. Hence, we stipulate that 70% of an economist time is spent performing analytical tasks. We show a complete example in Appendix B.3.

Similar to Yamagushi's (2012) Table 1, our Table 3.2 consists of the average task composition of one-digit occupations. We take the weighted average of four-digit occupation's tasks to analyse the task measure in one-digit occupations. We expect managers to get involved in negotiations, to coordinate and to lead. As the first line shows, 61.5% of the managers' activities are interactive. This occupation however cannot be seen as a proxy for interactive tasks. Column 2 shows that those tasks are also used by professionals, workers

[5]This limitation comes from the correspondence with the Brazilian occupation code of 1994, necessary in Funchal and Soares (2013).

[6]For simplicity, we refer to Non-Routine Analytic and Interactive tasks just as Analytic and Interactive.

TABLE 3.1: Task Description

As proposed by Spitz-Oener (2006)	Correspondence in CBO*
Non-Routine Analytic	Researching, Investigating, Analysing, Examining, Studying, Evaluating, Planning, Budgeting, Making diagnosis, Judging.
Non-Routine Interactive	Negotiating, Practising Law, Coordinating, Leading people, Teaching, Training, Spreading knowledge, Instructin,g Selling, Marketing.
Routine Cognitive	Calculating, Programming, Transforming, Bookkeeping, Recording, Measuring, Verifying.
Routine Manual	Operating, Distributing, Transporting, Equipping, Assembling.
Non-Routine Manual	Repairing, Renovating, Serving, Accommodating, Cleaning.

Source: Funchal et al (2010). Note: The column on the right of the table provides the kind of activities included in each task. *CBO is the Brazilian classification of occupations. It embraces four-digit occupational codes and their descriptions.

in service and sales and others, even though these are very different occupations and probably involve very different activities.

Professionals are equally intensive in analytic and interactive tasks (37.7% and 40.8% of use, respectively). Technicians are more intensive in routine cognitive tasks (48.5%) but also perform analytical tasks (31.3%). Clerical workers perform more routine cognitive tasks (58.1%) and some routine manual and interactive tasks (26.1% and 14.8%, respectively). Service and sales occupations have similar task composition, even though the actual activities are different. Machine operators are more intensive in routine manual tasks (53.9%) and Repair and Maintenance workers are more routine cognitive intensive, but also perform some analytical and routine manual tasks.

We present the standard deviations below the mean estimates. This is useful to illustrate that tasks are not just one-digit occupational dummies. For example, while machine operators may seem intensive in routine manual tasks (mean estimate of 53.9%), the standard error is not small (19.7 %), indicating that this one-digit occupation probably agglutinates task-heterogeneous four-digit occupations. The professionals, technicians, and service and sales occupations also present high standard errors in their task means.

Table 3.3 is similar to the previous table, but instead of observing the task composition of one-digit occupations we observe the task composition of workers from each schooling group. The table reports some trend of the task

Table 3.2: One-digit Occupation's Task Composition (%)

	Analytic	Interactive	Routine Cognitive	Routine Manual	Non-Routine Manual
Managers	20.8	61.5	17.6	0.0	0.1
	(8.3)	(7.3)	(9.5)	(0.0)	(1.1)
Professionals	37.7	40.8	18.2	2.9	0.3
	(14.4)	(14.3)	(10.4)	(6.1)	(2.0)
Technicians	31.3	15.2	48.5	5.0	0.0
	(17.3)	(12.1)	(16.7)	(10.6)	(0.1)
Clerical	1.0	14.8	58.1	26.1	0.0
	(3.9)	(5.2)	(8.7)	(8.9)	(0.0)
Service and Sales	1.3	24.3	54.7	16.9	2.8
	(5.1)	(13.4)	(8.5)	(10.9)	(5.5)
Machine Operators	7.2	5.3	29.7	53.9	3.9
	(9.8)	(8.5)	(17.0)	(19.7)	(6.7)
Repair and Maintenance	19.7	0.0	54.8	12.5	13.0
	(7.5)	(0.0)	(7.3)	(7.0)	(7.2)

Note: The table consists of one-digit occupations task intensity. The presented means are weighted average of four-digit occupations task composition. Horizontal sums of the means should be approximately 100%. Standard deviations are in parenthesis. Total sample size is 10,836,026 observations from 2,894,034 individuals. RAIS, 2003-2010.

composition across these groups. Workers with higher schooling spend more of their time at work exercising analytical and interactive tasks than workers with lower educational attainment. Those workers are more intensive in manual tasks. We can also notice that the share of routine cognitive tasks increases with schooling, except for college workers.

This points out that even if considering all the trends mentioned, college workers are very different from all other workers. The mean college worker is equally intensive in analytical, interactive and routine cognitive tasks, while workers with less schooling perform more manual or routine cognitive tasks.

As in the previous table, we should also notice that standard deviations are high for every schooling group, indicating that there is also great heterogeneity of task performance within workers in schooling groups.

We use this task data to disaggregate worker's experience into the five task-experience measures, according to the equation below.

$$TaskExp_{it}^{k} = \sum_{o=1}^{O_t}(OccTen_{oi} * Task_{o}^{k}) \qquad (3\text{-}1)$$

Here, the experience in task k of worker i in period t is defined as the sum of the worker's four-digit occupational history multiplied by the task k

Table 3.3: Task Composition by Schooling (%)

	Analytic	Interactive	Routine Cognitive	Routine Manual	Non-Routine Manual
Iliterate	3.0	3.7	23.9	58.5	10.8
	(7.3)	(8.2)	(26.1)	(23.0)	(8.6)
Incomplete Primary	3.1	5.6	25.7	55.4	10.3
	(7.6)	(10.8)	(26.5)	(26.3)	(9.2)
Primary	3.7	8.3	30.1	49.2	8.6
	(8.2)	(13.0)	(25.9)	(26.8)	(9.1)
Incomplete Middle School	3.5	9.0	32.0	47.1	8.3
	(8.1)	(12.9)	(25.2)	(26.8)	(9.3)
Middle School	4.1	11.3	34.0	43.0	7.6
	(8.9)	(14.2)	(24.5)	(26.7)	(9.0)
Incomplete High School	3.9	13.4	38.0	37.8	6.8
	(8.9)	(14.1)	(23.8)	(25.6)	(9.7)
High School	4.8	15.5	40.7	33.6	5.4
	(10.7)	(14.8)	(22.8)	(25.8)	(8.7)
Incomplete College	10.6	21.1	49.4	17.6	1.3
	(17.2)	(15.9)	(19.4)	(17.8)	(5.0)
College	29.2	33.8	30.0	6.6	0.4
	(19.9)	(18.9)	(20.6)	(12.0)	(2.7)

Note: The table consists of the task composition by worker‘s schooling. Horizontal sums of the means should be approximately 100%. Standard deviations are in parenthesis. Total sample size is 10,836,026 observations from 2,894,034 individuals. RAIS, 2003-2010.

content of these occupations. Note that the sum of the five task experience equals total experience.

For example, our task data tells us that 55% of the store sales activities are interactive, 35% are routine cognitive and 10% are routine manual. Therefore, an individual with five years of formal experience that has always been employed at this occupation has 2.75 years of interactive experience, 1.75 years of routine cognitive experience and 6 months of routine manual experience. Once again, the complete example is presented on Appendix B.3.

One feature of this approach is that we input the occupation mean task usage to the individual, while the ideal would be to observe tasks for each worker. In Appendix A, we show that under some assumptions, these imputations do not bias our estimates.

3.3 Descriptive Statistics

Descriptive statistics of our sample are shown by educational group in Table 3.4. The sample is of 9,393,006 observations from 2,556,049 workers, where 51.2% are classified as high school, 11.8% as middle school, 4.6% as college and 2.1% as primary school workers. For presentation purposes, we omit from this analysis workers with incomplete schooling.

Rows 2 and 3 show how mean real log wages and mean real wage growth increase with education. We report the sample's mean experience and tenure in rows 4 to 6. We use actual formal experience[7], not potential experience (age minus schooling years minus 6) as usual in the literature. Actual experience is measured by summing workers' tenure in each job and year. Mean experience varies between two and three years across educational groups, a low figure when compared to studies that use potential experience.

As previously described, Table 3.4 shows that the sum of the five task-experiences equals total experience. We note that in this sample, primary, middle and high school workers are more intensive in routine tasks. For these groups, almost 80% of their time at work is spent performing these types of task. For example, the mean routine manual experience for primary school workers is 1.1 year in our sample, out of 2.4 mean experience years. On the other hand, college workers have their experience distributed more equally into analytical, interactive and routine cognitive tasks, all with mean experience around one year. These more educated workers seldom perform manual tasks.

Occupational mobility varies from 12.4% to 32.3% and the sample's mean firm mobility is 27.6%. Table 3.4 also presents information on age. We observe workers from sixteen to thirty-six years old. Workers with college have higher mean ages since we observe those born in 1981 or after.

On the bottom of Table 3.4 we present the one-digit occupational composition of the schooling groups. Workers with primary, middle and high school are more employed in the machine operators (55.6%, 46.3% and 33.2%, respectively), and service and sales occupations (29.6%, 32.5% and 31.9%). One quarter of high school workers are employed in the clerical support occupations. For college workers the picture is distinct: 59.9% of these workers work in the professionals occupation, 17.1% in clerical support and 11.5% as technicians. This too shows how workers with college are distinct from other workers.

[7]as in Blau and Kahn (2013)

Table 3.4: Descriptive Statistics

	Primary School	Middle School	High School	College	TOTAL
% of total sample	2.1	11.8	51.2	4.6	100.0
Log Real Wages	6.5	6.5	6.6	7.8	6.7
Log Wages Growth (%)	7.0	7.8	8.8	12.0	8.9
Experience	2.4	2.4	2.6	3.0	2.6
Occupational Tenure	1.9	1.9	1.7	2.3	1.8
Firm Tenure	2.1	2.0	1.7	2.1	1.8
Task Experience:					
Analytical	0.1	0.1	0.1	0.9	0.2
Interactive	0.2	0.3	0.4	1.0	0.4
Routine Cognitive	0.8	0.8	1.1	0.9	1.0
Routine Manual	1.1	1.0	0.9	0.2	0.8
Non-Routine Manual	0.2	0.2	0.1	0.0	0.1
Occupational mobility (%)	12.4	18.3	32.3	21.6	29.0
Firm mobility(%)	6.5	12.8	31.2	25.7	27.6
Mean Age	22.0	21.5	22.0	26.3	22.2
Max Age	31.0	31.0	32.0	36.0	36.0
1-digit Occupations(%)					
Managers	1.0	1.5	1.8	5.3	2.0
Professionals	0.1	0.2	0.5	59.9	4.7
Technicians	1.4	2.2	5.7	11.5	5.5
Clerical support	8.0	12.6	23.1	17.1	20.8
Service and sales	29.6	32.5	31.9	3.9	30.0
Machine operators	55.6	46.3	33.2	2.1	33.4
Repair and Maintenance	4.4	4.8	3.7	0.2	3.6

Source: Employer-Employee Sample (RAIS - MTE), 2003-2010.

Note: The table reports means for the administrative panel data on workers' labor market histories and wages. Wages are deflated by IPCA (Brazilian consumer price index). Experience, firm tenure and occupational tenure are measured from the actual spells, excluding periods of unemployment and being out of the formal labor force. Occupational mobility is measured as the mean percentage of workers that switched occupations in each year. Firm mobility is measured in a similar way. Total sample size is 10,836,026 observations from 2,894,034 individuals.

4
Theoretical Framework

Mincerian, or log wage equations are recognized as one of the most studied and estimated equations by economists. While the returns to schooling in these equations are widely discussed, the parameter “return to experience” is usually treated as a black box. Here, we analyse the statistical and economic meaning of this parameter.

First of all, the parameter β_1 from the equation below[1] should not be treated as the the internal rate of return to some investment, or to experience. Instead, it is a rate at which the observed population transforms time at past work into (monetary) productivity in the current job. This definition embraces concepts like human capital accumulation, productive use of human capital and changing price of skills that we shall approach in the following sections.

$$\ln W_{i,t} = \beta_0 + \beta_1 Exp_{i,t} + u_{i,t} \tag{4-1}$$

In the following sections we present a modification in the log-wage equations: we divide experience into experience in tasks. This provides us more than one parameter related to experience measures.

4.1
Models with heterogeneous human capital accumulation

It is also widely recognized that workers may accumulate human capital while working, due to learning-by-doing or on-the-job training [2]. Here we show how the parameter β_1 from equation 4-1 depends on these processes.

Let‘s assume a general framework, where each worker i has a rate ($\gamma_{i,t}$) that transforms time at work ($I_{t,i}$) into human capital ($H_{t,i}$), according to equation 4-2. In each period t of their lives workers can have different rates of human capital accumulation[3].

$$H_{i,t+1} = H_{i,t} + \gamma_{i,t} I_{i,t} \tag{4-2}$$

The equation that characterizes the total amount of human capital that worker i has on period T is:[4]

[1] we omit schooling because in this article schooling is fixed for workers. We also omit the quadratic term for experience once our sample is constituted from young workers only.

[2] in this analysis we do not take into account the trade off “work versus training"

[3] This is in accordance with the quadratic term for experience in log wage equations.

[4] $\Gamma_{i,T}$ is the weighted mean of $\gamma_{i,t}$ from period 0 to T. If we suppose that each $I_{i,t}$ equals

$$H_{i,T} = H_{0,i} + \Gamma_{i,T} \sum_{t=0}^{T} I_{t,i} \tag{4-3}$$

Wages (W) equal productivity (S). Also, human capital has a direct relation with productivity, according to the equation below. For now, we think of skill prices (p) as constant across workers and time. We also include an individual error term ($v_{i,t}$), that could be interpreted as a psychological condition, illness, or anything else that affects workers productivity and it is not related with human capital.

$$W_{i,t} = S_{i,t} = pH_{i,t} + v_{i,t} \tag{4-4}$$

Replacing Equation 4-3 into 4-4, we have that,

$$W_{i,t} = pH_{0,i} + p\Gamma_{i,t}Exp_{i,t} + v_{i,t} \tag{4-5}$$

If we consider that $H_{0,i} = H_0 + h_{0,i}$, that $\Gamma_{i,t} = \Gamma + g_{i,t}$ and that $h_{0,i}$ and $g_{i,t}$ are normally distributed with zero mean, we have that:

$$W_{i,t} = pH_0 + p\Gamma Exp_{i,t} + [ph_{0,i} + pg_{i,t}Exp_{i,t} + v_{i,t}] \tag{4-6}$$

If we replace wages in the left side by their logarithms, the equation above becomes analogous to equation 4-1, where $\beta_0 = pH_0$, $\beta_1 = p\Gamma$ and $u_{i,t}$ equals the term on brackets. Therefore, β_1 is a function dependent of p, and Γ.

It is straightforward noticing that populations more intensive in learning by doing or on the job training are characterized with a distribution of γ_i with a greater mean (Γ). These populations will have higher β_1, ceteris paribus. However, the comparison of β_1 between different populations only gives correct inference about human capital accumulation processes if skill prices are equal across these populations.

In the next subsection we present the model above with a simple modification: that the type of task exercised by workers influence their human capital accumulation. In the section after that we introduce heterogeneous human capital too.

4.1.1 Model with two tasks

In this section we propose a novel specification of the traditional log-wage equations. We split experience into two parts (or by the number of tasks), where each part is the time accumulated in work in some specific type of task.

Let's assume that there are two types of tasks, routine (R) and non-routine (N), and that we can observe how workers spend their time at work

one year, it is straightforward that $\Gamma_{i,T} = \frac{\sum_{t=0}^{T} \gamma_{t,i}}{T}$

between these types of tasks. Then, the human capital accumulation equation can be written like this:

$$H_{i,t+1} = H_{i,t} + \delta^R_{i,t} I^R_{i,t} + \delta^N_{i,t} I^N_{i,t} \tag{4-7}$$

where $I^R_{i,t} + I^N_{i,t} = I_{i,t}$. The equation for the amount of human capital on period T would be:

$$H_{i,T} = H_{0,i} + \Gamma^R_{i,T} \sum_{t=0}^{T} I^R_{t,i} + \Gamma^N_{i,T} \sum_{t=0}^{T} I^N_{t,i} \tag{4-8}$$

Here, $\Gamma^R_{i,T}$ and $\Gamma^N_{i,T}$ are constructed analogously to $\Gamma_{i,T}$. Equation 4-4 is valid here, leaving to:

$$W_{i,t} = pH_{0,i} + p\Gamma^R_{i,t} Exp^R_{i,t} + p\Gamma^N_{i,t} Exp^N_{i,t} + v_{i,t} \tag{4-9}$$

If we consider that $H_{0,i} = H_0 + h_{0,i}$, $\Gamma^R_{i,t} = \Gamma^R + g^R_{i,t}$, $\Gamma^N_{i,t} = \Gamma^N + g^N_{i,t}$, and that $h_{0,i}$, $g^R_{i,t}$ and $g^N_{i,t}$ are normally distributed with zero mean, we have that:

$$W_{i,t} = pH_0 + p\Gamma^R Exp^R_{i,t} + p\Gamma^N Exp^N_{i,t} + [ph_{0,i} + pg^R_{i,t} Exp^R_{i,t} + pg^N_{i,t} Exp^N_{i,t} + v_{i,t}] \tag{4-10}$$

or,

$$W_{i,t} = \alpha_0 + \alpha^R Exp^R_{i,t} + \alpha^N Exp^N_{i,t} + \varrho_{i,t} \tag{4-11}$$

Under the assumptions of this model, if $\alpha^N > \alpha^R$, the distribution of the rate that transforms time at work into human capital has a greater mean for non-routine tasks than for routine tasks. That is, working with more non-routine tasks gives, in average, greater human capital accumulation to workers. As we will see in the next sections, this prescription may not be true when including other assumptions into the model.

4.1.2 Two tasks and two skills

In this section we include two skills (A and B) into the previous model. At first, we assume that any human capital can be accumulated through any task. Equation 4-7 of human capital accumulation becomes two equations:

$$H^A_{i,t+1} = H^A_{i,t} + \delta^{AR}_{i,t} I^R_{i,t} + \delta^{AN}_{i,t} I^N_{i,t} \tag{4-12}$$

$$H^B_{i,t+1} = H^B_{i,t} + \delta^{BR}_{i,t} I^R_{i,t} + \delta^{BN}_{i,t} I^N_{i,t} \tag{4-13}$$

Following similar steps, the equations that characterizes each skill amount at period T are:

$$H^A_{i,T} = H^A_{0,i} + \Gamma^{AR}_{i,T} \sum_{t=0}^{T} I^R_{t,i} + \Gamma^{AN}_{i,T} \sum_{t=0}^{T} I^N_{t,i} \tag{4-14}$$

$$H^B_{i,T} = H^B_{0,i} + \Gamma^{BR}_{i,T} \sum_{t=0}^{T} I^R_{t,i} + \Gamma^{BN}_{i,T} \sum_{t=0}^{T} I^N_{t,i} \tag{4-15}$$

With two skills, human capital relates to productivity and wages in a slightly different way, as in the equation below:

$$W_{i,t} = S_{i,t} = p^A H^A_{i,t} + p^B H^B_{i,t} + v_{i,t} \tag{4-16}$$

With similar assumptions and transformations, our log-wage equation becomes:

$$\ln W_{i,t} = \theta_0 + \theta^R Exp^R_{i,t} + \theta^N Exp^N_{i,t} + \varepsilon_{i,t} \tag{4-17}$$

Where
$\theta_0 = p^A H^A_0 + p^B H^B_0$;
$\theta^R = p^A \Gamma^{AR} + p^B \Gamma^{BR}$;
$\theta^N = p^A \Gamma^{AN} + p^B \Gamma^{BN}$;
and
$\varepsilon_{i,t} = p^A h^A_{0,i} + p^B h^B_{0,i} + (p^A g^{AR}_{i,t} + p^B g^{BR}_{i,t}) Exp^R_{i,t} + (p^A g^{AN}_{i,t} + p^B g^{BN}_{i,t}) Exp^N_{i,t} + v_{i,t}$

With this modification in the model and considering all assumptions as true, conclusions from the previous section may change. For example, if non-routine tasks allow, in average, more human capital accumulation to all skills [5], than $\theta^N > \theta^R$. However, observing $\theta^N > \theta^R$ does not give the backwards conclusion. Its is possible, for example, that non-routine tasks provides faster accumulation of the higher price skill and less of the low price skill.

4.1.3
Other factors to take into account

It is also important to notice that skill prices may change. If, for example, $p^A_2 > p^A_1$, we could be overestimating the importance of human capital accumulation in the difference $(\theta^N - \theta^R)$. In this case, it could be possible that non-routine tasks allow more accumulation of human capital of the skills which prices have raised. This is clearly a limitation of the reduced form. One consequence is that this approach should not be used to data that covers a wide range of time.

Another factor to take into account is the productive use of skills. In a model of multiple skills, we should be alert to the fact that not all skills are used in all occupations. Hence, one way to think of this is assuming that the price term in the previous equations is heterogeneous per occupation. This would give us $p^A_j H^A_{i,t} = j^A p^A H^A_{i,t}$, where $j \in [0,1]$ and A could be any type of skill. This means that skills can be acquired and not be putted into use. For

[5] $\Gamma^{AN} > \Gamma^{AR}$ and $\Gamma^{BN} > \Gamma^{BR}$

example, if a scientist decides to become a soccer player he probably will not be able to put into use the skills acquired as a scientist. Therefore, returns to experience would be underestimating human capital accumulation.

Thankfully for us, not many scientist are able (or want) to become soccer players. This could be also true for other distant occupations. Gathmann and Schonberg (2010) show that workers usually move between similar occupations in terms of skills. This probably happens because moving to distant occupations generate a wage loss, once workers may not be that productive when another set of skills is required. Therefore, taking occupational decisions into account, we observe p_j^A close to p^A (with j close to 1) if the worker has a greater stock of skill A.

5
Empirical Strategy

In this section, we present the empirical strategy used in this study. Due to an influential literature on specific human capital, we also include in our log wage equations firm and occupational tenure terms. First, we present a standard log wage equation,

$$\ln \omega_{it} = \alpha_0 FirmTenure_{it} + \alpha_1 OccupationalTenure_{it} + \beta Experience_{it} + \varepsilon_{ifot} \tag{5-1}$$

where the real log wage of worker i at period t depends on workers' firm tenure, occupational tenure and actual formal experience[1]. One more year of experience in the same job should raise worker's log wages by $\alpha_0 + \alpha_1 + \beta$. We assume that the unobserved error term ε_{ifot} has the following structure:

$$\varepsilon_{ifot} = \theta_i + \gamma_t + m_{if} + o_{io} + u_{ifot} \tag{5-2}$$

The first term represents individual ability, γ_t is an year fixed effect, m_{if} denotes the firm match between worker i and employer f and o_{io} denotes the occupational match. The error term u_{ifot} is independent and identically distributed.

Estimating Equation 5-1 by least squares generates biased estimated coefficients due to correlation of the experience variables with unobserved ability (θ_i), firm matches (m_{if}) and occupational matches (o_{io}). We estimate these equations by worker fixed effects, removing the first source of bias.

Next, we modify Equation 5-1 replacing experience by task-experience:

$$\ln \omega_{it} = \alpha_0 FirmTen_{it} + \alpha_1 OccTen_{it} + \sum_{k=1}^{5} \beta_k TaskExp_{it}^{k} + \varepsilon_{ifot} \tag{5-3}$$

We estimate Equation 5-3 by fixed effects and observe if the parameters associated with task experiences differ between each other.

In section 5 we show the results of the fixed effect estimations of Equations 5-1 and 5-3.

[1] Garcia (2013) shows evidence that informal experience is not valued in the formal sector. Therefore, its omission should not bias the returns to experience.

6
Results

In this section we first present and discuss the fixed effect estimates of Equations 5-1 and 5-3 for the entire sample. In subsection 6.1, we estimate the same equations for some schooling groups. In subsection 6.2 we separate workers between occupation movers and stayers to clarify our identification sources. Additionally, we group workers by their industry sector in another set of equations.

It is important to reaffirm that even though we call the parameters associated to the experience measures as returns, we do not mean that they actually are the internal rate of return from some investment. We think of them as the average rate at which workers from the analysed populations have all of their past time at work transformed into productivity in the present job. It should also take into account the changing price of skills and occupational decisions based on skill pricing.

Table 6.1 presents the estimation of the log wage equations described in the previous section. Column 1 estimates Equation 5-1 using worker and year fixed effects. In this regression, log wages depend only on firm tenure, occupational tenure and experience. For better comparison, experience is included only in the linear form[1].

The results show that one more year of experience has an average return of 12.4% over wages. For firm and occupational stayers, the average return to experience is of 9.3%. This value can be compared to Fernandes (2013). He estimates a log wage equation using a sample of RAIS from 1996 to 2009 that includes male workers from 18 to 55 years old. He finds that one year of experience has a return of 6.8% [2].

Returns to firm and occupational tenure are -0.5% and -2.6%, respectively. These coefficients can be interpreted as occupational movers having a larger return to experience than stayers, in the period of movement. One possible explanation for these coefficients being negative is that the self-knowledge of being a low skill worker would make individuals more willing to stay at their first job. Hence, in our sample, workers who stay a long time in their first job could be the less qualified and with more difficulty in learning.

[1]This is not too unusual if we remember that our sample is of young workers.

[2]The estimated coefficient for the quadratic term of experience is of -0.2%. Fernandes (2013) also includes age in this regression, which has a estimated coefficient of 2.6%.

Table 6.1: Log-Wage Equations. Fixed Effects Estimation.

	Traditional	Task-Approach
Firm Tenure	-0.005***	-0.004***
	(0.000)	(0.000)
Occupational Tenure	-0.026***	-0.026***
	(0.000)	(0.000)
Experience	0.124***	
	(0.001)	
Task Experience:		
Analytic		0.203***
		(0.001)
Interactive		0.123***
		(0.001)
Routine Cognitive		0.118***
		(0.001)
Routine Manual		0.103***
		(0.001)
Non-Routine Manual		0.109***
		(0.002)
Observations	9,393,006	9,393,006
R-squared	0.313	0.317
Number of workers	2,556,049	2,556,049

Note: Column 1 reports results from a regression of log real wages over firm tenure, occupational tenure and experience. Column 2 reports results from a regression of log real wages over firm tenure, occupational tenure and the five types of task experience. The specification includes year and worker fixed effects. Robust standard errors are in parenthesis (*** $p < .01$).

On the other hand, workers who switch firms and occupation are also those who are looking more for better matches.

In column 2 we present the estimates of Equation 5-3. In this specification, total experience is replaced by the measures of task experience. The estimated coefficients for firm and occupational tenure are similar to those in column 1. One year of experience in analytical tasks increases wages by 20.3%, the highest return among tasks. Experience in interactive, routine cognitive, non-routine manual and routine manual tasks have returns of 12.3%, 11.8%, 10.9% and 10.3%, respectively. An F-test rejects the null hypothesis of equality between the five returns to task experience.

Therefore, workers average returns to experience go from 10.3% to 20.3% of log wages, depending on the task intensity. For example, the average return to experience of workers whose job activities are entirely analytical is of 20.3%. For workers with half the activities being analytical and half being interactive, one more year of experience increases wages by 16.3% ((1/2)*.203 + (1/2)*.123). Furthermore, a worker with the average task intensity of the sample has a return to experience that should resemble the returns to experience in column 1.

As extensively discussed in previous sections, the estimated coefficients can be interpreted in different ways. If is reasonable to assume that working in different tasks generates accumulation of the same type of human capital, than these estimators induce us to believe that analytical tasks provide more opportunities for human capital accumulation than other tasks. Working in analytical tasks would provide almost the double of human capital accumulation opportunities[3] than working on routine manual tasks.

However, if considering the model with heterogeneous human capital, we cannot tell a part if analytical tasks are providing more learning opportunities for all skills or just for skills with greater price. Another explanation is that the price of the skills that analytical tasks accumulate more (relatively to other tasks) has increased during the period.

The task approach stimulates us to think on what workers actually do. For example, what would essentially differ an analytical task from a routine task? As Autor et al. (2003) mention, a routine task involves the repetition of the same activity, and from our knowledge, analytical tasks require comprehension and a thinking effort. Therefore, while routine tasks may involve some learning at first, usually few months of experience are sufficient for completely understanding the chore. On the other hand, analytical tasks would require constant mental effort.

This is more evident if we observe some occupations that still exist in developing countries like Brazil. For example, the elevator attendant occupation requires only the push of a few buttons. Hence, it is logical to assume that these workers will not accumulate as much human capital as a secretary will, for example[4].

6.1 Results by Schooling Groups

In this section, we extend the previous analysis by separating workers into schooling groups. Table 6.2 shows the specification of Table's 6.1 first column,

[3]This would include learning-by-doing and on-the-job training opportunities.

[4]The comparison may seem unfair at first sight, but most of the adds in a popular job finding website required complete high school to hire an elevator attendant, a qualification that could easily fit to work as secretary.

and Table 6.3 of the second column. We display results only for workers with completed primary school, middle school, high school or college.

Results in Table 6.2 show that higher schooling workers have greater returns to experience [5]. For firm and four-digit occupation movers, returns to experience go from 8.3% to 13.2%. Returns for stayers are between 2.1 and 4.4 percent points lower: one year more of experience in the same firm and occupation increases the mean worker real wage by 5.1% if he has only the primary school completed; by 6.5% if he has middle school completed; by 9.9% if he has completed high school; and by 8.8% if he completed college. We remind that college workers may not be strictly comparable to workers with lower schooling, since we observe them with higher initial age. The results suggest that higher schooling workers have more on-the-job training and learning-by-doing opportunities, or just more ease of learning.

Table 6.2: Traditional Log-Wage Equation. Fixed Effects Estimation.

	Primary School	Middle School	High School	College
Firm Tenure	-0.008***	-0.002***	-0.000	-0.014***
	(0.002)	(0.001)	(0.000)	(0.001)
Occupational Tenure	-0.024***	-0.030***	-0.021***	-0.030***
	(0.001)	(0.001)	(0.000)	(0.001)
Experience	0.083***	0.097***	0.120***	0.132***
	(0.004)	(0.002)	(0.001)	(0.003)
Observations	179,802	1,010,222	5,230,120	485,678
R-squared	0.296	0.320	0.299	0.372
Number of workers	54,641	300,664	1,308,094	117,285

Note: Each column reports results from a regression of log real wages over firm tenure, occupational tenure and experience. The specification includes year and worker fixed effects. Workers do not move between educational groups. Robust standard errors are in parenthesis (*** $p < .01$; ** $p < .05$).

With Table 6.2 as benchmark, Table 6.3 presents the estimation of the log wage equation with the tasks-experience as explanatory variables. The first column shows that one more year of experience for a worker with completed primary school, who changed firm and occupation, could imply a wage growth up to 15.2%. For this group of workers analytical tasks give the greatest return to experience, followed by routine manual (8.9%), interactive (8.7%), routine cognitive (7.6%) and non-routine manual tasks (3.2%).

[5] The results are in accordance with Braga (2014). He also uses actual experience instead of potential experience. He finds that, for the US, returns to experience increase with schooling.

Table 6.3: Log-Wage Equation. Task Approach. Fixed Effects Estimation.

	Primary School	Middle School	High School	College
Firm Tenure	-0.007***	-0.002***	-0.000	-0.014***
	(0.001)	(0.001)	(0.000)	(0.001)
Occupational Tenure	-0.025***	-0.029***	-0.020***	-0.029***
	(0.001)	(0.001)	(0.000)	(0.001)
Task Experience				
Analytic	0.152***	0.188***	0.221***	0.118***
	(0.008)	(0.004)	(0.002)	(0.004)
Interactive	0.087***	0.080***	0.108***	0.138***
	(0.006)	(0.003)	(0.001)	(0.004)
Routine Cognitive	0.076***	0.093***	0.116***	0.147***
	(0.004)	(0.002)	(0.001)	(0.004)
Routine Manual	0.089***	0.098***	0.104***	0.039***
	(0.005)	(0.002)	(0.001)	(0.006)
Non-Routine Manual	0.032***	0.071***	0.120***	0.352***
	(0.009)	(0.004)	(0.002)	(0.025)
Observations	179,802	1,010,222	5,230,120	485,678
R-squared	0.298	0.323	0.302	0.373
Number of workers	54,641	300,664	1,308,094	117,285

Note: Each column reports results from a regression of log real wages over firm tenure, occupational tenure and five task experience. The specification includes year and worker fixed effects. Workers do not move between educational groups. Robust standard errors are in parenthesis (*** $p < .01$).

For workers with completed middle school, analytical tasks still provide the greatest average returns to experience (18.8%). Non-routine manual tasks provide the lowest (7.1%).

In the third column, we observe the results for workers with completed high school, which represent more than 50% of our total sample. As expected from Table 6.2, the coefficients for tasks experience are larger than for middle school workers. The pattern of returns to task experience are similar to the one presented in Table 6.1. An additional year in a purely analytical job should raise wages by 22.1%, twice as larger than the returns to other tasks experiences. We remember that jobs are usually intensive in several tasks and that for stayers the returns are 2 p.p. lower.

A different pattern occurs for workers with college. Non-routine manual tasks appear to be the more rewarding in terms of wage growth. One more year performing this type of task raises wages by 35.2%. However, occupations are usually low intensive in this kind of task. On the other hand, college workers who are more intensives in routine manual tasks have a very little wage growth. The returns to experience in a position with only this type of task is of 3.9%, more than three time lower than the return to routine cognitive experience (14.7%). Experience has also high return if there is a specialization in interactive tasks, where one more year increases wages by 13.8%. Jobs purely analytical have a return to experience of 11.8%.

6.2 Could other stories explain these results?

In order to estimate Equation 5-3 with worker fixed effects, we exploit the variation in task experience across occupations and time. When workers change occupation, they also change the profile of their task experience accumulation.

One question may arise tough. Do we observe larger returns to analytical experience because this type of task allows more human capital accumulation or because mobility to more analytical occupations is usually a promotion in the worker's career? To answer that, in Table 6.4 we estimate a specification similar to Table 6.3 from the previous section. We divide the sample into occupational stayers in Sample A and occupational switchers in Sample B[6]. Since we do not include the firm and occupational tenure, Table 6.5 presents equivalent estimates for the entire sample.

What drives the results in the sample with no mobility is the variation in task experience within workers and across workers with different occupations. In the sample with mobility, this variation is also present. The other variation is the task usage change within workers, caused by occupational mobility. This variation helps identifying parameters, but at the expense of including the mobility from career progress.

In Sample A almost all the estimated coefficients to task experience are lower than in Sample B or in Table 6.5. This is not surprising, since the estimated returns to occupational tenure were negative in Table 6.3. Furthermore, this does not confirm that the results from analytical experience come from career progressions, since all returns decrease and their relation within educational group remains the same.

Results in Sample B also have similar patterns as the results in Table 6.3 or Table 6.5. For this sample of workers, the magnitudes of the returns to task are larger.

[6]For us, an occupational switcher is a worker that has switched four-digit occupations at least once.

TABLE 6.4: Log-Wage Equation. Task Approach. Sampling by Occupational Mobility.

	Primary School	Middle School	High School	College
Sample A: without occupational mobility				
Task Experience:				
Analytic	0.067***	0.121***	0.112***	0.046***
	(0.009)	(0.005)	(0.002)	(0.005)
Interactive	0.025***	0.011***	0.012***	0.056***
	(0.006)	(0.003)	(0.002)	(0.005)
Routine Cognitive	0.045***	0.047***	0.061***	0.070***
	(0.005)	(0.002)	(0.001)	(0.005)
Routine Manual	0.042***	0.043***	0.039***	-0.060***
	(0.004)	(0.002)	(0.001)	(0.008)
Non-Routine Manual	-0.002	0.013**	0.026***	0.417***
	(0.010)	(0.005)	(0.003)	(0.040)
Observations	125,753	618,710	2,088,241	271,009
R-squared	0.214	0.249	0.269	0.306
Number of workers	42,641	212,759	703,293	79,547
Sample B: only with occupational movers				
Task Experience:				
Analytic	0.168***	0.185***	0.234***	0.132***
	(0.014)	(0.005)	(0.002)	(0.005)
Interactive	0.088***	0.094***	0.125***	0.151***
	(0.010)	(0.004)	(0.002)	(0.005)
Routine Cognitive	0.046***	0.081***	0.113***	0.135***
	(0.007)	(0.002)	(0.001)	(0.006)
Routine Manual	0.075***	0.092***	0.104***	0.111***
	(0.007)	(0.002)	(0.001)	(0.010)
Non-Routine Manual	0.024*	0.084***	0.141***	0.200***
	(0.014)	(0.006)	(0.003)	(0.032)
Observations	54,049	391,512	3,141,879	214,669
R-squared	0.405	0.379	0.315	0.416
Number of workers	12,000	87,905	604,801	37,738

Note: The top panel shows regression results for Sample A, comprising workers that have never switched four-digit occupations. The bottom panel shows regression results for Sample B, comprising workers that have switched four-digit occupations at least once. Each column reports results from a regression of log real wages on five task experience. The specification includes worker and year fixed effects. Workers do not move between educational groups. Robust standard errors are in parenthesis (*** $p < .01$).

Table 6.5: Log-Wage Equation. Task Approach. Entire Sample

	Primary School	Middle School	High School	College
Task Experience:				
Analytic	0.126***	0.160***	0.207***	0.086***
	(0.008)	(0.004)	(0.002)	(0.004)
Interactive	0.050***	0.042***	0.087***	0.114***
	(0.005)	(0.002)	(0.001)	(0.004)
Routine Cognitive	0.048***	0.064***	0.095***	0.125***
	(0.004)	(0.002)	(0.001)	(0.004)
Routine Manual	0.055***	0.064***	0.085***	-0.001
	(0.004)	(0.002)	(0.001)	(0.006)
Non-Routine Manual	0.011	0.043***	0.101***	0.328***
	(0.008)	(0.004)	(0.002)	(0.026)
Observations	179,802	1,010,222	5,230,120	485,678
R-squared	0.292	0.316	0.300	0.367
Number of workers	54,641	300,664	1,308,094	117,285

Note: This table reports results from one regression of log real wages over experience disaggregated into five tasks experiences, all interacted with schooling. The specification includes worker fixed and year fixed effects. Results are reported into four columns and workers do not move between educational groups. Robust standard errors are in parenthesis (*** $p < .01$).

In Table 6.6 we group workers by their industry sector[7]. This is a very modest tentative to keep workers skill set constant. As it can be seen, results are very similar to Table 6.1. For all sectors, analytical experience has the greatest returns to experience. It is usually followed by routine cognitive or interactive tasks. It is interest, for example, that for workers in the service industry, interactive tasks are as important as analytic tasks. These results show that the explanation of the differences between parameters associated with experience do not appear to rely only on industry composition.

[7]We only include workers that have never moved from sector.

Table 6.6: Log-Wage Equation. Task Approach. Sectors

	(1) Comerce	(2) Construction	(3) Industry	(4) Service
Firm Tenure	-0.010***	-0.016***	-0.003***	-0.011***
	(0.000)	(0.001)	(0.000)	(0.001)
Occupational Tenure	-0.031***	-0.048***	-0.027***	-0.035***
	(0.000)	(0.001)	(0.000)	(0.001)
Task Experience:				
Analytic	0.174***	0.212***	0.178***	0.150***
	(0.002)	(0.007)	(0.002)	(0.003)
Interactive	0.113***	0.173***	0.120***	0.150***
	(0.002)	(0.008)	(0.002)	(0.002)
Routine Cognitive	0.123***	0.158***	0.133***	0.089***
	(0.001)	(0.004)	(0.002)	(0.002)
Routine Manual	0.100***	0.113***	0.087***	0.089***
	(0.001)	(0.003)	(0.002)	(0.002)
Non-Routine Manual	0.097***	-0.002	0.156***	0.007*
	(0.003)	(0.008)	(0.003)	(0.004)
Observations	2,529,766	371,920	1,800,775	2,085,930
R-squared	0.359	0.262	0.408	0.307
Number of workers	764,247	135,312	522,870	642,539

Note: This table reports results from one regression of log real wages over experience disaggregated into five tasks experiences, all interacted with schooling. The specification includes worker fixed and year fixed effects. Results are reported into four columns and workers do not move between educational groups. Robust standard errors are in parenthesis (*** $p < .01$).

7
Conclusion

This study presents estimates of log wage equations for young men in the formal labor force in Brazil. We presented results using the traditional approach, where log wages depend on firm tenure, occupational tenure and experience. We also propose a task-approach to this log-wage equation. Instead of experience, we include the constructed measures of task experience as explanatory variables.

Our findings indicate that workers have higher wage growth due to experience in analytical tasks than in routine or interactive tasks. These results are robust to different specifications. In fact, we show that our results do not exclusively reflect occupational mobility or industry composition. Results are similar for a sample of occupational stayers. Some results are also similar across workers from different industries.

We develop an intuitive model that helps understanding how this findings are related to human capital accumulation, changing price of skills and occupational decisions. But we also try to keep a very statistical view of what underlies the parameters associated with experience measures.

The results bring attention to the jobs profile of young workers in developing countries. Essentially, routine manual and interactive tasks provide few opportunities for wage growth. These types of tasks are widely used in such countries. For example, occupations such as elevator attendant, door attendant, market cashier, bus cashier, toll collector and gas station attendant are very common in developing countries.

The literature on technological change complements this evidence. In this view, routine manual tasks are more substitutable by technological improvements. Therefore, we identify this group of workers as being more vulnerable to economic conditions. Technological implementation may reduce the labor demand for this kind of task, which means that these workers may have higher unemployment risk. When unemployed, these workers may face a tough competition in the labor market, since they did not acquired skills that distinguish them from other entrants.

8
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A
Measurement Bias

As mentioned on section 3.3, task data may be measured with error. Here, we provide a simple analysis of how this error may affect the estimated coefficients.

For simplicity, suppose there are only two possible tasks, analytic (a) and manual (m), and that we only observe workers with exactly one year of experience. Log wages are synthesized by ω_i and we assume that the error term has a Normal distribution ($\nu_i \sim N(0,1)$). We present the equation of interest below:

$$\omega_i = \beta_1 a_i + \beta_2 m_i + \nu_i \tag{A-1}$$

since $a_i + m_i = 1$, we rearrange in

$$\omega_i = \beta_2 + (\beta_1 - \beta_2)a_i + \nu_i \tag{A-2}$$

and therefore,

$$\omega_i = \gamma_0 + \gamma_1 a_i + \nu_i \tag{A-3}$$

Suppose that we cannot observe a and m. Instead we observe A and M, the occupations mean task. The following equations describe the structure of our observed task measures A and M:

$$A_i + M_i = 1 \tag{A-4}$$

$$A_i = a_i + e_{ai} \tag{A-5}$$

$$M_i = m_i + e_{mi} \tag{A-6}$$

This leaves to $e_{mi} = -e_{ai}$. It can be noted that the error term must be between $-a_i$ and $1-a_i$. However, in order to simplify the problem, we assume that this error has a Normal distribution with mean 0 and a small variance σ_e. Hence, we can calculate the bias in the estimated coefficients in an OLS estimation.

$$\hat{\gamma_1} = \frac{Cov(A,\omega)}{Var(A)} = \frac{Cov(a+e_a,\omega)}{Var(a+e_a)} = \frac{Cov(a,\omega)}{Var(a)+Var(e_a)} \tag{A-7}$$

$$\hat{\gamma_1} \longrightarrow \gamma_1 \left(\frac{\sigma_a^2}{\sigma_a^2+\sigma_e^2}\right) \tag{A-8}$$

$$\hat{\gamma_0} \longrightarrow \bar{\omega} - \hat{\gamma_1}\bar{A} = \bar{\omega} - \gamma_1 \left(\frac{\sigma_a^2}{\sigma_a^2+\sigma_e^2}\right)(\bar{a}+\bar{e_a}) \tag{A-9}$$

$$\hat{\gamma_0} \longrightarrow \gamma_0 + \gamma_1 \bar{a}\left(1 - \frac{\sigma_a^2}{\sigma_a^2+\sigma_e^2}\right) \tag{A-10}$$

Mathematically, $\hat{\gamma_0} = \hat{\beta_2}$, $\gamma_0 = \beta_2$, $\hat{\gamma_1} = \widehat{\beta_1 - \beta_2}$ and $\gamma_1 = \beta_1 - \beta_2$. Furthermore,

$\widehat{\beta_1 - \beta_2}$ converges in probability to $\hat{\beta}_1 - \hat{\beta}_2$. Than,

$$\widehat{\beta_1 - \beta_2} \longrightarrow (\beta_1 - \beta_2)\left(\frac{\sigma_a^2}{\sigma_a^2 + \sigma_e^2}\right) \tag{A-11}$$

$$\hat{\beta}_2 \longrightarrow \beta_2 + (\beta_1 - \beta_2)\bar{a}\left(\frac{\sigma_e^2}{\sigma_a^2 + \sigma_e^2}\right) \tag{A-12}$$

and,

$$\hat{\beta}_1 \longrightarrow \beta_1 - (\beta_1 - \beta_2)\bar{m}\left(\frac{\sigma_e^2}{\sigma_a^2 + \sigma_e^2}\right) \tag{A-13}$$

Equations 12, 13 and 14 above identify the bias due to measurement error. Equation 12 implies that the estimators of the coefficients difference are underestimated. Equations 13 and 14 identify the bias magnitude of each estimator. This bias depends on the real difference between coefficients, on the cross task experience mean $\bar{a}$ and $\bar{m}$, and on the ratio between the error variance and the task experience variance. The later term should be small if we take into account the problem's structure.

Some conditions of our approach differentiate it from the previous analysis. Nonetheless, this analysis provides us an intuition on how this measurement error should affect our results.

B
Data Structure

B.1
Worker Data cleaning

In this section we clarify the data construction and cleaning. We start from a database of male and young workers that were observed on more than one year. As Table B.1 shows, this base constitutes of 110,462,972 observations from 17,381,244 workers.

An observation of worker data is an end of period match between firm and worker. End of period can be the end of year or end of contract. Therefore, we can observe multiple observations per worker per year. If the worker stays on the same job for the entire year, we observe him only once in this year. For every observation, earnings are taken as the mean wage of the period.

The first cleaning procedure is dropping all workers whose schooling has changed during the observed years. We take this approach because we cannot know if this change on schooling is due to typing error or due to increases in schooling. Actually, 30% of the changes were reductions in schooling, indicating that 60% of the changes were probably typing errors. This procedure reduces the number of workers and observations substantially (by 53.3% and 63.5%, respectively). It is also notable that this reduction is higher for workers with low education.

In the second step, we only kept workers who were 18 years or less in 2003 (or 22 years old or less if they have college). This restriction is done to be sure that we are not missing workers formal experience. This restriction reduces the number of observations in the data base by 66.9%, and is also more punitive for low schooling workers.

Finally, the third reduction on our data base comes from the merge of worker and task data. We have tasks mapped to 87% of occupations. Therefore, we have to drop at least 13%of the observations. The number increases because we also need to drop the observations we have from individuals after they worked in an occupation that is not mapped. That is, if a worker was in 10 occupations during his life course, but the fifth was not mapped into tasks, we only keep the observations related to the first four occupations.

Table B.1: Steps of data cleaning

Sample	Observations / Workers	Primary School	Middle School	High School	College	As % of the previous
Contracts						
Original	110,462,972	**6.1%**	**17.0%**	**38.6%**	**5.8%**	
Step 1	40,290,923	4.3%	12.9%	49.3%	8.9%	36.5%
Step 2	13,349,16	2.2%	10.8%	53.4%	7.8%	33.1%
Final	9,393,006	1.9%	10.8%	55.7%	5.2%	70.8%
Workers						
Original	17,381,244	**6.8%**	**18.3%**	**33.0%**	**4.7%**	
Step 1	8,120,844	4.4%	14.1%	45.9%	7.7%	46.7%
Step 2	4,145,908	2.6%	12.1%	49.6%	7.5%	51.1%
Final	2,556,049	2.1%	11.8%	51.2%	4.6%	61.7%

B.2 Schooling

In Table B.2 we show how the schooling measure in RAIS can be translated into years of schooling.

Table B.2: Schooling Measure in RAIS.

Education Level	RAIS Education	Years of Schooling
Illiterate	1	0
Primary School Dropout	2	1 to 3
Primary School Graduate	3	4
Middle School Dropout	4	5 to 7
Middle School Graduate	5	8
High School Dropout	6	9 to 11
High School Graduate	7	12
College Dropout	8	13 to 15
College Graduate	9	16 or more

Note: The Table shows the description of the education variable in the RAIS dataset.

B.3 An example of the task data construction

In this section we explain how the task data was constructed. For that, we use a fiction worker as an example.

Suppose we observe John since he entered the labor market, on January of 2003. His first job was as a truck driver for firm A. After one year and a half, he switched to firm B. He worked there for two years until he got fired. Six months later, John got a job as a baker in firm C. We observe him for another two years.

The calculus of John‘s experience, firm tenure and occupational tenure are straightforward. However, to calculate his task experiences we need the task composition of his occupations. In the table below we show how is the description of the truck driver occupation. We use Table 3.1 to set the type of task that each activity belongs. For example, the first activity is categorized as routine manual, since it involves transporting.

Table B.3: Description and categorization of the truck driver occupation

Activity	Type of task
Transport Cargo	Routine Manual
Repair the vehicle	Non-Routine Manual
Verify documents of the vehicle and the cargo	Routine Cognitive
vistoria cargo	Routine Cognitive
Define routes	Routine Cognitive
Communicate in real time	Interactive
guinchar e destombar veiculos	Routine Manual
Operate equipments	Routine Manual
assegurar regularidade do transporte	Routine Manual
Move big and heavy cargo	Routine Manual

The categorization of the truck driver activities gives us the task composition of the occupation. In order to translate these descriptions into time at work, we need weights that tell how much time workers spend at each activity. Since this data is improbable to exist for all occupation, our best assumption is that workers spend the same time on each described activity. Under this assumption, Equation B-1 shows how the task composition is established from the table above. Table B.4 shows the results for the truck driver and baker occupation.

$$Task_o^k = \frac{\text{number of activities of type k in occupation o}}{\text{total number of activities in occupation o}} \tag{B-1}$$

Table B.4: Task composition by occupation

Type of task	Truck Driver	Baker
Analytic	$0/10 = 0\%$	$1/11 = 9.1\%$
Interactive	$1/10 = 10\%$	$0/11 = 0\%$
Routine Cognitive	$3/10 = 30\%$	$1/11 = 9.1\%$
Routine Manual	$5/10 = 50\%$	$8/11 = 72.7\%$
Non-Routine Manual	$1/10 = 10\%$	$1/11 = 9.1\%$

Having this information, we can calculate John's task experience based on Equation 3-1. Another assumption we take is that the time spent in each activity is constant across workers in the same occupation. The measures of tenure, occupational tenure, experience and task experience are presented on Table B.5.

Table B.5: Tenure and experience measures for the fictitious John

Start of period	End of period	Firm	Occupation	Firm Tenure	Occ. Tenure	Experience	Task Experience				
							Analitical	Interactive	Routine Cognitive	Routine Manual	Non-Routine Manual
Jan-03	Dec-03	A	Truck Driver	1	1	1	0	0.1	0.3	0.5	0.1
Jan-04	Jun-04	A	Truck Driver	1.5	1.5	1.5	0	0.15	0.45	0.75	0.15
Jun-04	Dec-04	B	Truck Driver	0.5	2	2	0	0.2	0.6	1	0.2
Jan-05	Dec-05	B	Truck Driver	1.5	3	3	0	0.3	0.9	1.5	0.3
Jan-06	Jun-06	B	Truck Driver	2	3.5	3.5	0	0.35	1.05	1.75	0.35
Jun-06	Dec-06	-	Unemployed	-	-		-	-	-	-	-
Jan-07	Dec-07	C	Baker	1	1	4.5	0.091	0.35	1.141	2.477	0.441
Jan-08	Dec-08	C	Baker	2	2	5.5	0.182	0.35	1.232	3.204	0.532