Segmentation in the Brazilian Labor Market*

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PRELIMINARY AND INCOMPLETE
SUGGESTIONS ARE VERY WELCOME

Abstract

In this paper we measure the degree of segmentation in the Brazilian labor market, by investigating the wage differential between formal and informal workers. We use data from the *Monthly Employment Survey (PME)*, a rotating panel of individuals in six metropolitan regions. Controlling for observable and unobservable characteristics, we find that workers earn more in the formal sector, which is an evidence of segmentation. Contrary to other studies that rely on *two-step procedures* to correct for self-selection bias or *repeated cross-sections* to account for fixed effects, our true panel allows us, under certain conditions, to solve both issues, providing a better estimate of the wage differential. We also propose a two-stage panel probit model to solve a potential weakness of our simple fixed-effects estimator.

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1 Introduction

Is the Brazilian labor market segmented? Or, do workers in the formal sector earn more than their counterparts in the underground economy? According to the model proposed by Rosen (1986), in a frictionless labor market, average earnings should be higher in the informal sector in order to compensate for the non-pecuniary benefits granted to workers in the formal sector. If this is not the case and the wage difference favors workers in the formal sector, then this is an evidence of the existence of segmentation in the labor market. Workers in the formal economy have access to indirect (non-pecuniary) rewards in the form of several fringe benefits. Assuming that the value of the benefits is non-negative, direct payments in the informal sector should be at least as high as those in the formal economy to offset the lack of benefits. Otherwise the absence of barriers to entry into the formal sector would attract all workers to the firms in the above ground economy. The coexistence of both markets and wage differentials favoring formal workers points out to barriers to entry into the formal economy or some other friction that prevents workers from moving to high-paying jobs. That is, the market would be *segmented*.

From the point of view of economic efficiency, a segmented market fails to optimally allocate workers to firms. There are two sources of inefficiency. Assume that firms hire workers up to the point where the marginal value of the productivity equals the prevailing wage rate. In this case, there would be workers currently employed in the low-productivity informal sector willing to supply labor to high-productivity firms in the formal sector at a lower cost (wages plus benefits). A segmented market prevents this efficient movement of workers across firms in different sectors, maintaining the productivity differential. The second source has to do with the wage/benefits composition in the formal sector. Workers may attach a lower value to the fringe benefits that the cost of providing them for the firm. Therefore, those workers would be willing to exchange benefits to a higher wage at a lower cost for the firm. Even though segmentation could arise due to asymmetric information between firms and workers in an efficiency-wage framework,[1] in the particular case under study in this paper, namely segmentation across formal and informal *sectors* in Brazil, the usual suspect is the labor legislation. These observations make the measurement of the degree of segmentation an important issue for the policy-makers.

To investigate the existence of segmentation is essentially an empirical endeavor, but not a simple one. Due to observable and unobservable characteristics, unconditional comparison of wage means would be misleading. For instance, workers in the formal sector may be

[1] See Shapiro and Stiglitz (1984) for a model in which segmentation and involuntary unemployment arise in equilibrium.

more educated compared to their peers in the informal sector. Therefore, part of of the wage differential would be explained by schooling differences. A naive approach to estimate the wage advantage of the formal workers by simply comparing means would result in an upward-biased estimate of the segmentation degree. One way to get around this problem is to add controls in a regression framework. In the literature the other variables usually added to the regression a controls include gender, experience, and race.[2]

A trickier issue that one has to tackle in order to identify the degree of segmentation is the endogeneity caused by unobservable characteristics of the individual, like ability and intrinsic preferences. The presence of unobservable attributes may cause bias in the estimates, since these characteristics may jointly determine the sector in which the individual will eventually work and his/her earnings. For instance, a more risk-averse individual tends to prefer the formal sector once the probability of dismissal is lower, and in case of lay-off, one is eligible for unemployment insurance. Furthermore, it is possible that risk averse workers are more prone to effort, resulting in higher wages.

In the literature, the endogeneity of the sectoral choice is dealt with by methods that address selection bias (a Heckman two-stage procedure). This procedure consists in estimating a sectoral choice equation in the first stage by a probit model, and constructing the correction terms to be used as regressors in the main wage regression. Even though this model can be identified without the exclusion of any variable from the main equation due to the non-linearity in the first stage, this procedure is considered unreliable since the correction term tends to be highly correlated with the other covariates, specially in the range in which the inverse Mills ratio is almost linear, inflating the standard errors, and reducing considerably the accuracy of the estimators. Therefore, it is important to have variables that can be simultaneously included in the first stage and excluded in the main regression. These excluded variables must have two properties. They should be orthogonal to the errors of the main equation and also relevant to determine the sectoral choice in the first stage.

To estimate the wage differential driven by labor market frictions we explore the panel data structure of the monthly employment survey conducted by the Brazilian national statistics agency. Our longitudinal dataset allows us to keep track of the same individual over several periods. Since the Brazilian labor market is characterized by significant labor force turnover, we observe several intersectoral *transitions* over time.

Compared to a cross-section structure, our approach allows us to calculate the wage variation during a transition from one sector to the other for the *same* individual. This strategy is consistent even if there are *unobservable* attributes which simultaneously deter-

[2]In section 4 we present some descriptive statistics for both groups.

mine sectoral choice and earnings as long as those characteristics are constant over time.[3] The previous works which use a cross-section structure cannot control for unobservable attributes, and consequently will obtain biased estimates when the observable characteristics jointly explain sectoral choice and earnings. Nevertheless, the fixed-effect estimator has a potential flaw. Whenever the relevant unobservable attributes changes over time and their variation is correlated with the earnings and sectoral choice variations, the fixed-effect estimator is inconsistent. For example, if workers anticipate their relative prospects in both sectors and make the sectoral choice decision based on those expectations (which are not observed), then the transition from one sector to the other is also endogenous.[4]

2 Brief Literature Review

The study of market segmentation is not a new theme in the literature, and particular attention has been devoted to the occurence of this phenomenonin the labor market, in developing as well as developed countries.[5] Our main concern in this paper is the measurement of the wage differentials between similar workers in different sectors, which is one of the central questions addressed by this literature. As pointed out by several authors, significant wage differentials that persist after controlling for individual attributes indicate the existence of barriers to entry in the formal/primary sector.[6] Broadly speaking, there are two views of the informal labor market. One of them sees informal work as a transitory phase for entrants in the labor market, and a buffer between formal employmentand employment transitory state during recessions. Therefore, lacking the ability to cross the barrier into the formal sector, where the good and desirable, but rationed, jobs are, workers take advantage of the flexibility of precarious positions in the underground economy. Due to institutional barriers (labor regulation, minimum wage, and unions), wages of formal worker do not fall to clear the market, and informal workers would prefer a positions held by their counterparts (with similar attributes) elsewhere. Several other authors, including Maloney (2004), point out

[3] Indeed, we just need the variation of the unobservable attributes not to be jointly correlated with the earnings and sectoral choice variation.

[4] Ideally, we would like to observe the same individual's earnings, at the time,in both sectors. In this hypothetical situation, the mean wage differential would be a clear and immediate indicator of the degree of segmentation in this labor market. However this strategy is not feasible.

[5] Leontaridi (1998) provides a comprehensive survey of this literature, whith some reference to the econometric issues involved in the measurement of segmentation.

[6] Another important branch of this literature investigates how one's attributes, like education and experience, are valued differently in the two sectors. In this respect, there is some evidence that the returns to education are lower in the informal sector. Since we estimate wage differentials in a panel data framework and there are only a few changes in educational attainment within individuals, there is not much we can say about this question without losing the ability to control for unobservable.

that the benefits of being in the formal sector are ellusive because public services offered to formal worker are inefficient. According to this view, informal jobs may be a desirable alternative, providing more flexibility, and allowing both sides of the market to avoid cumbersome and expensive regulations – and taxes. In this case, one could not assert that the labor market is segmented, since unregistered workers may prefer their current positions, sorting themselves into the informal sector. In the Brazlian case, even though the jobs in the informal sector may provide benefits invisible to the outside observer, we believe that formal sector positions are more desirable, holding pecuniary rewards constant. In this case, the test of the segmentation hypothesis hinges on the magnitude of wage differentials, with a wage premium in the formal sector supporting the first view.

Several authors have proposed a measure of the degree of segmentation, for Brazil as well as other LDC. The empirical strategies can be divided in three basic approaches: cross-sectional studies that correct for self-selection bias, repeated cross-sections that group individuals to control for observables, and longitudinal methods applied to panel data. Carneiro and Henley (2001) is an example of the first approach, finding some evidence against the segmentation hypothesis. More precisely, the empirical evidence does not reject a model in which some workers choose sector according to, among other things, the potential wage in each sectors. Therefore, the differential wage could be explained by differences in personal characteristics of separate sets of workers that make one sector more attractive due to a higher potential wage. The correct for the endogeneity of the occupational choice, a multi-stage estimation procedure is applied. This strategy consists in estimating a propensity to join the each sector in the first stage[7] and using the estimated Mills ratios to correct the selection bias in the earning equations. This approach strongly relies on the existence of a set of instruments that explain earning only indirectly, through the likelihood of choosing a sector.[8] Even reconizing that some workers may find the informal sector more attractive (or less *un*natractive), we believe that a direct measure of wage diferentials provides more direct evidence of the degree of segmentation. Moreover, cross-sectional studies are very susceptible to omitted variable bias due to the presence of unnobservable attributes.Magnac (1991) adopts a similar approach to investigate market segmentation in Colombia, failing to reject the null hypothesis that the market is integrated.

Filho *et al.* (2004), using a repeated cross-sections of Brazilian household surveys (*PNAD*), also concludes against the segmented labor market conjecture. Grouping the individuals according to age (birth cohort), education, and time, the authors try to control for unobservable

[7]One can interprete the equation of the first stage as determining the relative benefit of joining each sector, conditional on personal attributes.

[8]In the absence of instruments one is forced to rely on non-linearities in order to identify the main equation, which considerably reduces the precision of the estimator.

characteristics of the workers. By constructing a *pseudo-panel* and controlling for group fixed effects, the authors find that workers in the formal sector do not earn more than their counterparts in the informal market. Indeed, they find the opposite: informal workers earn much higher wage than similar workers in the above groud economy. This informal wage premium could be a compensation for the foregone benefits in the formal sector. The weakness of the method is its limited ability to control for unobservable attributes. With a genuine panel, we can explicitly control for unobservables which are constant over time.[9]

Closer to the approach adopted here, Maloney (1999) uses data from the *Encuesta Nacional de Empleo Urbano*, which, like the *PME*, is a rotating panel of urban households to gauge the degree of segmentation in the Mexican labor market. As argued blow , the longitudinal structure allows the author to examine how wage changes when the worker moves between formal and informal employment. Contrary to our conclusion, the Mexican labor market seems to be more integrated, with workers transiting to informal salaried work experiencing a pay increase. Therefore, as pointed out in the paper, it is hard to access to what extense the wage premium in the informal sector compesates for the loss of benefits. This conclusion supports the view that the informal paid work may be a viable option for certain groups – namely young, less skilled workers – who want to escape taxes and regulations that plaque the formal sector. Pratap and Quintin (2006) conclude that the evidence cannot reject the hypothesis that the Argentinian labor market is integrated. Applying a semi-parametric methods to a panel of Argentinian households, the authors found the wage differential between formal and informal employmet to be not significantly different from zero. Like the Mexican case, one cannot assert whether the absence of a wage premium in the informal sector compensates the absence of benefits of formal sector employment (if any).[10]

3 Brief Overview of the Brazilian Labor Market

Among the salient features of the Brazilian labor market, the high number of unregistered workers is the one that deserves most attention. Approximately 30% of urban employees are unregistered, not including the unregistered self-employed. The stringent labor legislation and the several macroeconomic crisis that affected the country in the last twenty years, with alternating periods of recession and high inflation, are usually blamed for this widespread

[9] Barros *et al.* (1993) apply the same technique and reach similar consclusions.

[10] Ulyssea (2005) is a comprehensive review of the literature addressing the informal market and the measurement of the degree of segmentation in Brazil.

phenomenon.[11]

Since labor regulation is pervasive and leaves little room for direct negotiation between workers and firms, full compliance with the labor codes is expensive and cumbersome. A good indicator of the degree of segmentation is whether the worker has a 'signed' work booklet (*Carteira Nacional de Trabalho*), an identification card issued by the Ministry of Labor. The terms of the contract between the employee and the employer are supposed to be registered in this booklet, and by making the registry (signing the booklet), the employer automatically agrees to comply to at the clauses of a standard labor contract, as defined by the Brazilian Labor Code (*Consolidação das Leis do Trabalho*), written in 1943 and slightly modified since then.[12] Among other things, that statute dictates that the worker is entitled to several benefits, like a thirteenth wage to be paid sometime between November and December, a one-month paid vacation, severance payment for unjustified dismissal (which must be communicated to the worker a month in advance), work week of forty two hours, at least fifty percent premium per hour for overtime work, food and transport subsidy, and a four-month paid pregnancy leave of absence for women. Moreover, wages must be at least as high as the minimum wage. Contracts that do not satisfy all of these conditions are considered void, and workers can sue their current and former employers for non-compliance with the legislation.[13]

As we mentioned in the introduction, there are two types of inefficiencies imposed by this legislation. On the one hand, the combination of wages and benefits may not be the most efficient: workers and firms would have an incentive to negotiate another mix of wages and benefits, cheaper for firms to pay and utility-improving for workers. On the other hand, by imposing a minimum wage which can be binding for less productive workers, the legislation may be destroying jobs and creating inefficiency, as argued extensively in the literature about the impact of the minimum wage. If workers and firms can bargain and reach agreements in the shadow of the law, how can we have market segmentation? Labor disputes in Brazil are adjudicated by a special branch of the judiciary, and the burden of proof falls on the employer. If a certain worker can prove that the labor relationship ever existed – and the standard of proof is low, being sufficient to provide a eye-witness — the firm is supposed to prove that the requirements imposed by the legislation were fulfilled. Otherwise, the firm may be subject by a fine and payment of compensation to the worker. Therefore, violations

[11]Increased trade openness during the 90's may also have contributed to increased informally by increasing the relative importance of the services sector – where informal employment is more prevalent – relative to manufacturing.

[12]The Federal Constitution that went into effect in 1988 changed some aspects of the labor legislation, modifying, among other things, the regulation concerning the duration of the work week and severance payment for unjustified dismissal.

[13]A comprehensive description of the legislation in Brazil is provided in Amadeo *et al.* (2000)

of the labor law is the employers' responsibility, even if an informal agreement was reached in advance between the parts. Even though spontaneous detection by the authorities is rather unusual, this labor law branch of the judiciary has been very active, adjudicating about 985.560 cases in 2003 in the states analyzed in this paper. This possibility of suing the employer after the relationship has been severe may deter some firms and (potential) employers from resorting to informal arrangement. This possibility is explorer in more depth in a companion paper.

4 The Data

The *Pesquisa Mensal de Emprego* (PME), or Monthly Employment Survey, is a monthly rotating panel of dwellers in six major metropolitan areas in Brazil (São Paulo, Rio de Janeiro, Belo Horizonte, Salvador, Porto Alegre e Recife). Together these six metropolitan regions encompass approximately 30% of the population. We used data from 1995 to 2001[14] to avoid the high inflation period before the monetary stabilization plan in 1994 (*Plano Real*).[15] This dataset is compiled by the Brazilian national statistical agency – *Instituto Nacional de Geografia e Estatística (IBGE).*

The survey investigates schooling, labor force, demographic, and earnings characteristics of each member of the household age 10 and over, for every interviewed household. Approximately 100,000 individuals in 35,000 households are interviewed every month. Households are interviewed once per month for four consecutive months, then there is an eight-month window when they stand by; after this period, the household is interview for another four month period. For instance, suppose that the first interview was conducted in January. The second, third, and fourth interviews will take place in February, March and April of the same year, respectively. From May to December the household will rotate out of the sample. From January to March of the following year the household is interviewed again, and after this spell the household is permanently excluded from the sample. Since the main purpose of this survey is to measure the unemployment in the major metropolitan areas in the country, individuals are not directly identified, but only their households. Therefore, we match individuals within households over time using gender, month and year of birth. The main questions for the purpose of our study are earnings and the hours worked in the month of reference, the legal status (with or without signed work booklet), the sector of activity, and some variables such as age, gender and schooling.

[14] December/1995 to September/2001

[15] Since our identification strategy relies on intertemporal comparisons, it is also important to deflate the nominal variables. Even though, this is less of a problem after 1995 after the fall in the inflation rate, we deflate the data using the deflator proposed by Corseuil and Foguel (2002).

To avoid seasonality issues, we use observations exactly one year apart. Our benchmark regressions include only the first and the fifth interviews. Since we lose track of some individuals along the interview period, this strategy maximizes the number of usable observations. The problem of attrition is usually found in longitudinal surveys, and the PME is not an exception. It is challenging to follow individuals for sixteen months in the urban environment of a developing country where most of the people do not own their dwellings, and move-overs are frequent. This effect could bias our estimates if the individuals who stay in the sample longer have different responses to change in the formal-informal wage gap. For example, since the household – not the individual – is the sampling unit, every time an individual moves out from the original dwelling, he/she is excluded from the sample. Moreover, our matching method to track individuals may not be foolproof. That is, due to coding errors, we may be unable to track the individual over time if one of the variables used to match him/her varies across interviews. This second source of attrition is less harmful since it is more likely to be unrelated to the outcome of interest.[16] The first cause of attrition could be more problematic, since the decision to move out is less likely to be orthogonal to both sectoral choice and earnings. In order to check whether this source of attrition is relevant we also run the regressions including only the fourth and eight interviews. Since this sample is more susceptible to attrition, in the presence of sample selection bias, we would expect different result from the benchmark regressions. However, this is not the case, suggesting that attrition is not a source of bias.[17]

We consider only employees in the private sector, excluding self-employed workers. Even though the so-called self employed constitute a significant - and growing - fraction of the labor market, this category is extremely heterogenous, including individuals as distinct as street vendors and doctors. Furthermore, self-employed workers are supposed to satisfy different criteria and regulations to join the formal sector.[18] Also wages in the public sector are dictated byfactors other than market forces.

[16] The results reported here are based on a filter that considers V101, V102 and V103 (*IBGE* id codes), V202 (gender), V206 (day of birth), V236 (month of birth), and V246 (year of birth). Out of the 190,742 individuals who had a first interview, 117,282 were located sucessufully one year after, resulting in an attrition rate of 38.5%. Nevertheless we tried several different combinations of variables to match individuals across time, including day, month and year of birth, gender, schooling and position in the household. The results obtained with the various specifications do not significantly differ from each other. The results are available upon request.

[17] These results are available upon request

[18] Self-employed workers are required by law to pay income taxes and social security contribution. The other fringe benefits, as one might expected, are not mandatory.

5 Empirical Strategy and Identification

As we mentioned above, workers in the formal sector have a set of benefits, which are not available for informal workers. The theory of compensating benefits implies that the equilibrium monetary wage in the formal sector should be lower than in the informal one, holding all other factors equal. This difference would offset the lack of benefits in the informal sector. Given the workers' preferences for benefits (compared to direct payments) and the cost of providing them (from the firm's standpoint), there would be a combination of wages and benefits that would maximize the joint surplus of the match. If this does not coincide with the standards established by law, the parties should bargain about the wage and compensation package, and move to an agreement in the shadow of the law.

Using a panel structure, we directly control for the total individual fixed effect. We estimate the following equation

$$\log(w_{i,t}) = \alpha_0 + \theta\, b_{i,t} + \beta'\, X_{i,t} + e_{i,t} \tag{1}$$

where $X_{i,t}$ is a vector of covariates for individual i in t. The term $u_{i,t}$ can be further decomposed into

$$e_{i,t} = \mu_i + \epsilon_{i,t} \tag{2}$$

with μ_i being the individual fixed effect and $\epsilon_{i,t}$ is a random error term. Our identifying assumption is that $\epsilon_{i,t}$ is uncorrelated with $b_{i,t}$ and $X_{i,t}$. The panel structure allows us to control for unobservable individual characteristics which do not change over time. Therefore, our approach does not require assumptions about the distribution of $\epsilon i, t$, since we are directly conditioning in the individual fixed effect. This is another advantage of the panel data structured is relation to two-step estimators that use cross-section data and require a joint normal distribution of the errors in both stages.

The consistency of fixed-effect estimator hinges on the assumption that conditional on the covariates and any other fixed characteristic of the individuals, the selection process is uncorrelated with the earnings. Assume the following selection process:

$$b_{it} = 1_{(\gamma Z_{it} + u_{it} \geq 0)}, \tag{3}$$

where Z_{it} is a set of variables explaining sectoral choice.

A sufficient condition for our identification assumption to be valid is that

$$E(u_{it}\; e_{it}) = 0. \tag{4}$$

However, this condition is too strong, and a much weaker assumption is necessary for consistency in our case. Let

$$u_{it} = \alpha_i + \upsilon_{it}, \tag{5}$$

where α_i is a fixed effect that captures individual characteristics that influence the sectoral choice. Even in case α_i and μ_i are correlated, as long as υ_{it} and ϵ_{it} are not, $\hat{\theta}$ will be a consistent estimator of the degree of segmentation.

This strategy is consistent even if there are *unobservable* attributes which simultaneously determine sectoral choice and earnings as long as those characteristics are constant over time.[19] The previous works which use a cross-section structure cannot control for unobservable attributes, and consequently will obtain biased estimates when the observable characteristics jointly explain sectoral choice and earnings. Nevertheless, the fixed-effect estimator has a potential flaw. Whenever the relevant unobservable attributes changes over time and their variation is correlated with the earnings and sectoral choice variations, the fixed-effect estimator is inconsistent. For example, if workers anticipate their relative prospects in both sectors and make the sectoral choice decision based on those expectations (which are not observed), then the transition from one sector to the other is also endogenous.[20] It is worth noticing that the fixed-effect strategy does not require any restriction on the distributions of the stochastic components. This constitutes another clear advantage of the longitudinal structure over the two-step procedure with cross-sectional data to correct for self-selection.

In summary, the fixed effect estimator will build consistent estimates of the degree of segmentation even in the presence of potential selection bias when the source of bias is a correlation between formal/informal sector and unobserved factors which made differ across individuals but constant over time for each individual. If selection into the sector takes this form, the simple fixed-effect estimator is a straightforward way to deal with selection bias. More details and derivations are provided in the appendix.

6 Results

This section presents the main findings and briefly discusses each one of them. Since our main purpose is the measurement of the segmentation degree, the various specifications provide a test of robustness. Sometimes they uncover interesting patterns, which are worthy mentioning. Moreover, since we are controlling for fixed effects, only variables that change

[19]Indeed, we just need the variation of the unobservable attributes not to be jointly correlated with the earnings and sectoral choice variation.

[20]Ideally, we would like to observe the same individual's earnings, at the time,in both sectors. In this hypothetical situation, the mean wage differential would be a clear and immediate indicator of the degree of segmentation in this labor market. However this strategy is not feasible.

over time for the individuals can be included. All tables and graphs are included in the appendix 1.

Table 1 below presents some simple descriptive statistics. We based the calculation in the first interview of each individual in the sample. It can be easily seen that formal workers have a much higher hourly wage than their informal counterparts. By the same token, the two groups also differ in observable attributes, with formal workers being older (more experienced) and more educated, and working more hours. To what extent can these differences explain the difference in earnings? By adding controls in an OLS regression, one can trivially isolated the fraction of the variation in earning that is not explained by the observables. The residual can be hardly attributed to sectoral choice only, since it can be itself correlated with the covariates/controls. As pointed out in the literature review section, some authors a two-step procedure to correct this problem. Since non-observable attributes, like talent, motivation, and ability may be related to sectoral choice and earnings, that strategy may fail to obtain a consistent estimator of the degree of segmentation, whereas a fixed-effect effect estimator may, under certain conditions, account for both issues – self-selection and unobservable variables. Indeed, the random effects model can account for the individual effects if their are not correlated with the other regressors. Table 3 presents the results of a Hausman test, which rejects this hypothesis, concluding that the individual effects are indeed correlated with the regressors and rendering the random effect model inconsistent. Therefore, we adopt a fixed-effect model in the regressions below.

We also included age and squared age as controls in the regressions to capture the trend pattern with wages associated with experience. In the fixed-effect approach, the age coefficient indicates the average annual growth of wages of the entire sample, regardless sectoral choice. In the table 4, we can see that this is figure is around 9% for the period investigated. The squared age coefficient was included to capture a possible non-linear trend related to experience, and, indeed, the results confirm that. For every ten additional years of experience, the increase in wages diminishes 10%. Our first set of regressions breaks down the transitions into two types – from formal to informal employment, and vice-versa – and investigates the earnings gains or losses associated with the transition. For formal to informal job transitions, individuals that stay in their formal sector jobs are used as a reference group, to account for overall wage gains. For the other type of transition, informal sector stayers are used as controls. The results are presented in the first two columns of table 2 in the appendix (column 1 for formal to informal transitions). In both cases, there appears to be a wage premium of about 8.5% in the formal sector, no matter the direction of transition.

As mentioned in one of the previous sections, formal sector workers are entitled to receive an extra salary at the end of the year. To prevent our conclusions from being contaminated by the effect of this thirteenth salary, we run the regression with a d*dummy* indicating the months of December and January. As can be seen from column three in table 4, those two months display a slightly higher degree of segmentation than the other months, but the coefficient is not statistically significant at the usual level of confidence.

Is the segmentation higher among men or women? By looking at the column (4) of the table, one can see that the degree of segmentation is lower among women (7.5% compared to 9.5% for men). Broadly speaking, that when transiting from informal to formal employment, earnings increase 7.5% on average for women and 9.5% for men. At a first look, this result seems to be contradictory to the intuition that inflexible labor laws are the main cause of the segmentation in the Brazilian labor market, since women in the formal sector have a 4-month remunerated pregnancy license as an additional benefit. We wondered that this seemly odd result could have been driven by differences in the position women usually has within the family in Brazil. Most households with both a man and women have the man as head of the family and maybe the result of the gender coefficient might be capturing that characteristic. However, this does not seem to be the case. It can been seen in column (5), that the segmentation among heads is actually smaller than for other members of the household. Moreover, in column (6), we observe that the segmentation of a female head is even further smaller. We also checked if those results were capturing differences in the number of members in the household headed by a man or a woman by including a set of interaction terms of sectoral choice and dummies variables indications number of members in the family. The results were very similar to those presented in column 6 and are available upon request.

The last column of table 4 presents the degree of segmentation in the metropolitan regions where the survey is undertaken. The reference region in the Greater Recife, Pernambuco, which displays the highest level of segmentation. The metropolitan regions of Rio de Janeiro and Porto Alegre seem to be less segmented than the other areas.[21]

Has the degree of segmentation changed during the period of analysis? To investigate this issue we construct a variable which is the interaction between the work status and a *dummy* indicating in the year in which the *first* interview took place. By including this variable in the regression, we are allowing the wage differential to differ according to the year of the first interview. Table 5 reports the results in the first column. Since the base year is 1995, the individuals who had the first interview in that year and transited from the informal to the informal sector experience a gain of approximately 4.5%. For workers who made the transition between 1997 and 1998, this differential rises to 11.9%. 1997 and 2000

[21] One should keep in mind that we are not controlling for the industry distribution of the labor force, which is not evenly distributed among the regions and maybe s potential lurking variable behind this result.

present a higher level of segmentation compared to the base year. The following column of table 5 shows the wage differentials for different levels of schooling attainment. In a inverse U-shaped relationship, segmentation first rises with education the falls again.

Next, we turn to the degree of segmentation over the life-cycle. By adding the interaction between labor status and age we can analyze how the segmentation changes as the individual ages. The interaction between labor status and age squared captures non-linearities in the relationship. Is the transition to informality more painful for younger workers as compared to mature adults? Our result shows that segmentation is actually more painful for young workers, specially in case of a transition from formal to informal employment. One can conjecture that a policy to make the access of young workers to the labor market should contemplate the question of segmentation, its causes and consequences. To account for other types of non-linearity, we divide the workers in ten-year brackets (less than 20, 20-29, 30-39, 40-49, 50-59, and more than 59) according to the age in the first interview. Segmentation fall with age, reaching its lowest point at the 40's, and increasing slightly later on.

One interesting question is to what the degree of segmentation is uniform over the entire distribution of the real wages. By running four separate regression – one for each wage quartile[22] – we can have a better understanding of the pattern of segmentation in different intervals of the wage distribution. Results are displayed in table 8. Regression number 1 refers to the firs quartile, and so on. An interesting pattern emerges from this table. The segmentation is much larger for low-wage workers, and is significantly smaller in the top quartile. Those results should be taken with caution, since low-wage workers also tend to be younger and less educated. However, even after controling for age and the interaction between age, schooling and education (Table 9), the same pattern remains.

Finally, we control for wage differentials between industries to disentangle the industry effect from the formal-informal effect.[23] By including industry *dummies* in the regression we control for wage differentials between sectors. As pointed out in table 7, column 1, our estimate of the degree of segmentation does not change, suggesting that the formal-informal dichotomy is significant even for inter-sectoral transitions. The second column has a different interpretation. When we interact industry in the first interview with labor status, we are measuring to what extent formal/informal transitions within the same industry affect earnings. Manufacturing is the reference group, with a wage differential of 12%. Contrary to our initial belief, construction and services present a lower degree of segmentation (around 7%). The last industry, which groups activities not well defined, displays the highest level

[22]Indeed the individuals were ranked according to the average wage in the two observed periods

[23]Even though interindustry transition are not so usual, the wage differentials paid to workers in different industries may be very significant, jeopardizing our conclusions.

of segmentation – and wages.

7 Conclusion and Directions for further Research

In this paper we have measured the degree of segmentation in the Brazilian labor market using a geneuine panel of individuals, which allowed us to control for unobservable individual attributes that are constant over time. We find the average wage differential between formal and informal workers to be 8.5%, suggesting that the Brazilian labor market is indeed segmented. Moreover, we observe that some individual characteristics have different impacts on the level of segmentation. For instance, females, head of households, older, and more educated workers experience smaller (larger) wage losses (gains) when transfering from formal (informal) to informal (formal) employment. The segmentation seems to be more pervasive among young, low-educated men, who are not the main bread earners of their respective families. Also, the wage differential is much higher in the manufacturing industry and smaller in services[24]. To the best of our knowledge, the strategy used in this paper has never been applied to study this phenomenon in Brazil, and we claimed that our method requires weaker assumptions for consistency than the other approaches used so far to measure segmentation. Nevertheless, as explained in the empirical strategy section, our results rely on the assumption that the sectoral choice is not correlated with wages through the non-fixed part of the error terms. In order to relax that assumption, we developed a two-step estimation method, which estimates a random effect probit in the first method to construct correction terms for the second stage. The second stage still uses a fixed-effect approach and will deliver consistent estimator even in the presence of correlation between wage and sectoral choice through non-fixed elements of the error terms. Another big advantage of this approach is that it creates a very straightforward way to test if the simple fixed-effect model utilized in this paper is consistent, i.e., if the only source of endogeneity of sectoral choice comes from individual fixed characteristics. In the appendix 2, the estimator is derived.

[24] Different levels of labor union power may be behind this finding.

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Appendix 1 – Tables and Graphs

Table 1: Descriptive Statistics

Variable	**Count**		**Frequency**	
	Informal	**Formal**	**Informal**	**Formal**
sample size	52,584	138,158	0.276	0.724
male	29,024	84,645	0.255	0.745
female	23,560	53,513	0.306	0.694
	Mean		**Difference**	**Standard Error**
	Informal	**Formal**		
wage	1.777	2.599	0.822	0.011
hours worked	40.692	41.586	0.894	0.035
age	31.609	34.052	2.443	0.034
years of schooling	7.192	8.246	1.054	0.012

Table 2: Transitions between Sectors

	Informal		**Formal**	
	Count	**Frequency**	**Count**	**Frequency**
Informal	18,131	64.09%	10,160	35.91%
Formal	7,867	8.84%	81,124	91.16%
Total	25,998	22.17%	91,284	77.83%

Table 3: Hausman Test

	(b) A	(B)	(b-B) Difference	$(diag(V_b - V_B)^2$ S.E.
book	0.0866971	0.210483	-0.123786	0.0026646
age	0.093145	0.0933088	-0.0001638	0.0049418
age^2	-0.001124	-0.0010161	-0.0001079	0.000068

b = consistent under H_0 and H_a

B = inconsistent under Ha, efficient under H_0

Test: Ho: difference in coefficients not systematic.

$\chi^2_{(3)} = (b - B)'[(V_b - V_B)^{-1}](b - B) = 2225.79$

p-value=0.0000

Table 4: Direction of Transition, Gender, Position in the Household, and State

Variable	**Coefficient** (Std. Error)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
book	0.087	0.089	0.083	0.097	0.095	0.115	0.103
	(0.006)	(0.008)	(0.004)	(0.005)	(0.005)	(0.007)	(0.013)
age	0.075	0.133	0.093	0.093	0.093	0.092	0.093
	(0.006)	(0.011)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
age^2	-0.001	-0.002	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
intercept	-1.011	-2.048	-1.354	-1.339	-1.355	-1.335	-1.350
	(0.108)	(0.203)	(0.091)	(0.091)	(0.091)	(0.091)	(0.091)
Dec/Jan	–	–	0.019	–	–	–	–
			(0.011)				
$book \times head$	–	–	–	-0.023	–	-0.035	–
				(0.008)		(0.009)	
$book \times women$	–	–	–	–	-0.020	-0.032	–
					(0.008)	(0.009)	
$book \times BA$	–	–	–	–	–	–	-0.020
							(0.017)
$book \times MG$	–	–	–	–	–	–	-0.003
							(0.015)
$book \times RJ$	–	–	–	–	–	–	-0.033
							(0.016)
$book \times SP$	–	–	–	–	–	–	-0.009
							(0.015)
$book \times RS$	–	–	–	–	–	–	-0.040
							(0.016)
N	203,743	71,479	275,222	275,222	275,222	275,222	275,222

Table 5: Year Effect ans Schooling

Variable	**Coefficient** (Std. Error) (1)	(2)
book	0.046 (0.024)	0.022 (0.022)
age	0.093 (0.005)	0.093 (0.005)
age^2	-0.001 (0.000)	-0.001 (0.000)
intercept	-1.354 (0.091)	-1.346 (0.091)
$book \times 1996$	0.025 (0.025)	–
$book \times 1997$	0.073 (0.027)	–
$book \times 1998$	0.029 (0.025)	–
$book \times 1999$	0.044 (0.027)	–
$book \times 2000$	0.058 (0.025)	–
$book \times schooling1$	–	0.044 (0.025)
$book \times schooling2$	–	0.076 (0.023)
$book \times schooling3$	–	0.064 (0.023)
$book \times schooling4$	–	0.065 (0.025)
N	275,222	275,222

Table 6: Life Cycle (Age)

Variable	**Coefficient** (Std. Error)	
	(1)	(2)
book	0.182	0.121
	(0.034)	(0.012)
age	0.090	0.091
	(0.005)	(0.005)
age^2	-0.001	-0.001
	(0.000)	(0.000)
intercept	-1.298	-1.306
	(0.091)	(0.091)
$book \times age$	-0.003	–
	(0.002)	
$book \times age^2$	0.000	–
	(0.000)	
$book \times age2$	–	-0.010
		(0.014)
$bool \times age3$	–	-0.041
		(0.015)
$bool \times age4$	–	-0.053
		(0.015)
$book \times age5$	–	-0.118
		(0.019)
$book \times age6$	–	-0.092
		(0.032)
N	275222	275222

Table 7: Industry

Variable	**Coefficient** (Std. Error) (1)	(2)
book	0.086	0.120
	(0.004)	(0.009)
age	0.093	0.093
	(0.005)	(0.005)
age^2	-0.001	-0.001
	(0.000)	(0.000)
intercept	-1.328	-1.350
	(0.091)	(0.091)
construction	-0.029	–
	(0.010)	
commerce	-0.047	–
	(0.007)	
services	-0.032	–
	(0.006)	
other	-0.092	–
	(0.022)	
book × *construction*	–	-0.047
		(0.018)
book × *commerce*	–	-0.013
		(0.014)
book × *services*	–	-0.051
		(0.011)
book × *other*	–	0.214
		(0.045)
N	275,222	275,222

Table 8: Segmentation by Earning Quartiles

Variable	**Coefficient** (Std. Error)			
	(1)	(2)	(3)	(4)
book	0.145	0.082	0.072	0.017
	(0.007)	(0.007)	(0.009)	(0.009)
age	0.111	0.084	0.056	0.080
	(0.009)	(0.009)	(0.011)	(0.012)
age^2	-0.001	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)
intercept	-2.894	-1.618	-0.504	0.246
	(0.148)	(0.159)	(0.197)	(0.237)
N	69,061	66,567	62,460	77,131

Table 9: INSERT NAME HERE

Variable	**Coefficient** (Std. Error)				
	(1)	(2)	(3)	(4)	(5)
book	-0.045	0.037	-0.208	-0.372	0.128
	(0.081)	(0.097)	(0.132)	(0.205	(0.052)
$book \times gender$	-0.022	-0.028	-0.081	-0.019	-0.010
	(0.016)	(0.017)	(0.021)	(0.024)	(0.009)
$book \times head$	0.030	0.028	-0.039	0.011	-0.001
	(0.018)	(0.019)	(0.023)	(0.026)	(0.010)
$Ibook \times 1996$	0.005	0.135	0.049	0.056	0.052
	(0.045)	(0.051)	(0.060)	(0.066)	(0.027)
$book \times 1997$	0.066	0.146	0.080	0.153	0.095
	(0.048)	(0.053)	(0.062)	(0.069)	(0.029)
$book \times 1998$	0.002	0.156	0.072	0.042	0.059
	(0.045)	(0.051)	(0.059)	(0.066)	(0.027)
$book \times 1999$	-0.017	0.146	0.047	0.110	0.066
	(0.046)	(0.053)	(0.062)	(0.068)	(0.028)
$book \times 2000$	0.064	0.142	0.116	0.055	0.089
	(0.045)	(0.051)	(0.059)	(0.066)	(0.027)
$book \times BA$	-0.040	0.019	-0.011	-0.048	-0.020
	(0.023)	(0.035)	(0.048)	(0.051)	(0.017)
$book \times MG$	0.011	-0.026	0.012	0.049	-0.013
	(0.022)	(0.031)	(0.040)	(0.041)	(0.015)
$book \times RJ$	0.005	-0.010	0.020	-0.015	-0.031
	(0.026)	(0.031)	(0.040)	(0.043)	(0.016)
$book \times SP$	0.105	0.041	0.078	0.005	-0.018
	(0.032)	(0.031)	(0.038)	(0.039)	(0.015)
$book \times RS$	-0.006	-0.079	0.019	0.034	-0.050
	(0.027)	(0.031)	(0.041)	(0.043)	(0.016)
Dec/Jan	0.037	0.027	-0.005	0.052	0.026
	(0.021)	(0.022)	(0.026)	(0.027)	(0.012)

Table 10: INSERT NAME HERE

Variable	**Coefficient** (Std. Error)				
	(1)	(2)	(3)	(4)	(5)
$book \times age$	0.006	-0.005	0.014	0.006	-0.003
	(0.004)	(0.004)	(0.005)	(0.006)	(0.002)
$book \times age^2$	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$book \times schooling1$	0.087	0.099	-0.043	0.257	0.054
	(0.034)	(0.045)	(0.073)	(0.154)	(0.025)
$book \times schooling2$	0.092	0.062	-0.028	0.214	0.030
	(0.032)	(0.045)	(0.072)	(0.152)	(0.024)
$book \times schooling3$	0.094	0.109	0.015	0.253	0.019
	(0.035)	(0.046)	(0.073)	(0.151)	(0.024)
$book \times schooling4$	0.612	0.078	0.129	0.335	0.037
	(0.094)	(0.059)	(0.077)	(0.151)	(0.026)
$book \times construction$	-0.008	-0.068	-0.071	-0.146	-0.049
	(0.032)	(0.031)	(0.039)	(0.058)	(0.018)
$book \times commerce$	0.001	-0.055	-0.033	-0.007	-0.018
	(0.026)	(0.024)	(0.031)	(0.037)	(0.014)
$book \times services$	-0.018	-0.064	-0.031	-0.092	-0.043
	(0.021)	(0.020)	(0.023)	(0.025)	(0.011)
$book \times others$	0.208	0.136	0.233	0.010	0.207
	(0.056)	(0.097)	(0.128)	(0.174)	(0.045)
age	0.108	0.080	0.056	0.079	0.090
	(0.009)	(0.009)	(0.011)	(0.012)	(0.005)
$agesq$	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Intercept$	-2.857	-1.549	-0.490	0.247	-1.300
	(0.148)	(0.160)	(0.197)	(0.238)	(0.091)
N	69032	66596	62459	77132	275222

Appendix 2 – Model

As discussed in the text, suppose the following model:

$$w_{it} = \theta b_{it} + \beta' X_{it} + \mu_i + \epsilon_{it}$$
$$b_{it} = 1_{(\gamma' Z_{it} + \alpha_i + \upsilon_{it} \geq 0)}$$

Assume that X_{it} is a vector exogenous variables, and Z_{it} is predetermined. In this case

$$E\left(w_{it} \mid \mathbf{X}_i, \mathbf{Z}_i, \mathbf{b}_i\right) = \theta b_{it} + \beta' X_{it} + E\left(\mu_i \mid \mathbf{X}_i, \mathbf{Z}_i, \mathbf{b}_i\right) + E\left(\epsilon_{it} \mid \mathbf{X}_i, \mathbf{Z}_i, \mathbf{b}_i\right)$$

Taking the first difference to eliminate the fixed effect in the main regression, we obtain

$$E\left(\Delta w_i \mid \mathbf{X}_i, \mathbf{Z}_i, \mathbf{b}_i\right) = \theta\ \Delta b_i + \beta'\ \Delta X_i + E\left(\Delta \epsilon_i \mid \mathbf{X}_i, \mathbf{Z}_i, \mathbf{b}_i\right)$$

It is easy to see that the fixed effect estimator is consistent if

$$E\left(\Delta \epsilon_i \mid \mathbf{X}_i, \mathbf{Z}_i, \mathbf{b}_i\right) = 0$$

This would be true if ϵ_{it} and υ_{it} are uncorrelated. Otherwise, the fixed-effect estimator will not deliver an unbiased estimate of the degree of segmentation.

In order to deal with that potential source of bias, we propose a correction term to be added to the main regression such that the fixed effect will shielded from the potential selection bias. Define $\mathbf{u}_i = \alpha_i\ \iota + \upsilon_i$, where ι is the unitary column vector of appropriate dimension. To construct that estimator we need to impose the following structure to the model:

$$\begin{bmatrix} \eta_i \\ \mu_i \iota \\ \alpha_i \iota + \upsilon_i \end{bmatrix} \sim N\left(\begin{bmatrix} \mathbf{0} \\ \mathbf{0} \\ \mathbf{0} \end{bmatrix}, \begin{bmatrix} \sigma_\eta^2\ \mathbf{I} & \mathbf{0} & \rho_{\eta\upsilon}\ \sigma_\eta\ \sigma_\upsilon\ \mathbf{I} \\ \mathbf{0} & \sigma_\mu\ \mathbf{I} & \rho_{\mu\alpha}\ \sigma_\mu\ \sigma_\alpha\ \mathbf{I} \\ \rho_{\eta\upsilon}\ \sigma_\eta\ \sigma_\upsilon\ \mathbf{I} & \rho_{\mu\alpha}\ \sigma_\mu\ \sigma_\alpha\ \mathbf{I} & \sigma_\alpha^2\ \iota\ \iota' + \sigma_\upsilon^2\ \mathbf{I} \end{bmatrix} \right)$$

Under these assumptions, it is straightforward to show that

$$E\left(\epsilon_i \mid \mathbf{u}_i\right) = \rho_{\epsilon\upsilon}\ \sigma_\epsilon\ \sigma_\upsilon\ \mathbf{I}\ \left[\sigma_\alpha^2\ \iota\ \iota' + \sigma_\upsilon^2\ \mathbf{I}\right]^{-1} \mathbf{u}_i = \frac{\rho_{\epsilon\upsilon}\ \sigma_\epsilon\ \sigma_\upsilon}{\sigma_\upsilon^2\ \left(\sigma_\upsilon^2 + 2\ \sigma_\alpha^2\right)} \begin{bmatrix} \sigma_\upsilon^2 + \sigma_\alpha^2 & -\sigma_\alpha^2 \\ -\sigma_\alpha^2 & \sigma_\upsilon^2 + \sigma_\alpha^2 \end{bmatrix} \mathbf{u}_i$$
$$= \frac{\rho_{\epsilon\upsilon}\ \sigma_\epsilon\ \sigma_\upsilon}{\sigma_\upsilon^2} \left[\mathbf{I} - \frac{\sigma_\alpha^2}{\sigma_\upsilon^2 + 2\ \sigma_\alpha^2} \iota\iota'\right] \mathbf{u}_i$$

Each element of this vector has the form

$$E\left(\epsilon_{it} \mid \mathbf{u}_i\right) = \frac{\rho_{\epsilon\upsilon}\ \sigma_\epsilon\ \sigma_\upsilon}{\sigma_\upsilon^2}\left[u_{it} - \frac{2\ \sigma_\alpha^2}{\sigma_\upsilon^2 + 2\ \sigma_\alpha^2}\ \frac{\sum_{s=1}^2 u_{is}}{2}\right].$$

Now, conditioning on the appropriate interval, we obtain

$$E\left(\epsilon_{it} \mid \mathbf{b}_i, \mathbf{Z}_i\right) = \frac{\rho_{\epsilon\upsilon}\ \sigma_\epsilon\ \sigma_\upsilon}{\sigma_\upsilon^2}\left[E\left(u_{it} \mid \mathbf{b}_i\right) - \frac{2\ \sigma_\alpha^2}{\sigma_\upsilon^2 + 2\ \sigma_\alpha^2}\ \frac{\sum_{s=1}^2 E\left(u_{is} \mid \mathbf{b}_i\right)}{2}\right]$$

Finally, by taking first differences we have

$$\begin{aligned} E\left(\Delta\epsilon_i \mid \mathbf{b}_i, \mathbf{Z}_i\right) &= \frac{\rho_{\epsilon\upsilon}\ \sigma_\epsilon\ \sigma_\upsilon}{\sigma_\upsilon^2}\left[E\left(u_{i2} \mid \mathbf{b}_i, \mathbf{Z}_i\right) - E\left(u_{i1} \mid \mathbf{b}_i, \mathbf{Z}_i\right)\right] \\ &= \frac{\rho_{\epsilon\upsilon}\ \sigma_\epsilon\ \sigma_\upsilon}{\sigma_\upsilon^2}\left[E\left(\alpha_i + \upsilon_{i2} \mid \mathbf{b}_i, \mathbf{Z}_i\right) - E\left(\alpha_i + \upsilon_{i1} \mid \mathbf{b}_i, \mathbf{Z}_i\right)\right] \\ &= \frac{\rho_{\epsilon\upsilon}\ \sigma_\epsilon\ \sigma_\upsilon}{\sigma_\upsilon^2}\left[E\left(\upsilon_{i2} - \upsilon_{i1} \mid \mathbf{b}_i\right)\right] \end{aligned}$$

This difficulty of this procedure is to calculate $E\left(\upsilon_{it} \mid \mathbf{b}_i, \mathbf{Z}_i\right)$, since b_i is depend of α_i and the vector υ_i. Therefore, one would have to integrate a bivariate normal distribution over the range defined by b_i. However, to avoid this numericaly cumbersome procedure, we observe that

$$E\left(\upsilon_{it} \mid \mathbf{b}_i, \mathbf{Z}_i\right) = \int E\left(\upsilon_{it} \mid \mathbf{b}_i, \mathbf{Z}_i, \alpha_i\right) f\left(\alpha_i \mid \mathbf{b}_i, \mathbf{Z}_i\right) d\alpha_i.$$

It can be seen that

$$E\left(\upsilon_{it} \mid \mathbf{b}_i, \mathbf{Z}_i, \alpha_i\right) = E\left(\upsilon_{it} \mid b_{it}, Z_{it}, \alpha_i\right) = \frac{(2\ b_{it} - 1)\ \phi(\gamma' Z_{it} + \alpha_i)}{\Phi[(2\ b_{it} - 1)(\gamma' Z_{it} + \alpha_i)]},$$

and the Bayes rule implies

$$f\left(\alpha_i \mid \mathbf{b}_i, \mathbf{Z}_i\right) = \frac{f\left(\mathbf{b}_i \mid \mathbf{Z}_i, \alpha_i\right) f\left(\alpha_i \mid \mathbf{Z}_i\right)}{\int f\left(\mathbf{b}_i \mid \mathbf{Z}_i, \alpha_i'\right) f\left(\alpha_i' \mid \mathbf{Z}_i\right) d\alpha_i'}$$

One of the advantages of this procedure is to allow us to perform two one-dimensional instead of one two-dimensional numerical integrations.

Our method consists in estimating the model in two steps. First, we have to estimate γ and σ_{alpha} consistently. This is done by a random effect probit in the selection equation.

Notice that an important for the consistency of those estimators in the first step is

$$f\left(\alpha_i \mid \mathbf{Z}_i\right) = f\left(\alpha_i\right).$$

In words, it means that fixed effect in the selection equation (α_i) is orthogonal to the vector of instruments ($\mathbf{Z}_i$). Therefore,

$$\frac{f\left(\mathbf{b}_i \mid \mathbf{Z}_i, \alpha_i\right) f\left(\alpha_i\right)}{\int f\left(\mathbf{b}_i \mid \mathbf{Z}_i, \alpha_i'\right) f\left(\alpha_i'\right) d\alpha_i'} = \frac{\Phi[(2\ b_{it}-1)(\gamma' Z_{it}+\alpha_i)]\frac{1}{\sqrt{2\pi\sigma_\alpha^2}}\exp\left(-\frac{1}{2}\left(\frac{\alpha_i}{\sigma_\alpha}\right)^2\right)}{\int \Phi[(2\ b_{it}-1)(\gamma' Z_{it}+\alpha_i')]\frac{1}{\sqrt{2\pi\sigma_\alpha^2}}\exp\left(-\frac{1}{2}\left(\frac{\alpha_i'}{\sigma_\alpha}\right)^2\right) d\alpha_i'},$$

so the correction term is given by

$$E\left(\upsilon_{it} \mid \mathbf{b}_i, \mathbf{Z}_i\right) = \int \frac{(2\ b_{it}-1)\ \phi(\gamma' Z_{it}+\alpha_i)}{\Phi[(2\ b_{it}-1)(\gamma' Z_{it}+\alpha_i)]} \times \frac{\Phi[(2\ b_{it}-1)(\gamma' Z_{it}+\alpha_i)]\frac{1}{\sqrt{2\pi\sigma_\alpha^2}}\exp\left(-\frac{1}{2}\left(\frac{\alpha_i}{\sigma_\alpha}\right)^2\right)}{\int \Phi[(2\ b_{it}-1)(\gamma' Z_{it}+\alpha_i')]\frac{1}{\sqrt{2\pi\sigma_\alpha^2}}\exp\left(-\frac{1}{2}\left(\frac{\alpha_i'}{\sigma_\alpha}\right)^2\right) d\alpha_i'} d\alpha_i$$

In order to have a standard normal distribution of the fixed effect, we have to redefine the integration variable as

$$r_i = \frac{\alpha_i}{\sqrt{2\sigma_\alpha^2}} \rightarrow \alpha_i = s\ r_i$$

Finally, the correction term can be written as

$$\begin{aligned} E\left(\upsilon_{it} \mid \mathbf{b}_i, \mathbf{Z}_i\right) &= \int \frac{(2\ b_{it}-1)\ \phi(\gamma' Z_{it}+s\ r_i)}{\Phi[(2\ b_{it}-1)(\gamma' Z_{it}+s\ r_i)]} \times \frac{\Phi[(2\ b_{it}-1)(\gamma' Z_{it}+s\ r_i)]\exp\left(-r_i^2\right)}{\int \Phi[(2\ b_{it}-1)(\gamma' Z_{it}+s\ r_i')]\exp\left(-r_i'^2\right) dr_i'} dr_i \\ &\approx \sum_{r_i \in R} \frac{(2\ b_{it}-1)\ \phi(\gamma' Z_{it}+s\ r_i)}{\Phi[(2\ b_{it}-1)(\gamma' Z_{it}+s\ r_i)]} \times \frac{\Phi[(2\ b_{it}-1)(\gamma' Z_{it}+s\ r_i)]\exp\left(-r_i^2\right)}{\sum_{r_i' \in R} \Phi[(2\ b_{it}-1)(\gamma' Z_{it}+s\ r_i')]\exp\left(-r_i'^2\right)} \end{aligned}$$

The last term is a numerical approximation obtained by the Gauss-Hermite numeric integration method.