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The Structure of Worker Compensation in Brazil, With a Comparison to France and the United States*

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Abstract

We employ a comprehensive matched employer-employee data set for Brazil to analyze wage determinants and compare results to Abowd, Kramarz, Margolis and Troske (2001) for French and U.S. manufacturing. Returns to education and experience in Brazilian manufacturing exceed those of the other countries, while occupation differentials are similar. The gender differential in Brazilian and U.S. manufacturing coincides, and is considerably smaller than in France. Estimates are unaffected by selectivity of Brazilian workers into formal employment. The links between firm performance and wage components in Brazil resemble those of France. Worker characteristics have comparable explanatory power for manufacturing wage variability in the three countries but establishment-fixed effects explain relatively less of the Brazilian wage variation. Despite the inclusion of establishment effects, regressors predict at most sixty percent of wage variability in any Brazilian sector, suggesting that explanations for earnings variability ought to focus on worker characteristics, not establishment wage policies.

Keywords: Wage structure; wage inequality; matched employer-employee data; formal and informal employment; selectivity; Brazil

JEL Classification: J31, D21

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This paper examines the relationship between earnings, worker characteristics and firm performance in a developing country. We employ an extensive matched employer-employee data set for Brazil that is comparable to data sets for France and the U.S. as studied by Abowd, Kramarz, Margolis and Troske (2001). The data quality enables us to analyze compensation determinants, controlling for employer-fixed effects and detailed firm and worker characteristics. As far as we are aware, we report the first direct comparison of this kind between a developing country and industrialized countries.

Considerable recent progress has been made in exploiting matched panel data sets to assess important aspects of wage structure.[1] Due to data limitations, however, far less attention has been paid to developing countries. This has precluded the evaluation of wage determination theories beyond the context of industrialized economies. Moreover, many issues in labor market policy relate to the wage structure. This information has heretofore been largely restricted to a small set of countries and sectors.[2]

Beyond prior studies for developing countries, we estimate by sector composite establishment-level fixed effects for a complete cross section of formally employed workers and capture unobserved establishment-average worker characteristics along with unobserved establishment characteristics. We are particularly interested in contrasting the Brazilian wage structure with industrialized country benchmarks and adopt the statistical specification of Abowd et al. (2001) who compare matched employer-worker panels for manufacturing in France in 1992 and the U.S. in 1990. This allows us to evaluate the relationships between wages and observable worker characteristics, controlling for otherwise unmeasured effects.

We use Brazil's establishment-worker data set *Relação Anual de Informações Sociais*, or *RAIS*. This is an annual record of workers formally employed in any sector (agriculture, commerce, construction, manufacturing, utilities, services and public), with demographic information for individual workers, along with establishment identifiers. We restrict attention to São Paulo state, which is among the most developed of Brazilian states. More than half of Brazil's manufacturing value added originates in São Paulo state. We focus on four sectors and two years—manufacturing,

[1] Abowd, Kramarz and Margolis (1999) and Arai (2003) show for France and Sweden that substantial person-fixed and, to a lesser degree, employer-fixed effects account for wage dispersion. Postel-Vinay and Robin (2002) decompose wage variation across workers further by occupation and find that the portion of cross-sectional wage variance explained by person-fixed effects lies close to 40 percent for high-skilled white collar workers but quickly decreases to zero as the skill intensity of the job decreases.

[2] Matched employer-employee data sets exist for Algeria (Chennouf, Levy and Montmarquette 1997), Zimbabwe (Velenchik 1997), Guatemala (Funkhouser 1998), Peru (Schaffner 1998), Morocco and Tunisia (Nordman and Destre 2002), Slovenia (Haltiwanger and Vodopivec 2003), Colombia (as mentioned in Abowd, Haltiwanger and Lane 2004), Bulgaria (Dobbelaere 2004), and Mexico (Kaplan, Mártinez González and Robertson 2004). Using *RAIS* too, Mizala and Romaguera (1998) draw a random sample of 12,580 workers from 172 São Paulo state manufacturing firms in 1987.

services, commerce and agriculture in 1990 and 1997. These two years provide us with snap shots of the Brazilian labor market at the beginning and the end of a period of major economic reforms. For the manufacturing sector, we augment the establishment-worker data with matched firm-level information.

Our results show that Brazilian manufacturing worker compensation resembles the wage structure in French and U.S. manufacturing (Abowd et al. 2001) in many regards, with the notable exception of returns to human capital. We find manufacturing earnings to increase with occupational skill intensity in a very similar manner in all three countries. The overall gender wage gap is essentially the same in Brazilian and U.S. manufacturing, but wider in French manufacturing.

In all three countries, the predicted wages of manufacturing workers based on their observable characteristics play a dominant role in total compensation—accounting for around half of overall manufacturing wage inequality in Brazil in 1990 and 1997. Establishment-fixed effects, in contrast, have relatively less relevance in explaining Brazilian wages than they do in the other countries mostly because the variability of residual earnings, controlling for worker and establishment characteristics, is much greater in Brazilian manufacturing. We inspect whether selection of Brazilian workers into formal employment induces a detectable bias in the log wage component estimates for Brazil but, under the assumption of jointly normally distributed formality selection disturbances and log wage residuals, we find no such evidence.

As the traditional literature emphasizes for developing countries, returns to human capital, and to college education in particular, are considerably higher than in industrialized economies. A typical male manufacturing worker in Brazil with at least some college attendance receives wages that are 180 percent higher than a comparable worker with at least some high-school education. This premium stands at 70 percent in the U.S., and in France it is only 60 percent.

Using matched firm-worker data for Brazilian manufacturing, we show that the firm-average predicted worker characteristics and establishment-fixed components of wages each relate positively and significantly to firm size, capital intensity, occupational skill intensity, and worker productivity in Brazilian manufacturing. Both work force composition and unmeasured establishment-specific factors are important in explaining the higher wages paid by large, capital- and skill-intensive, and highly-productive firms. The relationship between wages and firm characteristics is similar for Brazil and France, while the U.S. differ in several respects.

Worker characteristics account for 45 percent of log wage variation in manufacturing but predict a considerably smaller portion of the variability in non-manufacturing sectors in 1997, ranging from 37 percent in services to 20 percent in agriculture. The establishment-fixed effect accounts for around a quarter of otherwise unexplained log wage inequality in manufacturing and services, but for close to half in agriculture. Even after controlling for establishment-fixed effects, however, regressors cannot predict more than sixty percent of wage variability in any sector. We conclude that explanations for Brazilian wage inequality therefore ought to focus on factors that operate through worker characteristics rather than through establishment compensation policies.

The paper proceeds as follows. We discuss our main data sources *RAIS* (for worker and establishment information) and *PIA* (for manufacturing firm information) in Section 1, along with a complementary but unmatched household survey. Section 2 describes the statistical models. Section 3 presents results on Brazil's manufacturing wage structure in 1990 and 1997, and compares findings to France in 1992 and the U.S. in 1990. Section 6 reports a re-estimation of Brazil's manufacturing wage structure controlling for formal-job selectivity, verifying the robustness of results. Connections between firm characteristics and wage components are developed in Section 5. For the year 1997, Section 6 offers a comparison between manufacturing and non-manufacturing sectors. Section 7 concludes.

1 Data

We use comprehensive individual worker data with information on earnings, demographic characteristics and occupations, along with establishment ID codes for the place of work. From a separate source we obtain data on manufacturing firms that describe numerous firm-level characteristics. Establishment ID codes from the worker data set make it possible to match the worker and firm observations. To verify that our results are not affected by worker selectivity into formal employment, we obtain out-of-sample predictions of employment status from a separate household survey.

Worker data. Our individual worker data derive from the labor force census *RAIS* (*Relação Anual de Informações Sociais* of the Brazilian labor ministry *MTE*), which is a mandatory comprehensive annual record of workers formally employed in any sector (agriculture, commerce, construction, manufacturing, utilities, services and public). We restrict attention to workers employed in São Paulo state in four private sectors (agriculture, commerce, manufacturing and services) for the years 1990 and 1997. The samples consist of a total of 5.89 million workers in 1990 and 6.37 million in 1997.

RAIS reports compensation as the monthly average wage, expressed in multiples of the current minimum wage. We use the log of annual wages as our earnings measure, defined as the reported monthly wage times the December U.S. dollar equivalent of the current minimum wage times 12. See Appendix A.1 for further details concerning the compensation measure.

In the available version of *RAIS*, workers' ages are reported in terms of eight age ranges. We exclude workers in the two highest ranges (50 years and older) to avoid potential confounding effects stemming from workers who leave the labor force prior to the official retirement age. The remaining six age ranges are joined with the nine reported education categories to obtain a proxy for potential labor force

Table 1: Mean Log Wages and Employment Shares

	Mean Log Wage				Employment Shares			
	Manuf	Servcs	Comm	Agric	Manuf	Servcs	Comm	Agric
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Sector				
Year:								
1990	8.016	7.953	7.461	7.352	.398	.433	.151	.018
1997	8.872	8.797	8.406	8.056	.288	.500	.171	.041
				Education				
1990:								
Some college or more	9.014	8.589	8.261	8.146	.093	.217	.070	.027
High school or less	7.913	7.776	7.400	7.330	.907	.783	.930	.973
1997:								
Some college or more	9.891	9.462	9.202	9.128	.103	.225	.069	.022
High school or less	8.754	8.604	8.347	8.032	.897	.775	.931	.978
				Occupation				
1990:								
White collar	8.469	8.124	7.503	7.718	.292	.660	.679	.131
Blue collar	7.829	7.620	7.372	7.297	.708	.340	.321	.869
1997:								
White collar	9.288	8.923	8.420	8.727	.293	.720	.685	.092
Blue collar	8.699	8.475	8.377	7.988	.707	.280	.315	.908
				Gender				
1990:								
Male	8.174	8.040	7.549	7.421	.728	.558	.648	.802
Female	7.593	7.842	7.299	7.073	.272	.442	.352	.198
1997:								
Male	8.987	8.881	8.469	8.094	.744	.520	.625	.844
Female	8.536	8.706	8.301	7.854	.256	.480	.375	.156

Source: *RAIS* São Paulo state 1990 and 1997 (prime age workers in their highest-paying job). Wages in current USD (1990 and 1997 exchange rates). The log U.S. CPI change between 1990 and 1997 is .187.

experience. For example, a typical Early Career worker (34.5 years of age) who is also a Middle School Dropout (left school at 11 years of age) is assigned 23.5 years of potential labor force experience. Our education variable regroups the nine education categories included in *RAIS* to correspond to the categories considered by Abowd et al. (2001).[3] Appendix A.1 provides further details on the construction of our education and experience variables.

[3]The correspondence is imprecise in only one respect: the French and U.S. data allow Abowd et al. (2001) to distinguish between undergraduate and graduate degree attainment, while the *RAIS* combines these two categories. Our education indicator variables therefore distinguish four levels of schooling. "College Graduate" corresponds to the "Completed College" and "Completed Post-Graduate Degree" levels in Abowd et al. (2001).

Occupational classifications in *RAIS* follow the *CBO* (*Classificação Brasileira de Ocupações*). To make this system comparable to standard international classifications, we mapped the *CBO* for 1994 to the commonly-used *ISCO-88* (*International Standard Classification of Occupations*, Muendler, Poole, Ramey and Wajnberg (2004)). The *ISCO-88* reclassifications are in turn mapped into five broad occupational categories (professional and managerial, technical and supervisory, other white collar, skill-intensive blue collar, and other blue collar). These correspond to the categories that Abowd et al. (2001) use.[4]

RAIS also indicates the firm tax number and establishment ID number for the establishment employing each worker in the sample. This makes it possible to control for unobservable worker and establishment effects in explaining the wage structure.

Table 1 indicates the sectoral employment shares within the samples for each year. Agriculture represents less than five percent of the totals in both years, while manufacturing and services each account for about 40 percent of sample in 1990. For manufacturing, this falls to less than 30 percent in 1997, while rising to 50 percent for services. These shifts indicate a substantial reallocation of formal employment in São Paulo state away from manufacturing and toward services.

Table 1 also reports mean annual wages for selected demographic groups by sector and year, along with employment shares within sector. On average, manufacturing provides the highest level of earnings for males, and services provides the highest level for females. Males earn a wage premium in all sectors and years. The male wage premium in manufacturing declines sharply between 1990 and 1997, while it declines more modestly in the other sectors. Table 1 also indicates that workers with some college education earn a substantial premium in all sectors and years. The same holds true for workers in white collar occupations (professional and managerial, technical and supervisory, and other white collar), except for commerce in 1997 where wages across the two occupation groupings are nearly equal. Males make up the bulk of workers in agriculture and manufacturing, while females account for a substantial and growing proportion of employment in commerce and services. Outside of services, the vast majority of workers have no college education. Blue collar occupations predominate in agriculture and manufacturing, and white collar occupations comprise most of employment in commerce and services.

Firm data. For the firm-level data, we use the manufacturing survey *PIA* (*Pesquisa Industrial Anual* from *IBGE*, the Brazilian census bureau) for 1990 and 1997. The data are a random sample of all but the smallest manufacturing firms in São Paulo state, where more than half of value added in Brazilian manufacturing originates.

[4]Brazil's *CBO-94* generally provides classifications at a finer level of detail than does *ISCO-88*. The level of detail in the Brazilian system permits the reclassifications needed for transforming the more profession-based Brazilian classifications into the more skill-based international classifications. For a small number of 1990 observations, *RAIS* includes *CBO* codes that are not used in *CBO-94*. We set these to "Miscellaneous" within the relevant subcategory.

PIA includes a wide range of input, output and performance measures.

IBGE's publication rules allow data from *PIA* to be withdrawn in the form of tabulations of cells having at least three firms. We construct cells using three-firm random combinations drawn from within each *Nível 50* sector, calendar year and location (metropolitan São Paulo city or rural). The *Nível 50* sectors consist of 31 manufacturing sectors, corresponding roughly to the two-digit *SIC* sectors in the U.S. A single four- or five-firm cell is defined within a sector when the number of firms in the sector is not divisible by three. For each three-to-five-firm cell, we calculate the number of firms as well as the sum, mean, and standard deviation of the relevant *PIA* variables. While the observations are aggregated, we retain the firm identifiers behind each newly-created composite observation, permitting the matching of *RAIS* workers to the composite observations. This procedure yields samples of 1,169 and 679 matched cells for 1990 and 1997, respectively.

Complete lists of *RAIS* and *PIA* variables used in the paper are given in Appendix B.

Complementary household survey data. The widely used Brazilian household survey *PNAD* (*Pesquisa Nacional por Amostra de Domicílios*) provides separate and complementary information on informal and formal employment. We relegate a discussion of *PNAD* variable definitions, and a brief comparison with *RAIS*, to Appendix A.

2 Statistical Models

Individual wages. The availability of establishment information in our worker data set allows us to include an establishment variable in our wage regressions. Following Abowd et al. (2001), we model individual compensation in a given year as

$$\ln w_i = x_i\beta + \psi_{J(i)} + \varepsilon_i, \tag{1}$$

where w_i is annual wages, x_i is a vector of observable worker characteristics including gender, experience, education and occupation, β is a vector of parameters to be estimated, $\psi_{J(i)}$ is an establishment effect, $j = J(i)$ is the establishment that employs worker i, and ε_i is an error term. The establishment effect combines a pure establishment effect with the establishment average of pure worker effects:

$$\psi_j = \phi_j + \overline{\alpha}_j, \tag{2}$$

where ϕ_j is the pure establishment effect and $\overline{\alpha}_j$ is the average of pure worker effects α_i over workers employed at establishment j. The establishment effect controls for unobservable worker and establishment characteristics. Abowd and Kramarz (1999) show that omitting this effect will in general lead to bias in the estimation of β.

Selectivity. A large proportion of Brazilian employment is informal and not covered by *RAIS*. To capture potential bias from formal work status selectivity in the individual compensation model (1), we assess work status selection based on worker characteristics x_i.

Consider the probit prediction of formal employment

$$\Pr(\mathcal{I}_i|x_i) = \Phi(x_i\theta), \tag{3}$$

where θ is a vector of parameters to be estimated and $\Phi(\cdot)$ denotes the cumulative standard normal distribution function. Equivalently, formal employment $\mathcal{I}_i = 1$ is observed iff $x_i\theta + \eta_i > 0$ for a standard normal error term η_i. Applying this to the individual compensation model (1) yields

$$\begin{aligned} \mathbb{E}\left[\ln w_i \,|x_i\theta{+}\eta_i > 0\right] &= x_i\beta + \psi_{J(i)} + \mathbb{E}\left[\varepsilon_i \,|x_i\theta{>}{-}\eta_i\right] \\ &= x_i\beta + \psi_{J(i)} + \rho_{\varepsilon\eta}\sigma_\varepsilon \cdot \Lambda_i, \end{aligned}$$

by the properties of a truncated joint normal density, where $\rho_{\varepsilon\eta}\sigma_\varepsilon$ is the covariance between ε_i and η_i ($\sigma_\eta = 1$ by a common probit assumption) and $\Lambda_i \equiv \phi(-x_i\theta/\sigma_\eta)/[1-\Phi(-x_i\theta/\sigma_\eta)]$ is the inverse of Mills' ratio. $\phi(\cdot)$ denotes the standard normal density. The set of regressors x_i in (1) and (3) coincides unless there are individual worker variables that predict formality but do not correlate with compensation. We have no evidence for the existence of such instruments. Instead, we rely on the assumption that error terms are jointly normally distributed to inspect the potential presence of selectivity in the individual compensation model (1).

Since *RAIS* covers formal workers only, we use comparable variables x_i from household data (*PNAD*) to predict formal work status. In the spirit of Heckman's (1979) two-stage procedure, we obtain $\hat{\theta}$ from a probit regression (3) on household data. Using *RAIS* data, we include the out-of-sample prediction of the inverse of Mills' ratio $\hat{\Lambda}_i$ as a regressor in the individual compensation model (1) to estimate

$$\ln w_i = x_i\beta + \psi_{J(i)} + \hat{\Lambda}_i\delta + \varepsilon_i, \tag{4}$$

where $\delta = \rho_{\varepsilon\eta}\sigma_\varepsilon$.

Firm characteristics. For the firm-level analysis, the predicted wage component due to worker characteristics, $x_i\widehat{\beta}$, as well as the predicted establishment-fixed component, $\widehat{\psi}_j$, are matched to firms and aggregated to firm-level averages $\overline{\widehat{\psi}}_k$ and $\overline{x}_k\widehat{\beta}$. We then relate these firm-level components of individual compensation to firm-level variables q_k according to

$$q_k = \overline{\widehat{\psi}}_k\gamma_1 + (\overline{x}_k\widehat{\beta})\gamma_2 + \omega_{S(k)} + \nu_k, \tag{5}$$

where γ_1 and γ_2 are parameters to be estimated, ω_s is a sector effect, $s = S(k)$ is the *Nível 50* manufacturing sector in which firm k operates, and ν_k is an error term.

3 Individual Wage Structure in Manufacturing

Our specification of the individual compensation model (1) uses potential worker experience and indicator variables for gender, education and occupation as measures of individual characteristics. Quadratic, cubic and quartic terms for potential experience are included. Gender is interacted with all other variables. Table 2 presents results for the manufacturing sector in 1990 and 1997. Comparable estimates for manufacturing workers in France in 1992 and the U.S. in 1990, drawn from Abowd et al. (2001), are also reported.[5]

Wages and worker characteristics in Brazil. To facilitate the interpretation of earnings components, Table 3 summarizes the wage differentials for education, occupation and gender implied by Table 2 estimates. As regards education, Brazilian manufacturing workers with some college education earn almost twice as much on average as high school graduates, and college graduates earn two-and-a-half times as much. The profiles of education differentials for men and women display striking similarity, and change little between 1990 and 1997.[6]

With respect to occupations, relative wages in Brazil rise for both men and women as occupations increase in skill intensity. Professional and managerial workers, for example, earn over twice as much as non-skill-intensive blue collar workers. The profile is steeper for men. Male skill-intensive blue collar workers earn a premium of nearly 30 percent relative to their non-skill-intensive blue collar counterparts, while among women the wages of all blue collar workers are roughly similar. Differences in the occupational returns between 1990 and 1997 are very small.

Figure 1 displays average wages by years of experience for male and female workers, as derived from the Table 2 estimates. For both sexes, wages in Brazilian manufacturing rise with experience throughout the range of years considered, with returns to experience being much higher for males but relatively less steep in 1997 than in 1990.

Comparison with France and the U.S. Our wage structure estimates for Brazil can be directly contrasted with the findings of Abowd et al. (2001) for France and the U.S., given the comparability of our variable definitions and econometric specification. Figure 1 and Table 3 report the estimated experience-wage profiles and education, occupation and gender differentials for all three countries. For men, the experience

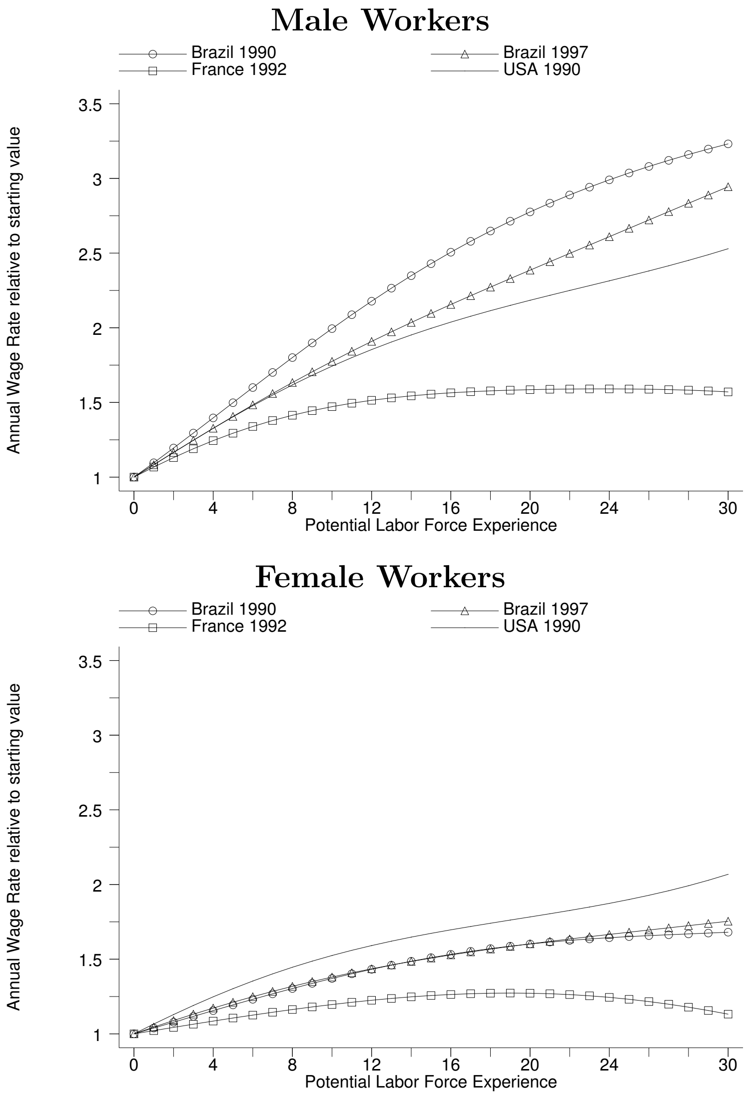
[5] Data for France derive from the *Enquête sur la Structure des Salaires* (*ESS*), which samples responses to an annual administrative census of business enterprises. Data for the U.S. derive from the *Worker-Establishment Characteristic Database* (*WECD*), which matches individual census responses to manufacturing establishments surveyed in the *Longitudinal Research Database* (*LRD*). See Abowd et al. (2001) for further details.

[6] Arbache (2001) stresses the stable Brazilian wage structure in micro data despite a series of policy reforms. We confirm stability of manufacturing wages between 1990 and 1997 for returns to education and for occupation premia (but not for returns to experience).

Table 2: Manufacturing Wages in Brazil, France and the U.S.

	Brazil 1990	Brazil 1997	France 1992	U.S. 1990
	(1)	(2)	(3)	(4)
Primary School Education (or less)	-1.075	-1.000	-.338	-.526
	(.002)	(.002)	(.009)	(.008)
Some High School Education	-.923	-.881	-.256	-.404
	(.002)	(.002)	(.009)	(.007)
Some College Education	-.339	-.316	-.200	-.334
	(.003)	(.003)	(.009)	(.007)
College Graduate			-.064	-.123
			(.016)	(.007)
Professional or Managerial Occupation	.856	.912	.760	.359
	(.002)	(.002)	(.009)	(.004)
Technical or Supervisory Occupation	.600	.632	.401	.206
	(.002)	(.002)	(.007)	(.004)
Other White Collar Occupation	.262	.249	.169	-.039
	(.002)	(.002)	(.011)	(.005)
Skill Intensive Blue Collar Occupation	.239	.225	.155	.083
	(.001)	(.001)	(.007)	(.003)
Potential Labor Force Experience	.095	.082	.069	.083
	(.0005)	(.0007)	(.003)	(.002)
Quadratic Experience Term	-.003	-.003	-.004	-.003
	(.00005)	(.00007)	(.0002)	(.0001)
Cubic Experience Term	.00005	.00008	.0001	.00007
	(2.29e-06)	(2.86e-06)	(1.00e-05)	
Quartic Experience Term	-3.01e-07	-7.64e-07	-1.20e-06	-4.70e-07
	(3.24e-08)	(3.89e-08)	(1.00e-07)	(3.00e-08)
Female	.060	.070	.052	-.078
	(.005)	(.006)	(.024)	(.019)
Female × Primary School Education (or less)	.106	.051	*-.0006*	.041
	(.004)	(.004)	(.021)	(.016)
Female × Some High School Education	-.016	-.058	*-.016*	*-.009*
	(.004)	(.004)	(.021)	(.015)
Female × Some College Education	.018	*-.005*	*.025*	*-.019*
	(.005)	(.005)	(.021)	(.015)
Female × College Graduate			-.062	*-.022*
			(.029)	(.015)
Female × Professional or Managerial Occupation	-.101	-.058	-.049	-.086
	(.004)	(.005)	(.016)	(.007)
Female × Technical or Supervisory Occupation	-.173	-.250	*-.006*	.037
	(.003)	(.004)	(.011)	(.008)
Female × Other White Collar Occupation	.088	.071	.033	.046
	(.003)	(.003)	(.013)	(.006)
Female × Skill Intensive Blue Collar Occupation	-.208	-.167	-.045	-.043
	(.002)	(.003)	(.010)	(.008)
Female × Potential Labor Force Experience	-.056	-.036	-.047	-.016
	(.0008)	(.001)	(.004)	(.003)
Female × Quadratic Experience Term	.002	.002	.004	*.0003*
	(.0001)	(.0001)	(.0003)	(.0002)
Female × Cubic Experience Term	-.00006	-.00005	-.0001	.00000
	(4.35e-06)	(5.63e-06)	(1.00e-05)	
Female × Quartic Experience Term	7.06e-07	5.40e-07	1.20e-06	*1.80e-08*
	(6.32e-08)	(7.78e-08)	(1.10e-07)	(4.00e-08)
R^2 (within)	.508	.468	.817	.617
Residual degrees of freedom	2,326,428	1,828,049	23,920	148,992

Sources: *RAIS* São Paulo state manufacturing 1990 and 1997 (prime age workers in their highest-paying job), Abowd et al. (2001) for France and the U.S., controlling for establishment fixed effects. Estimates for Brazil relative to college graduates, for France and the U.S. relative to workers with post-graduate degree. Standard errors in parentheses (insignificant point estimates at the five percent level in *italics*).



Sources: *RAIS* São Paulo state manufacturing 1990 and 1997 (prime age workers in their highest-paying job), Abowd et al. (2001) for France 1992 and the U.S. 1990. Wage levels relative to zero experience wage levels from wage component estimates (Table 2). Calculations for France 1992 and the U.S. 1990 based on Abowd et al.'s (2001) estimates and summary statistics.

Figure 1: **Potential experience profiles in Brazil, France and the U.S.**

Table 3: Relative Manufacturing Wages in Brazil, France and the U.S.

	Brazil 1990	Brazil 1997	France 1992	U.S. 1990
	(1)	(2)	(3)	(4)
		Education[a]		
Male worker:				
College Degree	2.516	2.412	1.376	1.693
Some College	1.793	1.758	1.057	1.073
Primary School (or less)	.859	.888	.920	.885
Female worker:				
College Degree	2.556	2.556	1.488	1.746
Some College	1.855	1.854	1.101	1.062
Primary School (or less)	.970	.990	.935	.930
		Occupation[b]		
Male worker:				
Professional or Managerial	2.355	2.488	2.139	1.432
Technical or Supervisory	1.821	1.882	1.493	1.228
Other White Collar	1.299	1.283	1.184	.962
Skill-intensive Blue Collar	1.270	1.252	1.168	1.087
Female worker:				
Professional or Managerial	2.128	2.348	2.037	1.313
Technical or Supervisory	1.532	1.466	1.484	1.275
Other White Collar	1.419	1.377	1.224	1.006
Skill-intensive Blue Collar	1.031	1.059	1.116	1.041
		Gender[c]		
Female worker	.893	.915	.803	.899

[a]Relative to worker with some or complete high school education, controlling for occupation.
[b]Relative to non-skill-intensive blue collar occupations, controlling for education.
[c]Female relative to male workers, controlling for education and occupation.

Sources: *RAIS* São Paulo state manufacturing 1990 and 1997 (prime age workers in their highest-paying job), Abowd et al. (2001) for France 1992 and the U.S. 1990. Wage levels relative to comparison-group wage levels from component estimates (Table 2). For France and the U.S., wage prediction of college graduates reassigned to predicted fixed effects component.

profile is steeper in Brazil than in the U.S., and much steeper than in France. A similar pattern holds with respect to education premia, where the returns to college for Brazilian men are dramatically higher than for either French or American men. In general, measured returns to human capital acquisition by men are highest in Brazil and lowest in France.

Women present a different picture. As Figure 1 shows, the experience profile for Brazilian women is much flatter than for men. Returns to experience for women in Brazil are below those in the U.S., while still being above those in France. Thus, while women earn lower compensation for experience relative to men in all three countries, the gap is far larger in Brazil. Similar to France and the U.S., women receive higher college premia in Brazil than men. Excepting the relatively small earnings increase from primary school to high school education for women in manufacturing, women realize higher returns to human capital acquisition relative to men in all three countries.

The results also reveal a striking similarity between occupation differentials in Brazil and France for both sexes. For Brazil, the male occupation profile by skill is slightly steeper than for France, while the female occupation profiles in Brazil and France are very similar in 1990 and close in 1997. U.S. occupation premia are much lower and exhibit a larger wage premium for skill-intensive blue-collar occupations than for other (non-skill-intensive) white collar occupations.

While Brazil's earnings pattern resembles that of France more closely in experience, education and occupation premia than that of the U.S., the gender gap in wages is less pronounced in Brazil than in France and closer to U.S. manufacturing. The overall Brazilian female/male wage ratio of around 90 percent lies very near the U.S. figure and markedly above the level of 80 percent in France.

Components of individual wages. We next assess the overall explanatory power of the estimated worker characteristics and establishment-fixed components of individual wages, given by $x_i\widehat{\beta}$ and $\widehat{\psi}_j$, respectively. The worker characteristics component represents the predicted wages of a worker with observed characteristics x_i, before conditioning on his or her work place. As discussed above, the establishment-fixed component captures both establishment-average pure worker effects and pure establishment effects, so it gives predicted wages based on the establishment mean of unobserved worker characteristics together with unobserved establishment characteristics. To ensure comparability with Abowd et al. (2001), we exclude education variables and compute wage components from a re-estimated model.[7]

Table 4 assesses the importance of the two components in explaining wages. Column (1) of the table reports the means of log wages and the two wage components for the three countries expressed in 1990 U.S. dollars, and for Brazil in 1997 expressed in 1997 U.S. dollars. Standard deviations are given in column (2), and the remaining columns indicate simple correlations between log wages, the wage components and the regression residuals. For France and the U.S., we report the results from Abowd et al. (2001) that use the specifications excluding education.

In all three countries, the predicted wages of workers based on their observable characteristics play an important role in determining total compensation, as indicated by the high correlations between wages and the worker characteristics components. Worker characteristics have the highest correlation with wages in France (.79), and the lowest in the U.S. (.60), with Brazil's correlation becoming closer to the U.S. 1990 correlation (from .67 in 1990 to .62 in 1997). The establishment-fixed compo-

[7]The samples for France in 1990 and the U.S. used by Abowd et al. (2001) distinguish college and post graduate education, while our Brazilian data combine all college graduates into a single category. So we cannot directly compare estimated individual characteristics components across the samples unless education is excluded, a regression model that Abowd et al. (2001) also estimate.

Table 4: Variability of Manufacturing Wages in Brazil, France and the U.S.

	Mean	St.Dev.	Correlation with			
			$\ln w_i$	$x_i\widehat{\beta}$	$\widehat{\psi}_j$	$\widehat{\varepsilon}_i$
	(1)	(2)	(3)	(4)	(5)	(6)
Brazil 1990						
Log Annual Wage ($\ln w_i$)	8.019	.785	1.000			
Worker Characteristics ($x_i\widehat{\beta}$)	.962	.491	.667	1.000		
Establishment-Fixed ($\widehat{\psi}_j$)	7.056	.203	.358	.160	1.000	
Residual ($\widehat{\varepsilon}_i$)	.000	.550	.700	.000	-.000	1.000
Brazil 1997						
Log Annual Wage ($\ln w_i$)	8.872	.778	1.000			
Worker Characteristics ($x_i\widehat{\beta}$)	.878	.441	.622	1.000		
Establishment-Fixed ($\widehat{\psi}_j$)	7.994	.267	.435	.161	1.000	
Residual ($\widehat{\varepsilon}_i$)	-.000	.549	.705	-.000	-.000	1.000
France 1992[a]						
Log Annual Wage ($\ln w_i$)	10.158	.414	1.000			
Worker Characteristics ($x_i\widehat{\beta}$)	.637	.287	.791	1.000		
Establishment-Fixed ($\widehat{\psi}_j$)	9.521	.172	.581	.237	1.000	
Residual ($\widehat{\varepsilon}_i$)	.000	.190	.457	-.003	.000	1.000
U.S. 1990						
Log Annual Wage ($\ln w_i$)	10.174	.544	1.000			
Worker Characteristics ($x_i\widehat{\beta}$)	.672	.271	.598	1.000		
Establishment-Fixed ($\widehat{\psi}_j$)	9.502	.266	.610	.242	1.000	
Residual ($\widehat{\varepsilon}_i$)	.000	.350	.627	-.029	.000	1.000

[a]Means converted to USD (December 31st, 1990).

Sources: *RAIS* São Paulo state manufacturing 1990 and 1997 (prime age workers in their highest-paying job), Abowd et al. (2001) for France 1992 and the U.S. 1990. Estimates for all three countries from establishment-fixed effects wage regressions relative to other blue-collar occupations, *not* controlling for education to achieve comparability (not reported). Statistics based on estimation sample. The log U.S. CPI change between 1990 and 1997 is .187.

nent, in contrast, contributes relatively less to explaining compensation in Brazil, as its correlation with wages is only two-thirds of the French and U.S. levels. Moreover, the establishment-fixed component for Brazil exhibits much lower variability relative to overall wage variability (.20/.79 in 1990 and .27/.78 in 1997, compared to .17/.41 in France and .27/.54 in the U.S.). Similarly, the establishment-fixed component's correlation with worker characteristics is much lower in Brazil. Unmeasured characteristics at the establishment level appear to explain substantially less of the variation in log wages in Brazil relative to France and the U.S. This is consistent with the general finding that worker effects dominate firm effects in explaining wages.[8]

Finally, the two wage components considered jointly have lower explanatory power

[8]Abowd and Kramarz (1999) provide a review of the numerous studies establishing the relative importance of worker effects.

Table 5: COMPONENTS OF MANUFACTURING LOG WAGE INEQUALITY

	1990		1997	
	FE[a]	OLS[b]	FE[a]	OLS[b]
	(1)	(2)	(3)	(4)
Worker Characteristics ($x_i\widehat{\beta}$)	.501	.529	.445	.484
Experience	.158	.170	.110	.121
Occupation	.137	.139	.139	.141
Education	.134	.140	.145	.161
Gender	.072	.080	.051	.061
Establishment-Fixed Effect ($\widehat{\psi}_j$)[c]	.081		.131	
Residual ($\widehat{\varepsilon}_i$)	.418	.471	.424	.516

[a]Component estimates from log wage regressions in Table 2, columns 1 and 2.

[b]Component estimates from log wage estimates of model (1), but omitting the fixed effect.

[c]Regression constant for OLS.

Source: *RAIS* São Paulo state manufacturing 1990 and 1997 (prime age workers in their highest-paying job). Underlying inequality index: squared coefficient of deviation (Shorrocks 1982), based on estimation samples.

in Brazil. Comparing the R^2 (within) values in Table 2 relative to France and the U.S., Brazilian wages display much greater unexplained variability.

Components of wage inequality. Brazilian overall wage variability as measured by the standard deviation of log wages (.79 in 1990) markedly exceeds that in France (.41) and the U.S. (.54). We inquire further as to how the establishment-fixed and worker characteristics components contribute to log wage inequality in Brazilian manufacturing.[9] The individual earnings model (1) decomposes log wages into mutually exclusive additive components. Shorrocks (1982) shows that, under plausible invariance axioms, the unique decomposition of any inequality index is proportional to the additive decomposition of the squared coefficient of variation.[10]

Table 5 reports the Shorrocks (1982) decomposition of log annual wage inequality into its components. Worker characteristics account for around half of wage inequality. In 1997, the smaller contribution of experience and gender to log wage inequality also slightly reduces the overall importance of worker characteristics for log wage inequality. The unexplained residual in log wages, however, accounts for almost as much of log wage inequality as do observed worker characteristics.

Recall that the estimated establishment-fixed effect combines a pure establishment effect with the establishment average of pure worker effects. This combined establishment-fixed effect accounts for 8 to 13 percent of log wage inequality. Omit-

[9]Fishlow (1972) and subsequent studies investigate sources of income inequality in Brazil by demographic group; our focus lies on the estimated earnings components.

[10]The squared coefficient of variation is an inequality index in the generalized entropy family and equals two times the generalized entropy measure of degree two.

ting the establishment-fixed effect in straight OLS regressions induces a slight increase in the contribution of worker characteristics to log wage inequality of around three percentage points. This effect is tiny because the estimates of returns to experience and eduction, the premia on occupations, and the gender differential hardly change when establishment-fixed effects are removed.[11] The establishment-fixed effect mostly reduces the residual component in log wage inequality and accounts for about a sixth (in 1990) to a quarter (1997) of otherwise unexplained residual variability.

4 Formal Work Status Selectivity

We inspect whether selection of workers into formal work status affects estimates of the individual earnings model (1) for Brazil. We first estimate selectivity into formal work status for workers with manufacturing jobs using *PNAD* household data. Occupational reporting is less reliable in the household data, so we only discern between blue and white-collar jobs. To improve the fit, we distinguish nine levels of educational attainment. The categories are identically defined in the *PNAD* household and the *RAIS* labor force data.

Table 6 reports probit formality predictions for 1990 and 1997 (presenting each regression in two columns, the second column showing the interactions of regressors with the female indicator). The share of informal manufacturing workers in the household sample increases from around ten percent in 1990 to fifteen percent in 1997. In 1990, formality status is monotonically more frequent for higher educational attainment (the only exception being college dropouts who fare worse than high-school graduates). Formality becomes more likely as a worker's experience increases. In 1997, however, a variable relationship between educational attainment and formality selection emerges, with graduates more likely to hold a formal job than dropouts at the next higher education level (except at the lowest education levels). Gender has no statistically significant effect on the education and experience coefficients. Blue-collar occupation is a statistically insignificant predictor of formality selection, except for women in 1990.

We use the coefficient estimates from Table 6 to predict the presence of workers in the *RAIS* census of formal employment, conditional on the worker's observed characteristics in *RAIS*, and calculate the inverse of Mills' ratio for every worker. We then include the predicted inverse of Mills' ratio in our individual compensation model (4) to gauge the bearing of formality selection on compensation estimates.

The coefficients on the inverse of Mills' ratio in (4) measure the covariance between the error term in the selection equation and the error term in the individual compensation model. Our estimates are $-.259$ (with a standard error of .122) in

[11] Velenchik (1997) for Zimbabwe and Funkhouser (1998) for Guatemala also report only a small bias when employer-fixed effects are omitted.

Table 6: Probit Predictions of Formal Manufacturing Work Status

	Manufacturing 1990		Manufacturing 1997	
		Female ×		Female ×
	(1)	(2)	(3)	(4)
Illiterate	-1.330	*.681*	-.884	*.042*
	(.385)	(.725)	(.338)	(.748)
Primary School Dropout	-1.127	*.919*	-.690	*-.049*
	(.343)	(.660)	(.302)	(.614)
Primary School Graduate	-.777	*.458*	-.905	*.136*
	(.338)	(.643)	(.284)	(.582)
Middle School Dropout	-.621	*.333*	-.947	*-.118*
	(.334)	(.635)	(.272)	(.555)
Middle School Graduate	*-.526*	*.274*	*-.390*	*-.253*
	(.341)	(.645)	(.278)	(.564)
High School Dropout	*-.290*	*.383*	*-.403*	*-.151*
	(.337)	(.641)	(.270)	(.546)
High School Graduate	*.160*	*-.857*	*-.161*	*-.530*
	(.595)	(.928)	(.418)	(.765)
College Dropout	*-.225*	*.423*	*-.428*	*.250*
	(.356)	(.686)	(.291)	(.586)
Blue Collar Occupation	*.096*	-.495	*.014*	*-.086*
	(.094)	(.166)	(.080)	(.143)
Potential Labor Force Experience	.130	*-.196*	.146	*.088*
	(.077)	(.136)	(.067)	(.112)
Quadratic Experience Term	*-.002*	*.015*	*-.008*	*-.007*
	(.008)	(.014)	(.007)	(.012)
Cubic Experience Term	*-.0001*	*-.0005*	*.0002*	*.0002*
	(.0003)	(.0006)	(.0003)	(.0005)
Quartic Experience Term	*2.31e-06*	*5.90e-06*	*-2.19e-06*	*-2.99e-06*
	(4.26e-06)	(7.38e-06)	(3.85e-06)	(6.63e-06)
Constant	.794	*.618*	.676	*-.258*
	(.377)	(.710)	(.313)	(.620)
Observations	3,064		2,931	
Censored obs. (informal workers)	300		442	
Pseudo R^2	.088		.083	

Source: *PNAD* (prime age household members in September) São Paulo state manufacturing 1990 and 1997. Formality: labor ID card. Standard errors in parentheses (insignificant point estimates at the five percent level in *italics*).

RAIS 1990 and −.137 (standard error .037) in 1997. Because of the statistically significant negative correlation between the formality selection error and the log wage error, workers with characteristics that make informal employment more likely tend to receive higher wage compensation in their formal jobs, all else equal. Note that, conditional on worker characteristics, informal jobs pay a wage premium over formal jobs in Brazil, perhaps in compensation for foregone public benefits that formal jobs offer (Menezes Filho, Mendes and de Almeida 2004).[12] The negative correlation between the formality selection and the log wage error is consistent with the idea that

[12]Unconditionally, manufacturing workers with informal jobs face an earnings discount of about .4 log wage units in the *PNAD* household data (one third of the earnings of formally employed workers, $1-\exp(.4) \approx .33$). This discount is remarkably similar across gender and education groups, and remains largely unaltered between 1990 and 1997. The differential is a consequence of self-selection, however, and conceals an informal wage premium over formal wages given worker characteristics (Menezes Filho et al. 2004).

Table 7: RELATIVE MANUFACTURING WAGES IN BRAZIL UNDER SELECTIVITY

	RAIS 1990 (FE)		*RAIS* 1997 (FE)	
	Selectivity	No correction	Selectivity	No correction
	(1)	(2)	(3)	(4)
		Education[a]		
Male worker:				
College Degree	2.494	2.516	2.386	2.412
Some College	1.795	1.793	1.766	1.758
Primary School	.881	.859	.901	.888
Female worker:				
College Degree	2.504	2.556	2.488	2.556
Some College	1.794	1.855	1.812	1.854
Primary School	.974	.970	.996	.990
		Occupation[b]		
Male worker:				
Profess'l or Managerial	2.370	2.355	2.493	2.488
Technical or Superv.	1.836	1.821	1.887	1.882
Other White Collar	1.310	1.299	1.285	1.283
Skill-int. Blue Collar	1.269	1.270	1.252	1.252
Female worker:				
Profess'l or Managerial	2.065	2.128	2.341	2.348
Technical or Superv.	1.486	1.532	1.460	1.466
Other White Collar	1.376	1.419	1.372	1.377
Skill-int. Blue Collar	1.029	1.031	1.059	1.059
		Gender[c]		
Female worker	.901	.893	.917	.915

[a]Relative to worker with some or complete high school education, controlling for occupation.

[b]Relative to other blue collar occupations, controlling for education.

[c]Female relative to male workers, controlling for education and occupation.

Source: *Source*: *RAIS* São Paulo state manufacturing 1990 and 1997 (prime age workers in their highest-paying job). Out-of-sample predictions of formality status from *PNAD* (prime age household members in September) coefficient estimates (columns 1 and 2 in Table 6); wage levels relative to comparison-group wage levels from model (4) component estimates.

the informal sector exerts a slight upward pressure on formal-job wages for workers who are more likely to find employment in the informal sector. But selectivity hardly affects the main predictors of individual compensation, worker characteristics and the establishment-fixed effects.

Table 7 shows for 1990 and 1997 that returns to education, occupation premia, and gender differences are almost the same with and without the inverse of Mills' ratio in the compensation regression.[13] Measures of the returns to education are as steep as without correction, occupational premia continue to exhibit the same magnitudes as in France and the U.S., and gender differences remain close to those of the U.S. in

[13]In a similar vein, Carneiro and Henley (1998) find no significant bearing of the informal sector's size on Brazilian real wages in a short-term model of wage determination.

1990.

5 Wage Components and Firm Characteristics

We draw on the matched *RAIS-PIA* sample to relate the firm-average worker characteristics and establishment-fixed components of individual wages to the characteristics of manufacturing firms. The firm characteristics model (5) estimates partial correlations between selected firm characteristics and the two wage components. This allows us to assess what may be predicted about firm characteristics from one wage component, controlling for the other component. We consider five measures of inputs and three measures of productivity at the firm level, corresponding to the variables analyzed by Abowd et al. (2001). Results for Brazil in 1990 and 1997, along with France in 1992 and the U.S. in 1990, are reported in Table 8.

As seen in column (1) of Table 8, the size of Brazilian manufacturing firms, measured in terms of total employment, exhibits a mild positive correlation with both of the wage components. An increase of one percent in the characteristics-predicted wage levels of a firm's workers, holding constant the predicted wages of its establishments, is associated with a nearly 1.2 percent increase in firm size, while a one percent increase in the predicted wage levels of a firm's establishments, holding constant its characteristics-predicted worker wages, implies an increase in size that approaches 1.5 percent. Both firm-average wage components relate positively with total capital stock, with the wage elasticities of capital stock being in excess of two percent. Correspondingly, high-wage manufacturing firms, measured with respect to either of the wage components, tend to be more capital intensive.

Estimates for Brazilian manufacturing in 1997 are reported in column (2) of Table 8. Comparing columns (1) and (2), it may be seen that the worker characteristics component becomes less important in explaining employment, capital stock and capital intensity in Brazilian manufacturing firms in 1997. The establishment-fixed component in 1997 has equal predictive power for both employment and capital stock, so firms with high-wage establishments cease to be more capital intensive on average. The relationship between the establishment-fixed component and occupational skill intensity becomes weaker, while the relationship between both components and the sales-based productivity measure strengthens slightly. Returns to capital remain uncorrelated with the two wage components.

Comparing Brazil to France, the correlations of employment and capital stock with the worker characteristics component of wages are quite similar, but employment and capital stock have much stronger positive correlations with the establishment-fixed component in France. Controlling for predicted wages due to average worker characteristics, firms with high-wage establishments are much more likely to be large and capital intensive in France. For the U.S., in contrast, high predicted worker wages are associated with smaller firms, and the relationship with capital intensity is

Table 8: Manufacturing Firm Characteristics and Wages in Brazil, France and the U.S.

	Brazil 1990	Brazil 1997	France 1992	U.S. 1990
	(1)	(2)	(3)	(4)
Log Employment[a]				
Mean Worker Characteristics ($\overline{x}_k\widehat{\beta}$)	1.111	.783	1.103	-.486
	(.141)	(.144)	(.402)	(.130)
Mean Establishment-Fixed ($\overline{\widehat{\psi}}_k$)	1.496	1.716	4.588	.223
	(.187)	(.172)	(.495)	(.073)
Log Capital Stock				
Mean Worker Characteristics ($\overline{x}_k\widehat{\beta}$)	2.336	.841	2.290	*-.183*
	(.207)	(.185)	(.510)	(.154)
Mean Establishment-Fixed ($\overline{\widehat{\psi}}_k$)	2.403	1.703	6.751	.838
	(.274)	(.219)	(.628)	(.086)
Log Capital-Labor Ratio				
Mean Worker Characteristics ($\overline{x}_k\widehat{\beta}$)	1.244	.337	1.187	.303
	(.121)	(.149)	(.200)	(.060)
Mean Establishment-Fixed ($\overline{\widehat{\psi}}_k$)	.920	*.104*	2.163	.615
	(.160)	(.177)	(.247)	(.034)
Non-Production Worker Ratio[a]				
Mean Worker Characteristics ($\overline{x}_k\widehat{\beta}$)	.052	.055		.124
	(.016)	(.019)		(.014)
Mean Establishment-Fixed ($\overline{\widehat{\psi}}_k$)	.091	*.020*		-.036
	(.021)	(.022)		(.008)
High-Skill Occupation Ratio[b]				
Mean Worker Characteristics ($\overline{x}_k\widehat{\beta}$)	.441	.507	.572	
	(.021)	(.025)	(.031)	
Mean Establishment-Fixed ($\overline{\widehat{\psi}}_k$)	.279	.121	*.041*	
	(.028)	(.030)	(.036)	
Log Value Added per Employee				
Mean Worker Characteristics ($\overline{x}_k\widehat{\beta}$)	6.556	*-.183*	.818	.252
	(1.260)	(1.578)	(.084)	(.036)
Mean Establishment-Fixed ($\overline{\widehat{\psi}}_k$)	4.485	5.449	1.157	.453
	(1.668)	(1.889)	(.103)	(.020)
Log Sales per Employee				
Mean Worker Characteristics ($\overline{x}_k\widehat{\beta}$)	.488	.547	.930	.343
	(.069)	(.095)	(.152)	(.044)
Mean Establishment-Fixed ($\overline{\widehat{\psi}}_k$)	.264	.354	1.428	.505
	(.092)	(.113)	(.186)	(.025)
Return on Capital				
Mean Worker Characteristics ($\overline{x}_k\widehat{\beta}$)	*-1.329*	*.170*	-.084	*-.003*
	(1.107)	(.105)	(.020)	(.048)
Mean Establishment-Fixed ($\overline{\widehat{\psi}}_k$)	*-1.124*	*.003*	.098	-.205
	(1.462)	(.125)	(.025)	(.027)

[a]From *PIA* data.

[b]From *RAIS* data.

Sources: São Paulo state manufacturing firms in *PIA* and *RAIS* on December 31, 1990 and 1997. Abowd et al. (2001) for France 1992 and the U.S. 1990. Partial correlations from individual regressions on mean worker characteristics ($\overline{x}_k\widehat{\beta}$) and mean establishment effects ($\overline{\widehat{\psi}}_k$), controlling for sector-fixed effects. Standard errors in parentheses (insignificant point estimates at the five percent level in *italics*).

only slightly positive. The establishment-fixed component relates positively to firm size and capital stock in the U.S., but the partial correlations are much smaller than in Brazil and France. Thus, the link between input characteristics and the wage structure of firms, particularly as predicted by average worker characteristics, differs sharply between Brazil and France, on one hand, and the U.S., on the other.

The link between wage components and occupational structure is considered in two ways, consistent with the differing French and U.S. measures used by Abowd et al. (2001). The variable "High-Skill Occupation Ratio" (corresponding to the French measure) is defined by professional and managerial plus technical and supervisory employment, divided by total employment, using the skill categories from *RAIS*. The "Non-Production Worker Ratio," in contrast, divides the ratio of white collar workers by the sum of white and blue collar workers, where the data are drawn from *PIA*. Across occupation variables and countries, occupational skill intensity relates positively to predicted worker wages, as expected. The association between skill intensity and predicted establishment wages is positive for Brazil, but much smaller for the other countries, suggesting that the establishment-fixed earnings component in Brazil is more responsive to work force composition.

Worker productivity, based on either value added per employee or sales per employee, exhibits positive correlation with both wage components in all three countries. In Brazil, firms with high values of either wage component are especially likely to have highly productive workers, as measured by value added. The relationship is much weaker with respect to the sales measure, however. The two productivity measures produce nearly identical results for France and the U.S., with the relationship being more strongly positive in France. The results do not establish any significant relationship between return on capital and the wage components in any of the countries. Productivity gains for firms with high-wage workers or high-wage establishments appear to offset the higher wage costs.

6 Sectoral Comparisons in 1997

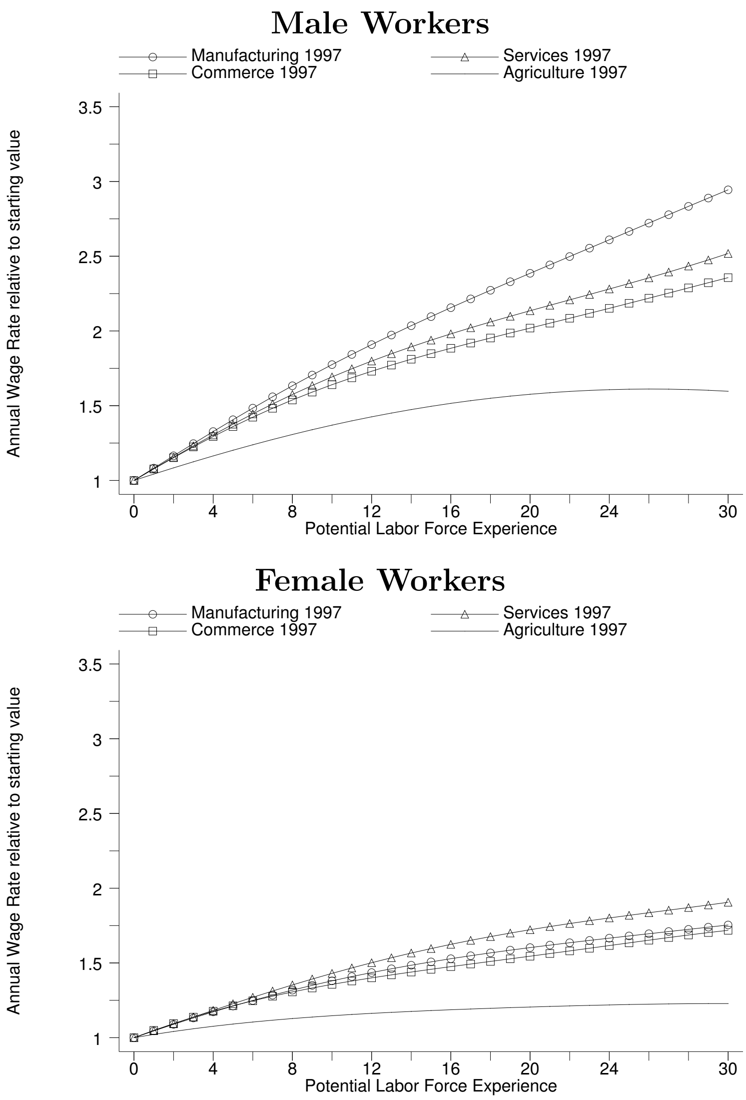
The sectoral scope of *RAIS* permits a wage analysis beyond manufacturing. Table 9 presents regression results for four sectors in 1997 (note that column (1) of Table 9 reproduces the results for Brazilian manufacturing reported in Table 2). We use the complete regression specification, including the education variable, in computing the wage components. We choose the more recent year 1997 for sectoral comparisons; results are similar across years.[14]

[14]Results do not markedly differ between 1990 and 1997 except for declining returns to experience in the manufacturing sector, which we discussed in section 3, and a widening gender gap in the services sector between 1990 and 1997.

Table 9: Wage Structure in Brazil 1997, by Sector

	Manufact. (1)	Services (2)	Commerce (3)	Agriculture (4)
Primary School Education (or less)	-1.000	-.826	-1.027	-.840
	(.002)	(.002)	(.004)	(.008)
Some High School Education	-.881	-.769	-.932	-.731
	(.002)	(.002)	(.004)	(.009)
Some College Education	-.316	-.173	-.337	-.374
	(.003)	(.003)	(.005)	(.014)
Professional or Managerial Occupation	.912	.740	.656	.736
	(.002)	(.002)	(.003)	(.007)
Technical or Supervisory Occupation	.632	.556	.093	.675
	(.002)	(.002)	(.002)	(.009)
Other White Collar Occupation	.249	.220	.007	.331
	(.002)	(.001)	(.002)	(.007)
Skill Intensive Blue Collar Occupation	.225	.301	.125	.085
	(.001)	(.002)	(.002)	(.004)
Potential Labor Force Experience	.082	.078	.078	.043
	(.0007)	(.0007)	(.0006)	(.001)
Quadratic Experience Term	-.003	-.003	-.004	-.001
	(.00007)	(.00007)	(.00007)	(.0001)
Cubic Experience Term	.00008	.00007	.0001	.00002
	(2.86e-06)	(2.97e-06)	(3.20e-06)	(5.47e-06)
Quartic Experience Term	-7.64e-07	-5.59e-07	-1.03e-06	-2.00e-07
	(3.89e-08)	(4.05e-08)	(4.65e-08)	(7.50e-08)
Female	.070	-.264	-.270	-.191
	(.006)	(.004)	(.007)	(.021)
Female × Primary School Education (or less)	.051	.146	.263	.208
	(.004)	(.002)	(.005)	(.018)
Female × Some High School Education	-.058	.068	.212	.143
	(.004)	(.002)	(.005)	(.018)
Female × Some College Education	*-.005*	.032	.114	.121
	(.005)	(.003)	(.007)	(.027)
Female × Professional or Managerial Occupation	-.058	.073	-.020	-.069
	(.005)	(.003)	(.005)	(.019)
Female × Technical or Supervisory Occupation	-.250	.140	.060	-.193
	(.004)	(.002)	(.003)	(.021)
Female × Other White Collar Occupation	.071	.187	.163	.034
	(.003)	(.002)	(.003)	(.013)
Female × Skill Intensive Blue Collar Occupation	-.167	-.074	-.046	-.075
	(.003)	(.005)	(.005)	(.010)
Female × Potential Labor Force Experience	-.036	-.032	-.027	-.020
	(.001)	(.001)	(.001)	(.003)
Female × Quadratic Experience Term	.002	.002	.001	*.0001*
	(.0001)	(.0001)	(.0001)	(.0003)
Female × Cubic Experience Term	-.00005	-.00007	-1.00e-05	*.00002*
	(5.63e-06)	(4.48e-06)	(5.51e-06)	(1.00e-05)
Female × Quartic Experience Term	5.40e-07	6.98e-07	*1.27e-08*	*-2.42e-07*
	(7.78e-08)	(6.11e-08)	(8.02e-08)	(1.71e-07)
Observations	1,831,566	3,185,721	1,087,388	261,579
R^2 (within)	.468	.376	.332	.259

Source: *RAIS* São Paulo state 1997 (prime age workers in their highest-paying job), controlling for establishment-worker fixed effects (manufacturing Table 2). Standard errors in parentheses (insignificant point estimates at the five percent level in *italics*).



Source: *RAIS* São Paulo state 1997 (prime age workers in their highest-paying job). Wage levels relative to zero experience wage levels from wage component estimates (Table 9).

Figure 2: **Potential experience in Brazil 1997, by sector**

Table 10: Relative Wages in Brazil by Sector

	Manufacturing		Services	Commerce	Agriculture
	1990	1997	1997	1997	1997
	(1)	(2)	(3)	(4)	(5)
			Education[a]		
Male worker:					
College Degree	2.516	2.412	2.159	2.539	2.078
Some College	1.793	1.758	1.815	1.813	1.430
Primary School	.859	.888	.945	.909	.897
Female worker:					
College Degree	2.556	2.556	2.017	2.054	1.801
Some College	1.855	1.854	1.751	1.643	1.398
Primary School	.970	.990	1.022	.957	.958
			Occupation[b]		
Male worker:					
Profess'l or Managerial	2.355	2.488	2.097	1.927	2.088
Technical or Supervisory	1.821	1.882	1.743	1.098	1.964
Other White Collar	1.299	1.283	1.247	1.007	1.393
Skill-intensive Blue Collar	1.270	1.252	1.351	1.134	1.089
Female worker:					
Profess'l or Managerial	2.128	2.348	2.254	1.889	1.949
Technical or Supervisory	1.532	1.466	2.004	1.165	1.619
Other White Collar	1.419	1.377	1.503	1.185	1.441
Skill-intensive Blue Collar	1.031	1.059	1.254	1.082	1.010
			Gender[c]		
Female worker	.893	.915	.882	.944	.958

[a]Relative to worker with some or complete high school education, controlling for occupation.
[b]Relative to non-skill-intensive blue collar occupations, controlling for education.
[c]Female relative to male workers, controlling for education and occupation.
Source: *Source*: *RAIS* São Paulo state 1997 (prime age workers in their highest-paying job). Wage levels relative to comparison-group wage levels from component estimates (Table 9).

Wages and worker characteristics. The profiles of experience premia for men and women in 1997 are shown in Figure 2. Male experience profiles for commerce and services closely resemble the profile for U.S. male manufacturing workers from Figure 1, while for agriculture the profile is quite flat. For male workers having 10 or fewer years of experience, returns to experience are essentially identical in commerce, manufacturing and services in 1997. As for manufacturing premia, the very steep 1990 profile shifts down markedly in 1997, with the largest declines suffered by workers with roughly 15 years of experience (Figure 1). As seen in Figure 2, female experience premia for services lie slightly above the levels for commerce and manufacturing in both years, and there is little change between 1990 and 1997.

Sectoral comparisons of education and occupation differentials appear in Table 10. Several of the key features highlighted above for Brazilian manufacturing hold broadly across sectors: wage premia for college are very high by French and U.S. standards and occupation-wage profiles are slightly steeper for men. Education premia decline significantly in manufacturing for all genders between 1990 and 1997, although the 1997 levels remain high in comparison to the 1990 figures for France and the U.S. (Table 3). In 1997, only men in the commerce sector receive education premia comparable to those in manufacturing, and for the other cases the premia are substantially lower. Outside of manufacturing, the education profiles of women are flatter than those of men in both years.

As Table 10 indicates, the returns to occupation exhibit strikingly different patterns across sectors. For commerce, the occupation profile is very flat up to the professional and supervisory level, where it takes a sharp upward jump. For services, in contrast, the technical and supervisory occupations receive wages that are much closer to professional and supervisory levels. At the other end of the scale, skill-intensive blue collar occupations receive substantial premia for men in commerce, manufacturing and services, and for women in services, but not for the other cases.

The overall female/male wage ratio is highest for agriculture and commerce, at around 90 percent. The ratio is lowest in the services sector, where it stands at about 77 percent.

Components of individual wages. Table 11 evaluates the explanatory power of the predicted worker characteristics and establishment-fixed components of wages across sectors. The correlations between log wages and the worker characteristics components for the other sectors are lower than for manufacturing, and substantially lower in the case of agriculture. Thus, worker characteristics play a smaller role in explaining wages in the other sectors. The establishment-fixed components in commerce, manufacturing and services are much less important than worker characteristics for explaining wages, whereas in agriculture the establishment-fixed component dominates. The correlations between the two components are substantially lower outside of manufacturing.

Components of wage inequality. Table 12 reports components of log annual wage inequality in 1997 across sectors. Worker characteristics account for 45 percent of log wage variation in manufacturing but predict a considerably smaller portion of the variability in non-manufacturing sectors, ranging from 37 percent in services to 20 percent in agriculture. Individual components among the worker characteristics matter to different degrees across sectors. Most notably, there is an inequality reducing gender effect in commerce, where women receive relatively high occupational premia and suffer less of a primary-school discount (Table 10).

The unexplained residual in log wages is larger in non-manufacturing sectors than in manufacturing. Omitting the establishment-fixed effect in straight OLS regressions induces a slight upward shift in the contribution of worker characteristics to log wage inequality in all four sectors. Similar to manufacturing, this change is small because

Table 11: Wage Variability in Brazil 1997, by Sector

	Mean	St.Dev.	Correlation with			
			$\ln w_i$	$x_i\widehat{\beta}$	$\widehat{\psi}_j$	$\widehat{\varepsilon}_i$
	(1)	(2)	(3)	(4)	(5)	(6)
Manufacturing 1997						
Log Annual Wage ($\ln w_i$)	8.872	.778	1.000			
Worker Characteristics ($x_i\widehat{\beta}$)	.084	.498	.695	1.000		
Establishment-Fixed ($\widehat{\psi}_j$)	8.788	.241	.423	.176	1.000	
Residual ($\widehat{\varepsilon}_i$)	.000	.507	.651	.000	.000	1.000
Services 1997						
Log Annual Wage ($\ln w_i$)	8.797	.805	1.000			
Worker Characteristics ($x_i\widehat{\beta}$)	.255	.483	.612	1.000		
Establishment-Fixed ($\widehat{\psi}_j$)	8.542	.292	.382	.033	1.000	
Residual ($\widehat{\varepsilon}_i$)	-.000	.566	.703	.000	.000	1.000
Commerce 1997						
Log Annual Wage ($\ln w_i$)	8.407	.628	1.000			
Worker Characteristics ($x_i\widehat{\beta}$)	-.356	.345	.580	1.000		
Establishment-Fixed ($\widehat{\psi}_j$)	8.763	.181	.347	.107	1.000	
Residual ($\widehat{\varepsilon}_i$)	-.000	.479	.763	-.000	.000	1.000
Agriculture 1997						
Log Annual Wage ($\ln w_i$)	8.056	.606	1.000			
Worker Characteristics ($x_i\widehat{\beta}$)	-.345	.253	.480	1.000		
Establishment-Fixed ($\widehat{\psi}_j$)	8.402	.351	.624	.108	1.000	
Residual ($\widehat{\varepsilon}_i$)	.000	.401	.662	.000	.000	1.000

Source: *RAIS* São Paulo state 1997 (prime age workers in their highest-paying job). Estimates from establishment-fixed effects wage regressions in Table 9. Statistics based on estimation sample. The log U.S. CPI change between 1990 and 1997 is .187.

the estimates of returns to experience and eduction, the premia on occupations, and the gender differential hardly change when controlling for establishment-fixed effects.

The establishment-fixed effect mostly reduces residual wage inequality. In 1997, the establishment-fixed effect accounts for around a quarter of otherwise unexplained log wage inequality in manufacturing and services, for only about a seventh in commerce, but for close to half of otherwise unexplained log wage inequality in agriculture. Even after controlling for establishment-fixed effects, however, regressors predict only forty percent of log wage variability in commerce and cannot predict more than sixty percent of wage variability in any sector.

7 Conclusion

Using a comprehensive matched employer-employee data set for a developing country, we provide estimates for key elements of the Brazilian wage structure that permit

Table 12: COMPONENTS OF LOG WAGE INEQUALITY 1997, BY SECTOR

	Manufacturing		Services		Commerce		Agriculture	
	FE[a]	OLS[b]	FE[a]	OLS[b]	FE[a]	OLS[b]	FE[a]	OLS[b]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Worker Char. ($x_i\widehat{\beta}$)	.445	.484	.367	.382	.318	.338	.200	.235
Experience	.110	.121	.043	.049	.122	.131	.035	.041
Occupation	.139	.141	.139	.129	.086	.087	.092	.117
Education	.145	.161	.177	.190	.115	.127	.052	.059
Gender	.051	.061	.008	.015	-.005	-.007	.021	.019
Establishm.-Fixed ($\widehat{\psi_j}$)[c]	.131		.139		.100		.362	
Residual ($\widehat{\varepsilon_i}$)	.424	.516	.494	.618	.581	.662	.438	.765

[a]Component estimates from log wage regressions in Table 9.

[b]Component estimates from log wage estimates of model (1), but omitting the fixed effect.

[c]Regression const. for OLS.

Source: *RAIS* São Paulo state 1997 (prime age workers in their highest-paying job). Inequality index: squared coefficient of deviation (Shorrocks 1982), based on estimation samples.

direct comparisons with estimates for industrialized countries. Across sectors and years, our results conform broadly to traditional findings of the wage structure literature. Contrasting our results with those of Abowd et al. (2001) for France and the U.S., we find that manufacturing wages in Brazil exhibit higher returns to experience and education, while occupation differentials are quite similar across the three countries. Brazilian women do not suffer a disproportionately large gender gap, although their experience premia are quite small relative to those of men. Between 1990 and 1997, the principle changes in the Brazilian manufacturing wage structure involve downward shifts in returns to education and a large decline in the returns to experience for men.

Predicted wages based on worker characteristics explain a similar portion of the overall wage variability in manufacturing across the three countries, while the predicted establishment-fixed component of wages has relatively lower explanatory power in Brazil. The predicted worker characteristics component does not performs worse for non-manufacturing sectors in Brazil, however, and accounts for 20 percent (agriculture) to 45 percent (manufacturing) of overall log wage variability.

Firm-average predicted wages based on both worker characteristics and establishments closely correlate with a variety of firm characteristics, including size, capital- and skill-intensity and productivity. While the firm-average establishment-fixed component appears to be more responsive to work force composition in Brazil than in France and the U.S., Brazil and France display much similarity in their relationships between firm characteristics and wage components.

The inclusion of an establishment-fixed component has only a minor effect on the coefficients on worker characteristics and reduces only slightly the role of worker characteristics in log wage variability. Up to sixty percent of log wage variability remains unaccounted within manufacturing and non-manufacturing sectors, however, even after controlling for an establishment-fixed component in compensation. This suggests that explanations for within-sector wage variability ought to focus on factors that operate through worker characteristics rather than through establishment compensation policies.

Overall, our results establish a close similarity between wage structures in a major developing country and two major industrialized countries. Key differences between the countries, in particular the high variability of Brazilian wages, emerge from the way worker characteristics are compensated and not from differences in establishment-level wage policies.

Appendix

A Data

A.1 Worker variables

Screening. Workers in *RAIS* are identified by individual-specific *PIS* (*Programa de Integração Social)*. *RAIS* information and the *PIS* worker ID numbers are used to administer a federal redistribution program, by which workers with formal employment during the calendar year receive the equivalent of a monthly minimum salary by the end of the year. A given establishment may report the same *PIS* multiple times within a single year in order to exploit the severance indemnity system ($FGTS$) through spurious layoffs and rehires. Bad compliance can cause certain *PIS* numbers to be recorded incorrectly or repeatedly. To handle these issues, we screen the sample as follows. (1) Observations with *PIS* numbers having fewer than 11 digits are eliminated. We suspect short *PIS* numbers to be due to faulty bookkeeping. (2) Observations with workers not employed on December 31st are removed; only the worker's job observation on December 31st with the highest annual average wage level is retained (in cases of ties, we randomly drop all but one job observation per worker on Dec 31st). This makes our sample comparable to Abowd et al. (2001), who consider full-time and full-year employees. As mentioned in the text, (3) observations of workers older than 50 years are dropped to avoid potential confounding effects stemming from workers who leave the labor force prior to official retirement age.

Compensation. The *RAIS* defines the average monthly wage as the arithmetic mean of all monthly remunerations for a given worker, divided by the value of the minimum wage that prevails during the respective month. In this conversion, *RAIS* counts only the months, or parts thereof, during which the workers are employed, excluding the "thirteenth salary," which is a special December payment made in some sectors. Months with missing wage information are disregarded in the calculation of this mean.

The *RAIS* manual for respondents states explicitly the forms of payment that are considered valid components of the monthly wage rate. Among other components, these include: salaries; extraordinary additions, supplements and bonuses; tips and gratuities; commissions and fees; contracted premia; overtime compensation for contracted extra hours; hazard compensation; executive compensation; cost reimbursement components if they exceed 50 percent of the base salary and are for travel or transfers necessary for the execution of the job; payments for periods of vacation, holidays and parental leave; vacation gratuities if they exceed 20 days of salary; piece wages; and in-kind remunerations such as room and board. As a rule, components are considered part of salary if they are taxable income or are subject to Brazilian social security contributions.

Payments that are not considered wage components include: severance payments for layoffs; indemnity payments for permanent maternal leave and any other indemnity payments; so-called "family payments" under Brazilian labor law; vacation gratuities if they do not exceed 20 days of salary; additional social security compensation due to a worker's illness; moving expenses; travel cost reimbursements if they do not exceed 50 percent of the base salary; scholarships for interns; meals, equipment and clothing for execution of the job; and participation in the employer's profits.

Experience, education and occupation. The following tables present age and education classifications from *RAIS*, along with the imputed ages used in construction of the potential experience variable. We use the age range information in our version of *RAIS* to infer the "typical" age of a worker in the age range as follows:

	RAIS Age Category	Imputed Age
1.	Child (10-14)	12
2.	Youth (15-17)	16
3.	Adolescent (18-24)	21
4.	Nascent Career (25-29)	27
5.	Early Career (30-39)	34.5
6.	Peak Career (40-49)	44.5
7.	Late Career (50-64)	*excluded*
8.	Post Retirement (65-)	*excluded*

We group age information in *PNAD* into the same categories and also ignore workers of age 50 and older.

To calculate potential labor force experience, we use the following inference schedule to impute the worker's age at the completion of his/her education for both *RAIS* and *PNAD* data:

	RAIS Education Category	Imputed Age at completion
1.	Illiterate	6
2.	Primary School Dropout	7
3.	Primary School Graduate	10
4.	Middle School Dropout	11
5.	Middle School Graduate	14
6.	High School Dropout	15
7.	High School Graduate	18
8.	College Dropout	19
9.	College Graduate	22

The preceding table also shows how we translate years of education in *PNAD* into the *RAIS* education categories.

Following Abowd et al. (2001), we define potential labor market experience for a worker as the imputed age for his/her age category minus the imputed age for his/her education category.

The occupation indicator variables are obtained from the *CBO* classification codes in the *RAIS*, as reclassified to conform with the *ISCO-88* categories (Muendler et al. 2004). Before we convert *CBO* to *ISCO-88*, we reset unknown *CBO* codes in *RAIS* at the four-digit level to the nearest applicable miscellaneous occupation category at the four-digit level. The mapping between *ISCO-88* categories and occupation levels is given as follows:

	ISCO-88 Category	Occupation Level
1.	Legislators, senior officials, and managers	Professional & Managerial
2.	Professionals	Professional & Managerial
3.	Technicians and associate professionals	Technical & Supervisory
4.	Clerks	Other White Collar
5.	Service workers and shop and market sales workers	Other White Collar
6.	Skilled agricultural and fishery workers	Skill Intensive Blue Collar
7.	Craft and related workers	Skill Intensive Blue Collar
8.	Plant and machine operators and assemblers	Skill Intensive Blue Collar
9.	Elementary occupations	Other Blue Collar

Finally, we define the education indicator variables as follows:

	Education Level	*RAIS* Education Categories
1.	Primary School (or less)[a]	1-3
2.	Some High School	4-7
3.	Some College	8
4.	College	9

[a]Including illiterates.

A.2 Firm data

Table 13 describes the match between *RAIS* establishments and *PIA* firms. For the year 1990, we can match 2,864 out of 58,192 establishments in São Paulo state to the *PIA* firm sample. In 1997, only 1,689 out of 62,969 establishments in São Paulo state can be identified in the *PIA* firm sample. In order to withdraw micro-level data from *PIA* at the Brazilian census bureau *IBGE*, we randomly tabulate cells of three (to five) firms. Some so-created cells contain firms for which do not have *RAIS* observations or for which we cannot predict establishment-level information within *RAIS*. Our random aggregation routine leaves some *PIA* firms unassigned to cells in certain years in order to create random cells of three firms that appear possibly many

Table 13: MATCHES BETWEEN *RAIS* AND *PIA* RANDOM FIRM TABULATIONS

Data Source	Frequency	Percent	Cumulated
1990:			
RAIS and PIA firms			
RAIS-SP establishments but no *PIA* firm	281,685	97.69	97.69
PIA firms but no *RAIS*-SP establishment	3,056	1.06	98.75
RAIS-SP establishments in *PIA* firms	3,616	1.25	100.00
Total	288,357	100.00	
Randomly tabulated three-firm cells			
RAIS & *PIA* firms but no cell match	724	37.05	37.05
Cells but no *RAIS* & *PIA* match	61	3.12	40.17
Cells matched with *RAIS* & *PIA*	1,169	59.83	100.00
Total	1,954	100.00	
1997:			
RAIS and PIA firms			
RAIS-SP establishments but no *PIA* firm	376,719	99.04	99.04
PIA firms but no *RAIS*-SP establishment	1,511	0.40	99.43
RAIS-SP establishments in *PIA* firms	2,158	0.57	100.00
Total	380,388	100.00	
Randomly tabulated three-firm cells			
RAIS & *PIA* firms but no cell match	305	28.21	28.21
Cells but no *RAIS* & *PIA* match	97	8.97	37.19
Cells matched with *RAIS* & *PIA*	679	62.81	100.00
Total	1,081	100.00	

Sources: São Paulo state manufacturing firms in *PIA* and *RAIS* on December 31, 1990 and 1997.

consecutive years during other periods between 1990 and 1998. For both reasons, we lose further firms.

A.3 Complementary household survey data

We retain formally and informally employed workers from *Pesquisa Nacional por Amostra de Domicílios* (*PNAD*) in São Paulo state in September 1990 and September 1997. We exclude both unemployed persons and employers and obtain 13,665 *PNAD* household-level observations of workers in 1990 and 14,414 observations in 1997. Similar to our procedure for December wages in *RAIS*, we convert September wages in *PNAD* first to December values in Brazilian currency (using the Brazilian CPI *Índice Nacional de Preços ao Consumidor*, *INPC*) and then into current U.S. dollars.[15]

[15]While *INPC* inflation was 59.4 percent between September and December 1990, the exchange rate devalued by 101.9 percent over the same period. To avoid distortions from exchange rate fluctuations in our comparisons, we first transform *PNAD* September wages to December values

The *PNAD* household data permit the distinction between formal employment (with a labor ID card *carteira*) and informal employment (without labor ID card). Informal employment is recorded in *PNAD* if it entails at least four paid hours per week. The labor ID card entitles workers to employment protection and social benefits, largely borne by the employer. As in *RAIS*, wages in *PNAD* are gross payments before taxes, social security contributions, and other deductions and exclude the "thirteenth salary," meals, and participation in the employer's profits. So-called "family pay" under Brazilian labor law, however, is an exception to the general congruence of wage definitions. Family pay is considered part of earnings in *PNAD* but excluded from *RAIS* wages.

B Summary Statistics

Tables 14 and 15 provide sample means and standard deviations of worker-sample variables.

using the Brazilian CPI *INPC*.

Table 14: SUMMARY STATISTICS, *RAIS* WORKER DATA 1990

	Manufact. 1990		Services 1990	
	Mean	St.Dev.	Mean	St.Dev.
	(1)	(2)	(3)	(4)
Log Annual Wage[a]	8.016	.786	7.953	.830
Primary School Education (or less)[b]	.533	.499	.545	.498
Some High School Education	.373	.484	.237	.425
Some College Education	.034	.182	.063	.242
College Graduate	.053	.225	.147	.354
Professional or Managerial Occupation	.079	.270	.224	.417
Technical or Supervisory Occupation	.096	.294	.155	.362
Other White Collar Occupation	.117	.321	.279	.448
Skill Intensive Blue Collar Occupation	.551	.497	.140	.346
Low-skill Intensive Blue Collar Occupation	.157	.364	.203	.402
Potential Labor Force Experience	16.079	9.458	17.137	9.283
Quadratic Experience Term (/100)	3.480	3.374	3.798	3.462
Cubic Experience Term (/1,000)	8.653	11.352	9.594	11.987
Quartic Experience Term (/10,000)	23.492	38.335	26.414	41.364
Tenure at establishment	.923	1.106	1.047	1.240
Female	.272	.445	.442	.497
Female × Log Annual Wage	2.062	3.393	3.469	3.930
Female × Primary School Education (or less)[b]	.140	.347	.232	.422
Female × Some High School Education	.106	.308	.086	.280
Female × Some College Education	.010	.101	.033	.179
Female × College Graduate	.013	.114	.088	.283
Female × Professional or Managerial Occupation	.014	.118	.130	.336
Female × Technical or Supervisory Occupation	.027	.163	.088	.283
Female × Other White Collar Occupation	.042	.201	.126	.332
Female × Skill Intensive Blue Collar Occupation	.140	.347	.012	.107
Female × Low-skill Intensive Blue Collar Occupation	.048	.215	.087	.282
Female × Potential Labor Force Experience	3.828	7.904	7.642	10.563
Female × Quadratic Experience Term (/100)	.771	2.060	1.700	3.003
Female × Cubic Experience Term (/1,000)	1.833	6.110	4.307	9.428
Female × Quartic Experience Term (/10,000)	4.837	19.379	11.909	31.123
Female × Tenure at establishment	.187	.542	.496	.987
Observations	2,364,007		2,585,223	

[a]Log annualized mean monthly wage (in current U.S. dollars on December 31).
[b]Including illiterates.

Table 15: Summary Statistics, *RAIS* Worker Data 1997

	Manufact. 1997		Services 1997	
	Mean	St.Dev.	Mean	St.Dev.
	(1)	(2)	(3)	(4)
Log Annual Wage[a]	8.872	.778	8.797	.805
Primary School Education (or less)[b]	.487	.500	.489	.500
Some High School Education	.409	.492	.285	.451
Some College Education	.037	.190	.051	.220
College Graduate	.066	.248	.175	.380
Professional or Managerial Occupation	.072	.259	.169	.375
Technical or Supervisory Occupation	.081	.273	.190	.393
Other White Collar Occupation	.140	.347	.361	.480
Skill Intensive Blue Collar Occupation	.589	.492	.089	.284
Low-skill Intensive Blue Collar Occupation	.117	.322	.191	.393
Potential Labor Force Experience	17.252	9.144	18.002	9.171
Quadratic Experience Term (/100)	3.813	3.406	4.082	3.496
Cubic Experience Term (/1,000)	9.575	11.696	10.433	12.226
Quartic Experience Term (/10,000)	26.140	40.007	28.880	42.441
Tenure at establishment	1.012	1.176	.953	1.163
Female	.256	.436	.480	.500
Female × Log Annual Wage	2.181	3.738	4.180	4.384
Female × Primary School Education (or less)[b]	.123	.328	.240	.427
Female × Some High School Education	.102	.303	.105	.307
Female × Some College Education	.011	.105	.027	.162
Female × College Graduate	.019	.137	.108	.310
Female × Professional or Managerial Occupation	.015	.122	.098	.297
Female × Technical or Supervisory Occupation	.022	.147	.126	.332
Female × Other White Collar Occupation	.058	.234	.167	.373
Female × Skill Intensive Blue Collar Occupation	.128	.334	.005	.072
Female × Low-skill Intensive Blue Collar Occupation	.033	.178	.084	.278
Female × Potential Labor Force Experience	4.134	8.388	8.760	11.118
Female × Quadratic Experience Term (/100)	.874	2.216	2.003	3.214
Female × Cubic Experience Term (/1,000)	2.127	6.614	5.154	10.151
Female × Quartic Experience Term (/10,000)	5.677	21.063	14.346	33.573
Female × Tenure at establishment	.214	.613	.399	.801
Observations	1,837,461		3,204,738	

[a]Log annualized mean monthly wage (in current U.S. dollars on December 31).
[b]Including illiterates.

Table 15: SUMMARY STATISTICS, *RAIS* WORKER DATA 1997, cont'd

	Commerce 1997		Agriculture 1997	
	Mean	St.Dev.	Mean	St.Dev.
	(1)	(2)	(3)	(4)
Log Annual Wage[a]	8.406	.628	8.056	.606
Primary School Education (or less)[b]	.489	.500	.754	.430
Some High School Education	.441	.497	.223	.416
Some College Education	.033	.178	.007	.082
College Graduate	.036	.187	.015	.122
Professional or Managerial Occupation	.057	.232	.035	.184
Technical or Supervisory Occupation	.271	.445	.014	.116
Other White Collar Occupation	.356	.479	.043	.203
Skill Intensive Blue Collar Occupation	.172	.378	.856	.352
Low-skill Intensive Blue Collar Occupation	.143	.350	.053	.224
Potential Labor Force Experience	14.282	9.007	18.064	9.683
Quadratic Experience Term (/100)	2.851	3.067	4.201	3.710
Cubic Experience Term (/1,000)	6.697	10.122	11.058	12.984
Quartic Experience Term (/10,000)	17.536	33.949	31.408	45.020
Tenure at establishment	.531	.672	.711	.920
Female	.375	.484	.156	.363
Female × Log Annual Wage	3.111	4.032	1.224	2.856
Female × Primary School Education (or less)[b]	.199	.399	.118	.322
Female × Some High School Education	.144	.351	.033	.178
Female × Some College Education	.015	.121	.002	.047
Female × College Graduate	.016	.126	.004	.059
Female × Professional or Managerial Occupation	.020	.140	.003	.056
Female × Technical or Supervisory Occupation	.137	.344	.002	.050
Female × Other White Collar Occupation	.170	.376	.015	.121
Female × Skill Intensive Blue Collar Occupation	.013	.113	.126	.332
Female × Low-skill Intensive Blue Collar Occupation	.034	.182	.010	.099
Female × Potential Labor Force Experience	5.137	8.482	2.796	7.566
Female × Quadratic Experience Term (/100)	.983	2.181	.651	2.116
Female × Cubic Experience Term (/1,000)	2.234	6.487	1.716	6.579
Female × Quartic Experience Term (/10,000)	5.722	20.798	4.899	21.656
Female × Tenure at establishment	.188	.455	.093	.367
Observations	1,090,146		262,683	

[a]Log annualized mean monthly wage (in current U.S. dollars on December 31).
[b]Including illiterates.

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