How Segmented is the Bogota Labor Market?

World Bank Staff Working Paper No. 434

October 1980

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The objective of this paper is to clarify the notions of labor market segmentation as they exist in the literature and then to examine the extent to which labor market segmentation can be said to be the cause of income inequality in the Bogota labor market. The paper suggests that, at a minimum, definitions of labor market segmentation should permit identification of who the segmenters are, what the nature of their segmenting actions is and what the effects of these actions are. A review of the literature reveals that few of the used definitions of segmentation measure up to these criteria. The empirical part of the paper first documents the existence of labor market heterogeneity in terms of the usual variables like sex, age, education, migrant status, industry of activity, occupation and location of residence in Bogota. Among male workers in Bogota it is found that workers in different industries do earn different incomes at the same age and education levels, but these differences are not large in magnitude and some differences are not statistically significant. Overall, only a weak correlation appears between income and occupation or industry of employment. Thus if segmentation exists in the sense of different earnings functions for different sets of otherwise equivalent people, only weak evidence is found in Bogota.

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PREFACE

I am pleased to acknowledge helpful discussions and comments on the first draft from Gregory Ingram, Kyu Sik Lee, and Rakesh Mohan of the World Bank and Jorge Ducci, Walter Galenson, and Olivia Mitchell of Cornell University. The views expressed herein are my own and not necessarily those of the World Bank or of Cornell University.

This paper is part of a program of research currently being conducted by the World Bank on Bogota and Cali, Colombia. The goal of the program, entitled The City Study, is to increase our understanding of the workings of five major urban sectors - housing, transport, employment location, labor markets and the public sector - in order that the impact of policies and projects can be assessed more accurately. This paper is part of the labor market and income distribution portion of the study which is coordinated by Rakesh Mohan. Other papers in this series are:

Rakesh Mohan "The People of Bogota: Who They Are, What They Earn, Where They Live". World Bank Staff Working Paper No. 390, May 1980.

Rakesh Mohan and Nancy Hartline "The Poor of Bogota: Who They Are, What They Do, Where They Live." World Bank: City Study Project Paper No. 11, June 1980.

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I. INTRODUCTION

The central question confronting development economists as we enter the 1980's is: "Who benefits how much from economic development and why?" In a book now in press (Fields, forthcoming), I try to inform concerned readers both of the lessons of the past and of the questions which remain to be answered. In addition, specifically for the case of Colombia, I have worked for several years to understand in depth what determines incomes and income inequality. Previous works were summarized in a paper recently completed for the World Bank (Fields, 1978a). The present paper is yet one more contribution to this line of research.

My point of departure is the question: What causes inequality in the distribution of labor market rewards? One answer that is increasingly being offered by analysts at the World Bank and elsewhere is: labor market segmentation.[1/] The purpose of this paper is to evaluate the analytical value of the proposition that labor market segmentation causes income inequality in Bogota.

Notions of labor market segmentation have a long intellectual history. Mill may have been the first to call attention to labor market imperfections with his analysis of non-competing groups. To Mill, these labor market differences were rooted in capital market differences; without collateral one could not get a loan, and without a loan one could not invest in human capital. Thus, the non-competing groups were seen as resulting from institutional barriers to the accumulation of human capital by the poor.

1/ e.g., Selowsky (1979, p.19) writes: "Two basic trends have prevented improvements in the distribution of income over time. One is demographic growth unparalleled in most development experiences; the second has been the emergence of strong tendencies in the economy toward dualism and <u>segmentation in most factor markets</u>..." (emphasis added).

Today, we mean something different by labor market segmentation. One definition, though by no means a universally agreed-upon one, is that labor market segmentation exists when workers face different earnings functions depending on their location in the labor market. In a competitive labor market in full equilibrium, workers with identical education and experience would expect equal earnings for equal hours worked. In a segmented market, workers in the less-favored group earn less than similarly-qualified workers in some other group.

Why do different earnings functions occur? The standard explanation of segmented markets in less developed countries (LDCs) focuses on the determinants of wage structure. For example the government may impose different minimum wage policies on firms in the modern and traditional sectors; modern sector firms are more likely to be unionized; and modern industries may pay higher wages to reduce worker turnover. Add to these such factors as discrimination, nepotism and favoritism, public/private sector differentials, foreign-owned/domestically owned differentials, and individual differences in ability, and we see that the possible reasons for different earnings functions are many.

There are other problems beyond just the differentials in earnings functions. Why don't workers in the lower earning groups enter the high earning labor markets? Why don't employers who pay high wages hire more workers until the value of the marginal product of labor is equal between groups? The issues then are what determines the size of the various groups, what determines different workers' access to employment and income opportunities, and why barriers to mobility among some groups persist over time. The answers to these questions turn on the nature of the groupings themselves.

Some groupings are based on fixed characteristics. Workers in poor countries cannot choose their sex in order to avoid sex discrimination, nor can they choose to be descendents of conquistadores rather than indios, or have parents who are professionals rather than peasants. In these cases, the determinants of group membership are not at issue; the reasons for earnings differentials are. Other groupings are not predetermined. For example, the number of jobs in various occupations and industries, as well as the access of various groups of workers to those jobs, vary with macroeconomic conditions, hiring practices, and the like. All these aspects of group membership are very much of interest to the following discussion, as are differences in earnings functions among these groups.

Part II of this paper formulates the question--how segmented is the Bogota labor market?--more precisely. After establishing criteria for a meaningful definition of segmentation, I evaluate various definitions that have been suggested in the literature, set up an economic model of how personal and employment characteristics interrelate to determine income in a segmented labor market, and formulate an econometric procedure for estimating these relationships.

In writing Part II, I searched for useful approaches in the existing empirical literature on labor market segmentation in developed countries; I reviewed the literature surveys by Gordon (1972), Flanagan (1973), Wachter (1974), Cain (1976), and Jackson, Solomon, et al. (1976), as well as many of the basic sources cited therein. I looked also at the less developed country literature, the two most comprehensive references to which are the works of Kannappan (1977) and Berry and Sabot (1978).[1/] Unfortunately, I was unable to draw much specific guidance from the available literature. I find the proposition that labor market segmentation causes inequality in the U.S. or LDC labor markets to be ill-defined in many existing studies, to have been "proven" with inappropriate evidence, and to be virtually indistinguishable empirically from alternative hypotheses which maintain that inequality arises from still-unmeasured human capital differences among workers, non-uniform utility functions, or compensating differentials. This is not to say that the labor market, in Bogota or elsewhere, is a single unified place with equal opportunity for all and equal outcomes for those who work in it, but rather that appeals to the existing segmentation literature do not get us very far in understanding the inequality and associated wage structures that exist.

Part III then presents the results of an empirical investigation of labor market segmentation in Bogota. I first present basic tabulations and cross-tabulations. Then turning to multiple regression analysis, I review existing studies and present new evidence using single-equation regression models. Next I proceed to different types schemata for segmenting the labor market and running separate earnings functions for workers in the different segments. Three segmentation schema are distinguished and treated empirically in what follows: segmentation by exogenous independent variables, segmentation by endogenous independent variables and segmentation by the dependent variable.

Part IV summarizes the paper's conclusions and discusses topics for further research.

1/ See also Fields (1978b).

II. THEORIES AND DEFINITIONS OF LABOR MARKET SEGMENTATION

A. Criteria for Defining Labor Market Segmentation

The purpose of defining and measuring segmentation is to see to what extent the segmentation concept helps explain the distribution of economic rewards. To be fully satisfactory, any definition of labor market segmentation should at a minimum meet the following criteria:

1. The definition should not be equivalent to the phenomena to be explained. If we are seeking to explain poverty and inequality, segmentation cannot be defined as the existence of poverty and inequality. Tautological "explanations" are not very informative.

2. A satisfactory definition of labor market segmentation must distinguish actions by segmenters which lead to labor market inequality from "justifiable" differences among workers. If persons with the same education and experience are paid more in one industry than another, is this *prima facie* evidence of discriminatory behavior by employers or other actors in the labor markets ? Or does it reflect unmeasured productivity differentials among individuals, attitudinal differences among groups toward work, or the luck that some people have in getting higher-paying jobs when not enough good jobs are available to go around? These latter influences do not constitute labor market segmentation in most people's minds. Hence:

3. The definition of segmentation should in principle permit identification of the segmenter. At minimum, any attempt to invoke segmentation as an explanation for unequal labor market outcomes should distinguish between segmentation which occurs *in* the labor market from

that which occurs prior to the labor market. While lack of educational opportunities for children may contribute to inequality in their earnings as adults, this cannot rightfully be attributed to labor market segmentation. A complete segmentation theory should thus establish who is doing the segmenting. The scheme suggested in Becker's (1957) classic treatment of discrimination--by employers, by employees, and by customers--remains equally relevant a quarter century later. In the development context, a further issue is that the lack of development itself may preclude mobility and cause so-called segmentation.

4. The definition of segmentation should in principle permit identification of how the segmenter effects segmentation. Employers, for example, may discriminate by only hiring persons from a given group. Alternatively, their discrimination may take the form of wage differentials in the "same" job. Either practice might be termed "labor market segmentation." The definition of segmentation should make clear what actions do and do not constitute segmentation.

If the aforementioned criteria are adhered to, segmentation analysis can potentially be of great help in explaining inequality and poverty. But these are stringent requirements seldom approached. Consequently, the potential of segmentation analysis far exceeds its realization to date.

Segmentation concepts have demonstrated beyond any doubt that labor market conditions are not uniform for different groups in the population. If non-uniformity is all we mean by such statements as: "there is labor market segmentation by sex," then "proof" of segmentation is neither surprising nor analytically helpful. However, the claim of segmentation by sex implies other stronger meanings beyond mere differences. Consider the statement: "Employers systematically discriminate against women by hiring identically qualified men preferentially." This is both more precise than the assertion that "there is labor market segmentation by sex" and, if it were true, would be interpreted by many as evidence of segmentation. Likewise, if it were shown that "employers systematically discriminate against women by paying them less than they do to comparably qualified men," this would also be seen as evidence of segmentation. In other words, there are many labor market actions like preferential hiring and wage discrimination, *any one of which* is evidence of segmentation by most definitions. Schematically, this might be indicated as:

$$\left.\begin{array}{c}\text{Action A}\\ \text{or}\\ \text{Action B}\\ \text{or}\\ \text{Action C}\\ \text{or}\\ \vdots\end{array}\right\} \Longrightarrow \text{Labor market segmentation exists.}$$

The literature on segmentation commonly suffers from two errors of logic. For example, wage differences between men and women are *consistent* with labor market segmentation but segmentation may not be inferred from such evidence. This fallacy may be illustrated schematically as:

Evidence consistent with action A

or

Evidence consistent with action B

or

Evidence consistent with action C

or

.
.

$\Longrightarrow$ Labor market segmentation exists

A more subtle fallacy derives from the vagueness of the claim that "labor markets are segmented." If there are 10 actions that constitute segmentation by a particular definition and if only one of those actions is shown to exist, there is still segmentation; it is not valid, however, to infer that all 10 possible actions in fact occur. This flawed reasoning can be illustrated as:

Labor market segmentation exists $\Longrightarrow$

Action A

and

Action B

and

Action C

and

.
.

Alas, the segmentation literature is replete with these very mistakes.

B. Five Suggested Definitions of Segmentation and Associated Tests

To define what segmentation is, it may be helpful to discuss what segmentation is not. In the standard textbook model of a non-segmented (i.e., homogeneous) labor market, (Reynolds, 1978, pp. 84-85):

1. The attractiveness of a job is measured by the wage.
2. All job vacancies are filled through the market.
3. The labor force is homogeneous.
4. There are as many jobs available as there are workers available.
5. Workers and employers are perfectly informed.
6. Vacancies are filled instantaneously.

Thus, supply and demand for labor determine the volume of employment and the wage rate paid. The model assumes that the labor market processes and outcomes are the same for everyone, i.e., that all workers receive the same labor market returns.

The simplest definition of labor market segmentation takes wage equality as the point of departure. Hence, we find in the literature:

Definition (i): Heterogeneity of Outcome.

Heterogeneity of outcome is the essential characteristic of many definitions of labor market segmentation. Indeed, heterogeneity of outcome is sometimes the sole defining characteristic in empirical research. According to Freedman (1976), segmentation is easy to document: professionals earn more than manual laborers; better educated workers receive higher incomes than less educated workers;

unionized industries pay a wage premium over non-unionized ones; urban incomes are higher than rural incomes; and men are paid more than women. By the heterogeneity of outcome definition, these observations are *prima facie* evidence of labor market segmentation.

These definitions and this type of evidence are unsatisfactory. One problem with the heterogeneity of outcome definition is that no attempt is made to standardize for possible compositional differences between groups. In the case of educational differences, allowance should be made for the period of time when the better educated individuals were in school and were not receiving income. As for male-female differences, it is desirable to standardize for length, quality, and continuity of labor market experience. Failure to consider heterogeneity of individuals is an important conceptual deficiency in some writings on segmentation.

More importantly, however, if the concept of segmentation were only to imply that different groups are rewarded differently in the labor market, there would be little controversy over its existence, since equality of outcome obviously does not obtain in modern economies. However, with such a definition, nothing can be explained: the statement "segmentation explains inequality" is a tautology, since by definition (i), segmentation *is* inequality. The definition of labor market segmentation as "heterogeneity of outcome" must therefore be rejected.

In an attempt to improve upon this definition, some writers have proposed:

Definition (ii). Heterogeneity of Outcome Among "Comparable" Workers as a Function of Group in the Labor Market (E.g., Occupation or Industry).

Souza and Tokman (1977), for instance, claim (p. 8): "For segmentation in the labor market to exist, persons with equal abilities ought to receive different incomes depending on the stratum of the productive units in which they work." (Translation mine, emphasis added.) Virtually the same conception is used by Altimir and Piñera (1977). Likewise, Bourguignon (1979, p. 56) regards segmentation as an "imperfection of the labor market or, in other words, the hypothesis that wages in the modern sector are above incomes in the traditional sector" for otherwise identical individuals. (Translation mine.). And, Mazumdar and Ahmed (1977) write (p.1): "A rather stringent definition of labor market segmentation is that a difference in earnings can be attributed to 'institutional' factors after we have allowed for variations in measurable human quality factors like education and experience." 1/

These authors present empirical tests in their respective studies covering several Latin American cities but excluding Bogota (Souza and Tokman), several Latin American countries including Colombia (Altimir and Pinera), several Colombian cities including Bogota (Bourguignon), and several Malaysian cities (Mazumdar and Ahmed). In each study, the empirical test follows the same form: multiple

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1/ Similar definitions of segmentation have been used in the housing market literature. For instance, Schnare and Struyk (1976) regard a housing market as being segmented when the price of an attribute varies with either structural or neighborhood characteristics.

regressions involving "human capital" and "segmentation" variables. After standardizing for measurable human capital factors like education and experience, these authors find that the occupation or industry of employment is associated with wages or incomes. Hence, they conclude that the respective labor markets are segmented to a greater or lesser degree. 1/, 2/

Another kind of empirical test consistent with Definition (ii) appears in the literature. This involves three steps: first stratifying the labor force by a variable thought to segment the labor market, then running separate earnings functions for the two groups, and finally comparing the regression coefficients using an appropriate analysis of variance test. 3/ The literature offers innumerable instances of segmented earnings functions based on such alternative segmentation variables as race, sex, region, occupation, and industry. 4/

1/ Bourguignon sees less segmentation in his evidence than do Souza and Tokman and Mazumdar and Ahmed in theirs. In reading these studies one should be careful to note that the criteria for establishing the existence of segmentation differ from one study to the next.

2/ In their analysis of housing market segmentation, Schnare and Struyk (1976) look at a sample of housing units in the Boston metropolitan area and at various sub-samples defined according to the number of rooms in the house, whether the house is located in an inner or outer suburb, and income. They find that there are statistically significant differences in the effects of various attributes on rent depending on the housing market in question. However, they also note that there is little gain in precision (as measured by the standard error of estimate) when the housing market is stratified by the above-mentioned variables. From this, they conclude that the Boston housing market is not particularly segmented, at least across the range of variables with which they deal.

3/ If the earnings function is a single equation, the appropriate test of equality of regression coefficients is the Chow test described in standard econometrics text, e.g., Johnston (1972). If the earnings model is a multi-equation recursive structure and fits the path-analytical modal of sociologists, the test for the system of equations is given by Specht and Warren (1976).

4/ See Fields and Ducci (forthcoming) for a review of this literature for less developed countries as a whole. The Colombian studies are cited below in Part III.

These approaches might be criticized at several different levels. At this point, I will mention just two of them.

One argument is an empirical problem. Some critics would contend that the included variables (years of schooling and age) fail to capture other important human capital characteristics such as quality of schooling, continuity of experience, extent of on-the-job training, and such personal characteristics as intelligence and motivation. Without statistical controls for these other influences, the possibility remains that workers in the better occupations or industries possess superior human capital which is reflected in their earnings. The missing variables argument clearly contains considerable truth but it can be pushed to the point of nonsense. Those human capital theorists who disbelieve segmentation arguments sometimes go so far as to attribute <u>all</u> of the unexplained earnings differentials to these omitted characteristics. That will not do. It is about as appealing as "explaining" differences in consumer behaviour by a specified but unmeasured list of "taste" differences in utility functions.

The second objection is fundamental. Take occupation and industry as examples of segmentation variables. If occupation or industry is significantly related to income after controlling for personal characteristics, or if different earnings functions are found in different occupations or industries, segmentation is said to exist. A severe interpretation problem arises: Does the test of segmentation "prove" segmentation? If it is established that "segmentation" exists by Definition (ii), what does it imply about the functioning of labor markets? Who are the segmenters? How do they segment the market? Is not the same regression result consistent with both benign and malevolent interpretations?[1/]

The observation that seemingly comparable workers earn more in some employment sectors than in others is consistent with discrimination, screening, and other exclusionary practices; it is also consistent with intersectoral differences in unmeasured working conditions, unmeasured differences among workers in productivity-related characteristics, and heterogeneity in workers' preferences. We have a classic identification problem. The "test" of the phenomenon under study is not a sufficient test--it is a necessary test of a particular kind of segmentation.

Definition (ii) is framed in terms of a symptom which may or may not reflect an underlying pathology: discriminatory barriers to

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1/ Here again, the parallel between the labor market and housing market segmentation literatures may offer insights. Just as Schnare and Struyck sought to claim from evidence of different hedonic prices of housing attributes in different markets that the housing market is segmented, many labor market analysts seek to claim that the labor market is segmented insofar as people in different labor force groups receive different gains in income for each additional year of education depending on their occupation or industry. But in Schnare and Struyk's analysis, and in others to which they refer, no attempt was made to explain why it is that people live in housing markets with higher hedonic prices. If, in fact, land is cheaper in Waltham, or if an extra bedroom costs less in Wellesley, why is this? Are there barriers to mobility? Or is the observed configuration an equilibrium one in the sense that people trade off number of rooms for number of acres? Whether the observed pattern can meaningfully be said to reflect segmentation or not depends on why these differences in prices of land and prices of rooms arise. The same holds for labor market segmentation. The critical questions are why there are different wage structures in some occupations or industries as compared with others and why people work in the particular occupations or industries that they do. The mere finding of differences is not sufficient to establish discrimination against some and in favor of others.

entry into the higher-paying occupations or industries. Besides studying differences in rewards among various groups in the labor market, we thus need to examine differences in access to earnings opportunities. This suggests:

Definition (iii): Heterogeneity of labor market functioning in various submarkets.

Edwards, Reich, and Gordon (1975) write:

> The labor market consists of those institutions which mediate, affect, or determine the purchase and sale of labor power; the labor process consists of the organization and conditioning of the activity of production itself, i.e., the consumption of labor power by the capitalists. Segmentation occurs when the labor market or labor process is divided into separate submarkets or subprocesses or segments, distinguished by different characteristics, behavioral rules, and working conditions. (Emphasis in the original) (p. xi)

This definition has been used in effect by many writers including dualists such as Doeringer and Piore (1971), Bluestone (1970) and Harrison (1972) and radicals such as Wachtel and Betsey (1972) and Bowles and Gintis (1975). This definition of labor market segmentation has the virtue of focusing on the functioning of labor markets; its limitation is that by itself it does not explain why the submarkets or subprocesses are heterogeneous.

Economists suggest many reasons why submarkets might differ: heterogeneity among workers, non-competing groups in the labor force, different non-monetary satisfactions received in different jobs, monopsony elements in the labor market, monopoly elements in the product market, limited and costly information,, limited and costly mobility, and institutional regidities and regulations. Any of these real world deviations from the simple textbook model of labor markets would result in non-uniform labor market processes and unequal outcomes.

While such occurrences suggest the existence of labor market segmentation, we must ask why segments differ. Indeed, segmentation theorists would have us believe that labor markets function in particularly restrictive ways, i.e., that some individuals are prevented from entering a preferred occupation, moving to a higher paying location, acquiring further education and training, or in some other way improving their economic position.

This suggests another, more specific definition:

Definition (iv). Limited access to good jobs.

A "good job"might be characterized by security, high wages, safe and pleasant working conditions, and/or opportunities for training and advancement. When good jobs are limited in number, "the crux of any theory of labor market segmentation is the mechanism or institutional barriers which truncate competition by precluding mobility between the various labor market segments" (Flanagan 1973, p. 253).

A particularly well-known segmentation theory is the dual labor market approach advanced by Doeringer and Piore (1971). As described by Wachter (1974), the dual labor market model advances four hypotheses:

> First, it is useful to dichotomize the economy into a primary and secondary sector, Second, the wage and employment mechanisms in the secondary sector are distinct from those in the primary sector. Third, economic mobility between these two sectors is sharply limited, and hence workers in the secondary sector are essentially trapped there. Finally, the secondary sector is marked by pervasive underemployment because workers who could be trained for skilled jobs at no more than the usual cost are confined to unskilled jobs. (p. 639).

The critical question that still remains, however, is what limits mobility from the secondary to the primary sector. Since good jobs are not available for all, they must be rationed. This suggests another possible definition:

Definition (v): Non-random access to the available jobs.

This definition is used in effect whenever one looks at the proportions of workers from particular groups (e.g., racial, sex, regional) who work in different kinds of jobs. Definition (v) differs from Definition (iv) in that it is concerned not just with different outcomes but with systematically different opportunities; it also takes as given that good jobs are limited in number. Definition (v) concentrates our attention on the rules by which the limited jobs are rationed. If the rationing is found to be at least partly systematic we may then examine why some groups of workers and not others have access to certain jobs.

Even now, I worry about using Definition (v) and calling the result "labor market segmentation." In an LDC, good jobs are scarce and must be allocated among would-be employees. What if differences in access among groups of workers are purely productivity based? Partly productivity-based? Not productivity-based at all. Should all non-random rationing of good jobs be considered segmentation? We have come to the same identification problem as before: the same phenomenon (non-random job access may result from varying causes, some discriminatory, some not). Regardless of whether we term the outcome segmentation or not, we have reached another researchable question: what labor market practices determine which groups get the available jobs?

Taken together definitions (ii) and (v) are the most helpful concepts of labor market segmentation yet devised because they direct our attention toward the actual wage- and employment-determination mechanisms in labor markets. They take the first step toward explaining why intergroup labor market differentials exist by showing that intergroup labor market differentials exist in particular dimensions.

This focus on real world labor market functioning, as distinct from knee-jerk applications of stylized textbook models, explains much of the appeal of theories of segmented labor markets. Segmentation theorists address fundamental questions about the operation of the labor market and of the economic system more generally. Why do some persons have better opportunities than others? Why is discrimination in the economic system perpetuated? Why is poverty transmitted across generations? Why do labor movements in many countries accept the legitimacy of the prevailing economic order? These and other root questions about the operation of labor markets have not received much attention among orthodox economists. As Gordon (1972) writes (p. 14): "Orthodox analysis... tended to take market structure for granted and probe the determinants of behaviour within those given structures. Some economists sought to develop economic models which dealt directly with these basic concerns about the relationship between labor market structure and income." This suggests that the heart of the distinction between orthodox theories of labor markets and segmentation theories may well lie in the nature of the questions that they address rather than in the way of conceptualizing the behavior of individuals and firms.

C. The Framework for Modelling a Segmented Labor Market

The preceding definitions of labor market segmentation direct our attention to the determinants of income and sector of employment as functions of other individual and environmental characteristics. To estimate the relationship among these variables in Bogota, we require a model of how the labor market might be segmented.

Eight alternative models are presented in Table 1. They employ the following notation:

Y = Income of the Individual

PERSCHAR = A vector of personal characteristics (e.g., education, age, migrant status, sex)

JOBCHAR = A vector of job characteristics (e.g., occupation, industry)

x = Other exogenous variables

ε = Error term.

The components of the PERSHAR and JOBCHAR vectors may differ in the two stages of the multi-equation models.

TABLE 1.

Eight Models of a Segmented Labor Market

Model Number and Name	Model Description	Form of Model
Model 1. Single Equation Structural Estimation, Linear Specification, Full Sample.	Income as a linear combination of personal and job characteristics.	$Y = \alpha + \beta$ PERSCHAR $+ \gamma$ JOBCHAR $+ \varepsilon$.
Model 2. Single Equation Structural Estimation, Linear Specification, Exogenous Subsamples.	Income as a linear combination of a subset of personal and job characteristics, other exogenous personal characteristics stratified for (e.g., sex).	$Y_i = \alpha_i + \beta_i$ PERSCHAR $+ \gamma_i$ JOBCHAR $+ \varepsilon_i$, Separate equations for various subsamples i.
Model 3. Single Equation Structural Estimation, Interactive Specification.	Income as a non-linear combination of personal and job characteristics.	$Y = \alpha + \beta$ PERSCHAR $*$ JOBCHAR $+ \varepsilon$.
Model 4. Single Equation Reduced Form Estimation.	Income as a function of personal characteristics only.	$Y = \alpha + \beta$ PERSCHAR $+ \varepsilon$.
Model 5. Multi-Equation Recursive Structure, Independent Errors.	Job as a function of personal characteristics; income as a function of job and personal characteristics; errors in the two equations independent.	JOB $= \alpha_1 + \beta_1$ PERSCHAR $+ \varepsilon_1$; $Y = \alpha_2 + \beta_2$ PERSCHAR $+ \gamma_2$ JOBCHAR $+ \varepsilon_2$; $COV(\varepsilon_1, \varepsilon_2) = 0$.
Model 6. Multi-Equation Recursive Structure, Dependent Errors.	Like Model 5 except errors in the two equations are dependent.	JOB $= \alpha_1 + \beta_1$ PERSCHAR $+ \varepsilon_1$; $Y = \alpha_2 + \beta_2$ PERSCHAR $+ \gamma_2$ JOBCHAR $+ \varepsilon_2$; $COV(\varepsilon_1, \varepsilon_2) \neq 0$.

Continued on next page

TABLE 1. continued

Eight Models of a Segmented Labor Market

Model Number and Name	Model Description	Form of Model
Model 7. Multi-Equation Structure Stratified by JOB.	One set of equations determining income within job groupings (e.g., occupations); a second set of equations determining job grouping.	$Y = \alpha_i + \beta_i$ PERSCHAR $+ \varepsilon_i$ for JOB i, JOB $= \eta + \theta X + \varepsilon$.
Model 8. Multi-Equation Structure Stratified by INCOME.	One set of equations determining income within an income grouping (e.g., poor versus non-poor); a second set of equations determining income grouping.	$Y = \alpha_i + \beta_i$ PERSCHAR $+ \varepsilon_i$ for INCOME GROUP i; INCOME GROUP $= \eta + \theta$ PERSCHAR $+ \varepsilon$.

The choice among these alternative models must be determined by two kinds of considerations: the characteristics of the labor market under investigation, and econometric theory.

To model the Bogota labor market, I conceptualize the interrelationships among income, occupation and industry, place of residence, and personal characeristics in the following ways:

(i) For workers of either sex, income depends directly on education, age, migrant status, industry, occupation, and residential sector.

(ii) Given a choice between two industries or occupations with different average rates of pay, individuals tend to choose the higher-paying one.

(iii) The likelihood of being offered a job in a high-paying industry or occupation is a function of the individual's personal characteristics and sector of residence.

(iv) **Within** an occupation or industry, incomes vary with education, age, and migrant status.

(v) The sector of residence is affected by income (i.e., a higher income tends to lead to residence in a high-income sector) and by education, age, and migrant status.

(vi) The individual's education, age, and migrant status are exogenous.

(vii) The average income in an industry or occupation is exogenous.

These seven propositions should be regarded as informed hypotheses; some are dubious and are included for purposes of completeness. In particular, one concern of the Bogota City Study is to test for possible spatial effects on economic status. Thus, Propositions (i) and (iii) allow for a direct role for residential location in determining income, industry, and occupation. In addition, although it is hypothesized that migrant status has both a direct role and an indirect role via occupation and industry, recent research findings by Jaramillo (1979) suggest that these effects may be insignificant.

The blocks in figure 1, depicting Bogota's labor market, indicate factors which are treated identically in the econometric estimation, where:

Y = Individual's income

EDUC = Individual's education

AGE = Individual's age

MIG = Individual's migrant status

$\overline{Y}_{IND}$ = Average incomes in each of M industries for individuals like i

$\overline{Y}_{OCCUP}$ = Average incomes in each of N occupations for individuals like i

IND = An M-dimensional vector of industries, one of which employs the individual

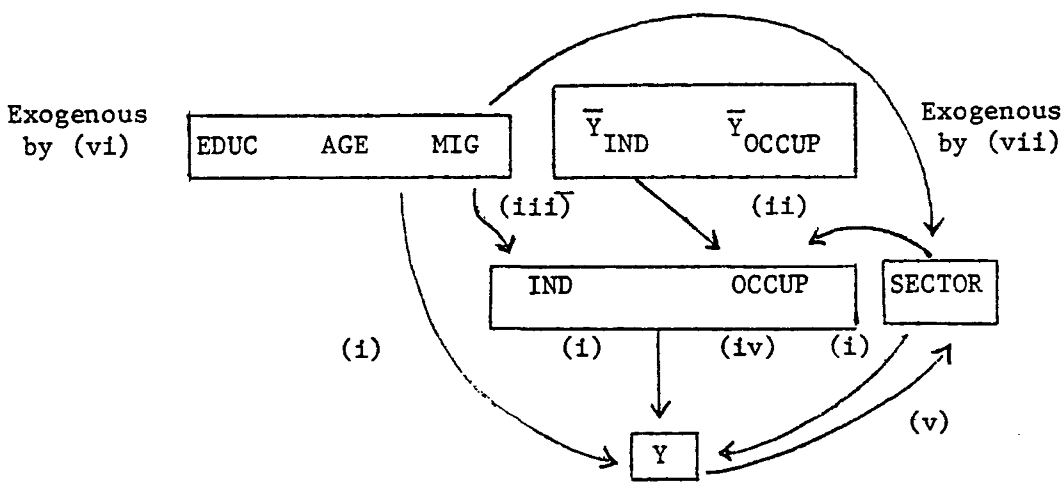
OCCUP = An N-dimensional vector of occupations, one of which employs the individual

SECTOR = A P-dimensional vector of residential locations, in one of which the individual lives.

Arrows depict causal structure. Lower case Roman numerals show how each proposition listed above enters the model.

Figure 1

CAUSAL ORDERING OF MODEL OF BOGOTA LABOR MARKET



The causal ordering illustrated in Figure 1 makes clear that there are four simultaneous equations and four endogenous variables:

(1) $Y = f\ (EDUC,\ AGE,\ MIG,\ IND,\ OCCUP,\ SECTOR)$

(2) $IND = g\ (EDUC,\ AGE,\ MIG,\ SECTOR,\ \overline{Y}_{IND})$

(3) $OCCUP = h\ (EDUC,\ AGE,\ MIG,\ SECTOR,\ \overline{Y}_{OCCUP})$

(4) $SECTOR = i\ (EDUC,\ AGE,\ MIG,\ Y)$

D. Econometric Issues

An examination of equations (1) - (4) reveals that the structure is a fully-simultaneous one --- each equation has at least one endogenous factor included as an explanatory variable on the right hand side.

Although ordinary multiple regressions frequently are used on such models, the resultant estimates suffer from simultaneous equations bias because of the endogeneity of the explanatory variables. To avoid these biases, the alternatives are either to include additional explanatory factors and apply simultaneous equations methods or to assume the absence of some of the simultaneity-producing effects shown in Figure 1. I follow the second course.

The most troublesome variable in our structure is sector of residence. Sector of residence enters the model in two ways: as a determinant of economic position (opportunities may depend upon place of residence) and as an outcome of economic position (higher income workers can affortd to live in better places). From my own experience in Bogota, I would suggest that the latter relationship is much the more important one.1/ If we regard sector of residence as a relatively unimportant determinant of income, industry, and occupation, a facilitating assumption is that those effects are absent entirely. That assumption produces a recursive model structure: education, age, and migrant status determine industry and occupation; industry and occupation along with the aforementioned variables determine income; income and the aforementioned variables determine sector of residence.

The empirical section below reports estimates of various of the income equations.

1/ Mohan also regards this as important: "It may be hypothesized that people in the poorer sectors have lower expectations of improvement (in income) over time: indeed they probably move to the richer sectors (of the city) if they do gain in income."

III. STATISTICAL AND ECONOMETRIC TESTS

The statistical and econometric work for Bogota is based on a sample of more than 66,000 persons, derived from the 1973 Census of Population. 1/ Persons over the age of 12 who reported that they had worked in the week preceding the Census and those who did not work but who had a job in that week were defined as workers. This group includes more than just wage and salary employees.

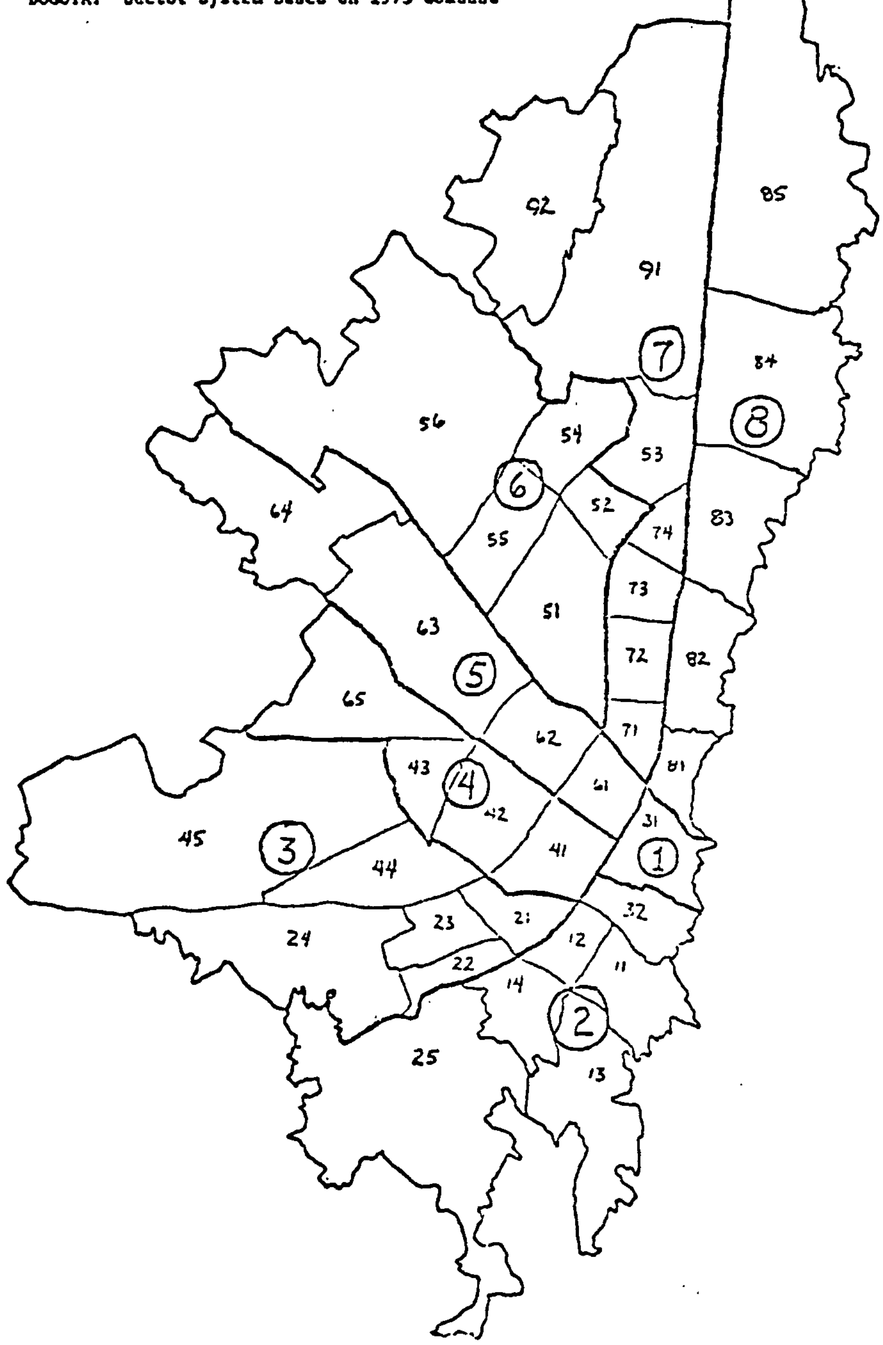
The variables used in the study are defined as follows:

LOGY	= Logarithm (natural) of worker's monthly income in pesos.
EDUC	= Coded into five categories: None; primary (some or all); secondary (some or all); higher (some or all); some education, level not ascertained.
AGE	= In years.
SEX	= Male or female.
MIG	= "Migrant," defined as an individual born outside Bogota.
INDUSTRY	= Coded into six categories: manufacturing; agriculture and mining; construction; commerce; services; other.
OCCUPATION	= Coded into seven categories: professional, technical and managerial; clerical; sales; production; construction and transport; services; other.
SECTOR OF RESIDENCE	= Divided into 8 sectors: see Figure 2.

1/ The sample of workers and the definitions of the several variables are as in Mohan (1979). The regression results reported below exclude from the sample zero-income workers, i.e., those individuals who reported themselves as having a job but who did not have income.

FIGURE 2

BOGOTA: Sector System Based on 1973 Comunas



A. Basic Tabulations and Cross-Tabulations[1/]

This section presents tabular evidence on income differentials among workers with different personal characteristics in different kinds of jobs and on the numbers of workers with different characteristics found in each job category. I would hardly claim to be the first to report such differentials. The earlier sources include studies by Prieto (1971), Isaza and Ortega (1971), Berry and Urrutia (1976), Musgrove (1978), and Mohan (1979) among others. I first present a simple table giving average incomes of workers in Bogota by various characteristics. That is followed by twelve cross-tabulations which examine interactions among these characteristics, along with a short discussion of each. Each cross-tabulation includes a cell count, the average income among workers in that cell, and row and column percentages. As a guide to what follows, the order in which the variables are included in the various cross-tabulations is:

TABLE NUMBER CORRESPONDING TO CROSSTABULATION

Characteristic	Characteristic			
	Sex	Age	Migrant Status	Education
Occupation	3	6	9	12
Industry	4	7	10	13
Sector of Residence	5	8	11	14

1/ All tabulations are based on weighted data, the weights adjusting for varying sampling ratios in various neighborhoods (comunas) of the city.

Some of the more interesting questions concerning the various patterns and the empirical answers to those questions are highlighted for easy reference. Further results from multivariate analysis are presented in later sections. To anticipate the results, the main conclusion from this section is:

If "labor market segmentation" is defined as "inequality of outcomes" (Definition (i)), then the Bogota labor market is segmented. However, since this is not a satisfactory definition of segmentation, the proposition that the Bogota labor market is segmented awaits more sophisticated formulations and tests.

1. Question: How do incomes of workers in Bogota vary by sex, age, education, migrant status, occupation, industry, and sector of residence in the city? (Table 2)

The evidence shows:

1. Men earn more than women;

2. Income rises with age in the cross section until the age category 45-54, at which point incomes are two-thirds higher than average;

3. Income increases with education, so that workers with higher education earn more than eleven times as much as the uneducated;

4. Migrants to Bogota on average earn about 15% less than workers who were born there;

5. Occupation is associated with income, e.g., administrators and managers have incomes five times as high as the average, while maids earn only one-fourth of the average;

6. Industry is associated with income, e. g., workers in finance, public instruction, and mining industries earn about twice the average income, while workers in personal and domestic service earn one-fourth the average;

7. Average income is four times greater in the highest income sector than in the lowest income sector.

TABLE 2

MEAN INCOMES OF WORKERS IN BOGOTA BY VARIOUS CHARACTERISTICS, 1973
(1973 pesos per month)

<u>Sex</u>	
Males	2159
Females	1027
Both sexes	(1775)
<u>Age</u>	
12-14	270
15-24	929
25-34	1865
35-44	2436
45-54	2897
55-64	2837
65 & over	2604
All ages	(1775)
<u>Education</u>	
None	604
Primary	984
Secondary	2158
Higher	7083
All education groups	(1775)
<u>Migrant Status</u>	
Migrant	1699
Native	2007
Both groups	(1775)
<u>Occupation</u>	
Professional & technical	4990
Admin & manager	8827
Clerk & typist	1962
Sales Manag., proprietor	3020
Other sales	1642
Service work, not maid	1109
Maid	373
Agriculture	2715
Prod. supervisors	1205
Prod. workers	1182
Construction workers	966
Transport workers	1389
Other	701
All occupation	(1790)
<u>Industry</u>	
Agriculture	3869
Mining	4056
Food prod., bev., tobacco	1545
Textiles & footwear	1318
Lumber & wood	1308
Paper, printing, publishing	1900
Mineral prod.	1492
Chem & petrochem	2497

TABLE 2 Continued

Industry Continued	
Metal ind	1827
Other ind	1857
Utilities	2487
Construction	1277
Wholesale trade	3421
Retail trade	2115
Other commerce	3169
Trans & communication	2578
Financial est	4638
Public adm., soc serv	3247
Public instruction	3684
Personal & domestic service	577
All industries	(1999)
Sector of the City	
Sector 1	1499
Sector 2	1066
Sector 3	1327
Sector 4	1536
Sector 5	1659
Sector 6	1530
Sector 7	2638
Sector 8	3940
All sectors	(1775)

Note: Overall averages differ accross characteristics because of differential non-reporting.

The simple tabulations may be open to misinterpretation. For example, in itself, the finding that natives of Bogota earn more than migrants might be considered evidence that migrant workers are disadvantaged in the Bogota labor force. Migrants are disproportionately young, however, and young workers have lower-paying occupations more often than prime age workers do, on average. It is therefore possible that migrants and natives earn the same within occupations but that the occupational mix differs for the two groups. If the occupational mix does differ, it may be because of age differences between the migrant and native populations or for some other reason. The question here is whether comparable workers receive different incomes in Bogota depending on whether they are migrants or natives, a question that cannot be answered by simple tabulations. Multivariate questions like this require finer breakdowns, which now follow.

2. Question: Do men earn more than women in Bogota because: a) men are disproportionately in higher-paying occupations? b) men earn more within any given occupation? or c) both? [Table 3]

Answer: Both, with more weight to the latter.

As Table 3 demonstrates, men in Bogota earn more than twice as much as women on average. Part of this difference is due to the fact that men are more likely to be administrators and managers, production workers, construction workers, and transport workers, while women are much more likely to be service workers, maids, and clerks and typists. Since administrators and managers and clerks and typists receive above average incomes, the occupational mix by sex does not clearly

TABLE 3.

CROSS-TABULATION: OCCUPATION BY SEX

	MALE	FEMALE	TOTAL	
	36226.1	17785.1	54011.2	COUNT
PROFESS	67.07	32.93	100.00	PROW
& TECH	8.33	8.01	8.22	PCOL
	6033.5	2739.5	4989.1	MEAN, INCOME
	9268.1	1055.9	10324.0	COUNT
ADMIN &	89.77	10.23	100.00	PROW
MANAGER	2.13	0.48	1.57	PCOL
	9412.3	3592.1	8827.2	MEAN, INCOME
	44639.0	38833.2	83472.2	COUNT
CLERK &	53.48	46.52	100.00	PROW
TYPISTS	10.26	17.49	12.70	PCOL
	2137.9	1760.6	1962.4	MEAN, INCOME
SALES MA	33983.7	8482.1	42465.8	COUNT
NAG.PROP	80.03	19.97	100.00	PROW
RIETOR	7.81	3.82	6.46	PCOL
	3339.1	1740.9	3019.9	MEAN, INCOME
	37445.1	17516.2	54961.3	COUNT
OTHER	68.13	31.87	100.00	PROW
SALES	8.61	7.89	8.36	PCOL
	2062.5	743.9	1642.2	MEAN, INCOME
SERV	30722.2	31311.1	62033.3	COUNT
WORK.NOT	49.53	50.47	100.00	PROW
MAID	7.06	14.10	9.44	PCOL
	1417.1	806.9	1109.1	MEAN, INCOME
	2089.8	66976.4	69066.1	COUNT
MAIDS	3.03	96.97	100.00	PROW
	0.48	30.16	10.51	PCOL
	564.0	366.9	372.8	MEAN, INCOME
	8313.9	448.2	8762.1	COUNT
AGRICULT	94.88	5.12	100.00	PROW
URE	1.91	0.20	1.33	PCOL
	2695.4	3031.8	2715.4	MEAN, INCOME
	22200.7	7730.0	29930.7	COUNT
PROD SUP	74.17	25.83	100.00	PROW
ERVISORS	5.10	3.48	4.55	PCOL
	1328.0	853.1	1205.3	MEAN, INCOME
	118080.8	31397.5	149478.3	COUNT
PROD	79.00	21.00	100.00	PROW
WORKERS	27.14	14.14	22.74	PCOL
	1281.1	808.9	1181.9	MEAN, INCOME
CONSTRUC	46929.2	258.1	47187.4	COUNT
T WORKER	99.45	0.55	100.00	PROW
S	10.78	0.12	7.18	PCOL
	968.6	486.8	966.0	MEAN, INCOME
TRANSPOR	36258.1	118.1	36376.2	COUNT
T WORKER	99.68	0.32	100.00	PROW
S	8.33	.532E-01	5.53	PCOL
	1388.5	1407.9	1388.6	MEAN, INCOME
	8983.6	156.2	9139.8	COUNT
OTHER	98.29	1.71	100.00	PROW
	2.06	.703E-01	1.39	PCOL
	702.7	597.4	700.9	MEAN, INCOME
	435140.4	222068.2	657209.6	COUNT
TOTAL	66.21	33.79	100.00	PROW
	100.00	100.00	100.00	PCOL
	2169.7	1046.3	1790.1	MEAN, INCOME
	59213.7	31570.8	90784.5	COUNT
NO INFO	65.22	34.78	100.00	PROW
	-	-	-	PCOL
	2082.0	887.0	1666.4	MEAN, INCOME

favor men. Hence, differences between men and women in occupational distribution do not account for the bulk of the difference in average income. 1/ It appears rather that income disparities by sex within these occupational groups must therefore account for the overall differential. For most occupational groups (except for clerks and typists, transport workers, and agricultural workers who comprise 20% of the labor force) men's earnings are at least 50% higher than women's.

3. Question: Do men earn more than women in Bogota because: a) men are disproportionately in higher-paying industries? b) men earn more within any given industry? or c) both? [Table 4]

Answer: Both, with substantial weight to each.

Men in Bogota do, in fact, work disproportionately more in the higher income industries. The five highest-paying industries shown in table 4, are finance (mean income = 5,634), mining (4,056), agriculture (3,869), public instruction (3,684), and wholesale trade (3,421), compared with an average income of 1,999. The proportions of men in these five industries are 70%, 91%, 90%, 42%, and 73%, respectively, as compared with 64% of men in the Bogota labor force overall. Public instruction is the only high-paying industry with a

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1/ Unlike the United States, where sex segregation is widely claimed as the explanation for male-female income differences. See Kahne (1975) and Lloyd (1975) for extensive bibliographies.

TABLE 4.

CROSS-TABULATION: INDUSTRY BY SEX

	MALE	FEMALE	TOTAL	
	6957.6	787.5	7745.1	COUNT
AGRICULT	89.83	10.17	100.00	PROW
URE	2.39	0.49	1.71	PCOL
	4028.6	2458.8	3869.0	MEAN, INCOME
	1948.2	193.9	2142.1	COUNT
MINING	90.95	9.05	100.00	PROW
	0.67	0.12	0.47	PCOL
	4060.2	4013.5	4056.0	MEAN, INCOME
FOOD	16947.8	6433.7	23381.5	COUNT
PROD.BEV	72.48	27.52	100.00	PROW
TABAC	5.82	3.98	5.17	PCOL
	1783.0	917.6	1544.9	MEAN, INCOME
TEXTILES	23519.5	24768.5	48337.0	COUNT
&	48.81	51.19	100.00	PROW
FOOTWEAR	8.12	15.33	10.69	PCOL
	1728.6	925.9	1317.7	MEAN, INCOME
	12742.4	738.5	13480.9	COUNT
LUMBER &	94.52	5.48	100.00	PROW
WOOD	4.38	0.46	2.98	PCOL
	1335.2	840.6	1308.1	MEAN, INCOME
PAPER,	7965.5	2975.2	10940.7	COUNT
PRINTING	72.81	27.19	100.00	PROW
PUBLISH	2.74	1.84	2.42	PCOL
	2249.8	1043.1	1899.8	MEAN, INCOME
	5149.9	1073.8	6223.7	COUNT
MINERAL	82.75	17.25	100.00	PROW
PROD	1.77	0.66	1.38	PCOL
	1624.7	852.1	1491.4	MEAN, INCOME
INDUS	9367.2	5548.3	14915.5	COUNT
CHEM	62.80	37.20	100.00	PROW
PETRO	3.22	3.43	3.30	PCOL
	3202.7	1304.7	2496.7	MEAN, INCOME
	24692.1	3626.2	28318.3	COUNT
METAL	87.19	12.81	100.00	PROW
INDUSTRY	8.48	2.24	6.26	PCOL
	1909.4	1266.5	1827.1	MEAN, INCOME
	14129.1	5584.7	19713.8	COUNT
OTHER	71.67	28.33	100.00	PROW
INDUSTRY	4.85	3.46	4.36	PCOL
	2146.9	1122.8	1856.8	MEAN, INCOME
	3302.1	419.4	3721.6	COUNT
UTILI	88.73	11.27	100.00	PROW
TIES	1.13	0.26	0.82	PCOL
	2562.7	1885.7	2486.4	MEAN, INCOME
	51967.0	1198.8	53165.8	COUNT
CONSTRUC	97.75	2.25	100.00	PROW
TION	17.86	0.74	11.75	PCOL
	1268.7	1631.5	1276.9	MEAN, INCOME
WHOLE	6518.8	2466.6	8985.4	COUNT
SALE	72.55	27.45	100.00	PROW
TRADE	2.24	1.53	1.99	PCOL
	3989.8	2185.3	3421.2	MEAN, INCOME
	23564.3	10634.2	34198.4	COUNT
RETAIL	68.90	31.10	100.00	PROW
TRADE	8.10	6.58	7.56	PCOL
	2579.1	1087.5	2115.3	MEAN, INCOME
	12559.6	7354.8	19914.4	COUNT
OTHER	63.07	36.93	100.00	PROW
COMMERCE	4.32	4.55	4.40	PCOL
	4323.6	1196.8	3168.8	MEAN, INCOME
TRANS &	15712.7	2029.3	17742.1	COUNT
COMMUNIC	88.56	11.44	100.00	PROW
ATION	5.40	1.26	3.92	PCOL
	2631.0	2165.9	2577.8	MEAN, INCOME
	13859.8	5925.8	19786.6	COUNT
FINAN-	70.05	29.95	100.00	PROW
CIAL EST	4.76	3.67	4.37	PCOL
	5634.4	2307.2	4637.7	MEAN, INCOME
PUBLIC	16389.1	6281.9	22671.1	COUNT
ADM.SOC	72.29	27.71	100.00	PROW
SERV	5.63	3.89	5.01	PCOL
	3650.1	2195.2	3247.0	MEAN, INCOME
PUBLIC I	11397.7	15246.1	26643.8	COUNT
NSTRUCTI	42.78	57.22	100.00	PROW
ON	3.92	9.44	5.89	PCOL
	5523.7	2309.1	3684.2	MEAN, INCOME
PERSNL &	12233.9	58282.8	70516.7	COUNT
DOMESTIC	17.35	82.65	100.00	PROW
SERV	4.20	36.07	15.58	PCOL
	1478.3	387.6	576.8	MEAN, INCOME
	291023.3	161571.2	452594.5	COUNT
TOTAL	64.30	35.70	100.00	PROW
	100.00	100.00	100.00	PCOL
	2517.5	1067.3	1999.8	MEAN, INCOME
	203339.8	92067.8	295399.6	COUNT
NO INFO	68.83	31.17	100.00	PROW
	-	-	-	PCOL
	1646.5	954.9	1430.9	MEAN, INCOME

below average share of men. On the other hand, the lowest paying industry--personal and domestic service -- has just 17% male workers. In addition, men often earn twice as much as women within an industry. The two exceptions to this generalization are construction, where women's average incomes are higher than men's, and mining, where incomes are virtually identical. In these cases it is likely that the few women in the construction and mining industries are disproportionately in non-manual occupations, e.g., secretarial work, which are higher-paying.

4. Question: a) Do male workers' incomes vary by sector of residence? b) Do female workers' incomes vary by sector of residence, and if so, how? c) Does the male-female income ratio vary by sector of residence, and if so, how? [Table 5]

Answers: Males' incomes, females' incomes, and the male-female income ratio all are highest in the high income sectors.

Not surprinsingly, the data in Table 5 indicate that both men and women who live in the high income sectors of Bogota earn more. Among males, the income ratio between Sector 8 and Sector 2 is more than five to one. Although women's income also vary by sector, intersectoral differences are smaller -- the average in Sector 8 is a little more than twice that in Sector 2. Male-female income ratios rise monotonically with sector income as indicated below.

Sector Number	Average Income	Male-Female Income Ratio
2	1066	1.67
3	1327	1.71
1	1498	1.80
6	1530	1.88
4	1536	1.94
5	1659	1.97
7	2638	2.81
8	3940	4.45

TABLE 5.

CROSS-TABULATION: SECTOR OF RESIDENCE BY SEX.

	MALE	FEMALE	TOTAL	
	14171.	8090.	22261.	COUNT
SECTOR 1	63.66	36.34	100.00	PROW
	2.87	3.19	2.98	PCOL
	1787.2	994.6	1499.1	MEAN, INCOME
	91005.	36251.	127256.	COUNT
SECTOR 2	71.51	28.49	100.00	PROW
	18.41	14.29	17.01	PCOL
	1202.7	721.4	1065.6	MEAN, INCOME
	124757.	52074.	176831.	COUNT
SECTOR 3	70.55	29.45	100.00	PROW
	25.24	20.53	23.64	PCOL
	1511.0	885.4	1326.8	MEAN, INCOME
	48509.	22673.	71182.	COUNT
SECTOR 4	68.15	31.85	100.00	PROW
	9.81	8.94	9.52	PCOL
	1815.9	935.6	1535.5	MEAN, INCOME
	37281.	17629.	54910.	COUNT
SECTOR 5	67.89	32.11	100.00	PROW
	7.54	6.95	7.34	PCOL
	1971.2	997.8	1658.7	MEAN, INCOME
	85278.	41371.	126648.	COUNT
SECTOR 6	67.33	32.67	100.00	PROW
	17.25	16.31	16.93	PCOL
	1806.5	960.1	1530.0	MEAN, INCOME
	60026.	44006.	104032.	COUNT
SECTOR 7	57.70	42.30	100.00	PROW
	12.14	17.35	13.91	PCOL
	3627.2	1289.2	2638.2	MEAN, INCOME
	33327.	31545.	64872.	COUNT
SECTOR 8	51.37	48.63	100.00	PROW
	6.74	12.44	8.67	PCOL
	6324.6	1420.3	3939.9	MEAN, INCOME
	494354.	253639.	747993.	COUNT
TOTAL	66.09	33.91	100.00	PROW
	100.00	100.00	100.00	PCOL
	2159.2	1026.5	1775.1	MEAN, INCOME

This rising differential has at least two explanations: women in high income families are more selective about the kind of work they are willing to perform, and low income females often work as maids in high income neighborhoods. This is reflected in the disproportionately large percentages of females in the high income sectors.

5. and 6. Questions: a) How do the occupational and and industrial distributions differ by age? b) Does income increase more with age in some occupations and industries than in others? [Tables 6 and 7]

Answers: a) Young workers are more at the extremes. b) Yes, larger gains in the better occupations, less pronounced patterns by industry.

The most noticeable difference in occupational distributions by age, shown in Table 6, is that younger workers are found disproportionately at the extremes of the distribution. On the one hand, we see that 34% of the workers in Bogota are between 15 and 24 years old, and 51% of the maids are that age group. On the other hand, while 31% of the workers are between the ages of 25 and 34, that age group comprises 40% of professional and technical workers, 34% of administrators and managers, 35% of production supervisors, and 41% of transport workers. Similar patterns occur by industry.

Concerning the question of income gains with age within occupations or industries, differences are apparent. In the cross section, the peak income for professional and technical workers is four times higher than starting incomes, and other high level

TABLE 6.

CROSS-TABULATION: OCCUPATION BY AGE

	(12,14)	(15,24)	(25,34)	(35,44)	(45,54)	(55,64)	(65,99)	TOTAL	
	65.6	11274.8	21530.8	11145.0	6554.5	2521.0	919.5	54011.2	COUNT
PROFESS	0.12	20.87	39.86	20.63	12.14	4.67	1.70	100.00	PROW
& TECH	0.60	5.06	10.51	9.34	10.06	9.72	10.96	8.22	PCOL
	1288.67	2093.74	4388.52	6761.93	7876.98	6577.59	8390.54	4989.12	MEAN, INCOME
	9.7	994.6	3497.2	2882.1	1910.5	847.9	182.0	10324.0	COUNT
ADMIN &	.940E-01	9.63	33.87	27.92	18.51	8.21	1.76	100.00	PROW
MANAGER	.895E-01	0.45	1.71	2.41	2.93	3.27	2.17	1.57	PCOL
	0.00	2674.36	6862.12	10355.21	12015.84	12085.27	7833.87	8827.22	MEAN, INCOME
	685.3	38177.4	26836.1	10635.2	5210.1	1470.3	457.8	83472.2	COUNT
CLERK &	0.82	45.74	32.15	12.74	6.24	1.76	0.55	100.00	PROW
TYPISTS	6.32	17.15	13.10	8.91	7.99	5.67	5.46	12.70	PCOL
	616.88	1330.43	2202.90	2662.49	3579.56	3316.81	3553.41	1962.35	MEAN, INCOME
SALES MA	230.7	7725.7	12489.8	10435.0	6922.2	3507.5	1154.9	42465.8	COUNT
NAG,PROP	0.54	18.19	29.41	24.57	16.30	8.26	2.72	100.00	PROW
RIETOR	2.13	3.47	6.10	8.74	10.62	13.52	13.76	6.46	PCOL
	300.06	1412.15	2405.90	3623.48	4712.15	3933.69	2586.79	3019.91	MEAN, INCOME
	844.5	21779.0	16594.0	8497.9	4293.9	2159.3	792.9	54961.3	COUNT
OTHER	1.54	39.63	30.19	15.46	7.81	3.93	1.44	100.00	PROW
SALES	7.79	9.78	8.10	7.12	6.59	8.32	9.45	8.36	PCOL
	265.52	899.86	2113.53	2327.87	2485.36	1908.08	997.28	1642.22	MEAN, INCOME
SERV	503.1	16512.7	20512.1	14048.7	7331.9	2357.3	767.5	62033.3	COUNT
WORK,NOT	0.81	26.62	33.07	22.65	11.82	3.80	1.24	100.00	PROW
MAID	4.64	7.42	10.01	11.77	11.25	9.09	9.15	9.44	PCOL
	223.77	780.68	1012.68	1250.07	1301.20	2811.79	1687.72	1109.11	MEAN, INCOME
	4995.7	35500.5	12554.0	9027.8	4631.0	1640.2	717.0	69066.1	COUNT
MAIDS	7.23	51.40	18.13	13.07	6.71	2.37	1.04	100.00	PROW
	46.10	15.94	6.13	7.56	7.11	6.32	8.55	10.51	PCOL
	195.57	358.29	422.99	419.87	439.80	414.33	330.55	372.84	MEAN, INCOME
	137.3	2231.3	1732.9	1510.9	1327.8	1163.2	658.7	8762.1	COUNT
AGRICULT	1.57	25.47	19.78	17.24	15.15	13.28	7.52	100.00	PROW
URE	1.27	1.00	0.85	1.27	2.04	4.48	7.85	1.33	PCOL
	77.57	1619.61	3157.67	2411.44	2734.98	2924.88	6278.72	27[illegible]5.44	MEAN, INCOME
	225.5	10951.5	10511.3	4830.5	2676.2	569.5	166.3	29930.7	COUNT
PROD SUP	0.75	36.59	35.12	16.14	8.94	1.90	0.56	100.00	PROW
ERVISORS	2.08	4.92	5.13	4.05	4.11	2.20	1.98	4.55	PCOL
	341.36	812.65	1191.91	1859.53	1782.26	1193.53	839.41	1205.34	MEAN, INCOME
	1986.7	55369.3	49838.5	25180.6	11567.8	4258.4	1277.1	149478.3	COUNT
PROD	1.33	37.04	33.34	16.85	7.74	2.85	0.85	100.00	PROW
WORKERS	18.33	24.87	24.33	21.10	17.75	16.42	15.22	22.74	PCOL
	330.94	840.05	1265.65	1572.85	1712.94	1352.33	976.73	1181.94	MEAN, INCOME
CONSTRUC	793.2	14525.5	11740.0	9095.2	6574.1	3530.1	929.3	47187.4	COUNT
T WORKER	1.68	30.78	24.88	19.27	13.93	7.48	1.97	100.00	PROW
S	7.32	6.52	5.73	7.62	10.09	13.61	11.08	7.18	PCOL
	318.30	661.79	1168.28	1128.41	1100.51	1030.30	932.54	965.99	MEAN, INCOME
TRANSPOR	14.6	4435.3	14773.4	10553.9	5068.5	1327.0	203.5	36376.2	COUNT
T WORKER	.401E-01	12.19	40.61	29.01	13.93	3.65	0.56	100.00	PROW
S	0.13	1.99	7.21	8.84	7.78	5.12	2.42	5.53	PCOL
	1200.00	1003.13	1280.47	1540.79	1717.88	1491.76	879.00	1388.56	MEAN, INCOME
	344.1	3171.0	2265.9	1498.2	1104.6	590.6	164.4	9139.8	COUNT
OTHER	3.76	34.69	24.80	16.39	12.09	6.46	1.80	100.00	PROW
	3.18	1.42	1.11	1.26	1.69	2.28	1.96	1.39	PCOL
	310.10	564.24	744.56	820.85	901.24	891.05	432.80	700.94	MEAN, INCOME
	10835.9	222648.6	204877.1	119340.9	65173.2	25942.3	8390.7	657208.6	COUNT
TOTAL	1.65	33.88	31.17	18.16	9.92	3.95	1.28	100.00	PROW
	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	PCOL
	277.97	934.45	1875.30	2450.57	2965.28	2806.19	2707.41	1790.15	MEAN, INCOME

	(12,14)	(15,24)	(25,34)	(35,44)	(45,54)	(55,64)	(65,99)	TOTAL	
	1420.3	31404.9	27215.7	17107.9	8483.1	3988.2	1164.4	90784.5	COUNT
NO INFO	1.56	34.59	29.98	18.84	9.34	4.39	1.28	100.00	PROW
	-	-	-	-	-	-	-	-	PCOL
	205.92	893.19	1788.23	2333.36	2367.82	3036.02	1856.89	1666.44	MEAN, INCOME

TABLE 7.

CROSS TABULATION: INDUSTRY BY AGE

	(12,14)	(15,24)	(25,34)	(35,44)	(45,54)	(55,64)	(55,99)	TOTAL	
AGRICULTURE	159.3	1915.1	1743.2	1372.1	1150.8	865.2	539.4	7745.1	COUNT
	2.06	24.73	22.51	17.72	14.86	11.17	6.96	100.00	PROW
	1.84	1.21	1.29	1.53	2.58	4.70	9.49	1.71	PCOL
	227.06	2333.76	4165.19	3956.62	5475.06	3646.58	7475.10	3368.93	MEAN, INCOME
MINING	32.3	543.9	477.9	617.3	268.0	175.3	24.8	2142.1	COUNT
	1.51	25.39	22.31	28.91	12.51	8.21	1.16	100.00	PROW
	0.37	0.34	0.35	0.76	0.60	0.96	0.44	0.47	PCOL
	81.08	1353.37	5497.81	5851.47	3259.38	4592.29	601.29	4055.98	MEAN, INCOME
FOOD PROD.BEV TABAC	378.3	7900.5	7700.7	4480.8	2064.5	708.2	139.4	23381.5	COUNT
	1.62	33.79	32.97	19.16	8.83	3.03	0.60	100.00	PROW
	4.36	5.00	5.69	5.51	4.62	3.95	2.45	5.17	PCOL
	313.60	785.13	1549.73	2088.19	3608.40	3011.66	1309.79	1544.08	MEAN, INCOME
TEXTILES & FOOTWEAR	374.4	17423.5	15695.5	8850.1	4292.2	1345.7	407.6	48387.0	COUNT
	0.77	36.01	32.44	18.31	8.85	2.78	0.84	100.00	PROW
	4.32	11.02	11.56	10.89	9.58	7.31	7.17	10.59	PCOL
	367.10	843.59	1377.25	1838.99	1900.14	1434.95	1025.12	1317.70	MEAN, INCOME
LUMBER & WOOD	260.2	4924.6	4215.4	2011.4	1216.9	653.6	193.8	13480.9	COUNT
	1.93	36.53	31.27	14.92	9.03	4.89	1.44	100.00	PROW
	3.00	3.12	3.11	2.47	2.72	3.59	3.41	2.98	PCOL
	521.85	858.48	1452.87	1742.92	1858.71	1697.62	1348.20	1308.14	MEAN, INCOME
PAPER, PRINTING PUBLISH	110.9	4327.9	3644.2	1607.4	798.6	378.2	75.6	10940.7	COUNT
	1.01	39.56	33.31	14.69	7.28	3.46	0.69	100.00	PROW
	1.28	2.74	2.68	1.99	1.78	2.05	1.33	2.42	PCOL
	258.33	1000.54	2041.65	2525.02	3505.98	5079.33	2830.53	1899.81	MEAN, INCOME
MINERAL PROD	152.2	2169.6	1904.2	1144.4	552.9	205.3	95.1	6223.7	COUNT
	2.45	34.85	30.60	18.39	8.89	3.30	1.53	100.00	PROW
	1.76	1.37	1.40	1.41	1.24	1.11	1.67	1.38	PCOL
	349.26	768.75	1255.61	2703.69	1992.34	1664.79	6593.41	1491.41	MEAN, INCOME
INDUS CHEM PETRO	33.2	5248.8	5540.5	2688.0	1095.1	206.5	103.4	14915.5	COUNT
	0.22	35.19	37.15	18.02	7.34	1.38	0.69	100.00	PROW
	0.38	3.32	4.08	3.30	2.45	1.12	1.82	3.30	PCOL
	387.20	1059.45	2765.01	3567.30	4777.62	4331.98	6095.97	2496.65	MEAN, INCOME
METAL INDUSTRY	256.4	11064.3	10981.1	3989.9	1552.3	337.9	136.5	28318.3	COUNT
	0.91	39.07	38.78	14.09	5.48	1.19	0.48	100.00	PROW
	2.96	7.00	8.09	4.90	3.47	1.84	2.40	6.25	PCOL
	285.90	993.56	1966.95	3110.43	3438.96	3433.60	1455.69	1827.09	MEAN, INCOME
OTHER INDUSTRY	187.6	8294.5	6609.5	2738.2	1289.0	437.4	159.5	19713.8	COUNT
	0.95	42.07	33.52	13.89	6.53	2.22	0.81	100.00	PROW
	2.16	5.25	4.87	3.37	2.88	2.39	2.81	4.36	PCOL
	460.10	1044.93	1651.11	3033.19	4181.42	5159.55	6214.68	1856.79	MEAN, INCOME
UTILITIES	40.1	836.4	1435.0	803.5	393.2	161.9	51.6	3721.6	COUNT
	1.08	22.47	38.55	21.59	10.56	4.35	1.39	100.00	PROW
	0.46	0.53	1.06	0.99	0.25	0.88	0.91	0.82	PCOL
	328.15	1604.15	2369.50	2765.33	4248.77	3059.67	1740.22	2406.41	MEAN, INCOME
CONSTRUCTION	953.9	16593.5	14337.2	9952.3	6814.3	3538.5	949.1	53165.8	COUNT
	1.85	31.21	26.97	18.72	12.82	6.66	1.78	100.00	PROW
	11.34	10.50	10.56	12.23	15.25	19.21	16.65	11.75	PCOL
	331.35	705.97	1464.80	1662.81	1742.96	1440.02	1401.09	1276.92	MEAN, INCOME
WHOLESALE TRADE	60.5	3202.2	3099.2	1503.4	804.1	238.5	77.5	8985.4	COUNT
	0.67	35.54	34.49	16.73	9.95	2.65	0.86	100.00	PROW
	0.70	2.03	2.28	1.85	1.80	1.29	1.36	1.99	PCOL
	626.85	1885.59	3946.64	4838.06	4631.43	4395.49	4975.91	3421.16	MEAN, INCOME
RETAIL TRADE	397.3	11073.6	9258.9	6699.1	4050.4	2121.6	597.5	34198.4	COUNT
	1.16	32.38	27.07	19.59	11.84	6.20	1.75	100.00	PROW
	4.58	7.01	6.82	8.23	9.09	11.52	10.52	7.56	PCOL
	355.82	914.50	1914.44	2757.03	4375.21	3404.66	1558.37	2115.29	MEAN, INCOME
OTHER COMMERCE	277.6	6061.4	5664.5	3837.7	2570.8	1065.5	437.1	19914.4	COUNT
	1.39	30.44	28.44	19.27	12.91	5.35	2.19	100.00	PROW
	3.20	3.84	4.17	4.72	5.75	5.79	7.69	4.40	PCOL
	290.27	1030.21	2747.05	4182.95	5529.09	8390.89	4604.16	3160.79	MEAN, INCOME
TRANS & COMMUNICATION	22.1	3389.9	6364.1	4921.9	2124.9	789.3	129.8	17742.1	COUNT
	0.12	19.11	35.87	27.74	11.98	4.45	0.73	100.00	PROW
	0.25	2.14	4.69	6.05	4.76	4.29	2.28	3.92	PCOL
	257.40	1301.24	2348.73	2999.59	3467.42	5253.27	719.88	2577.84	MEAN, INCOME
FINANCIAL EST	54.1	5912.2	6445.1	3737.4	2387.5	1048.1	202.0	19786.6	COUNT
	0.27	29.88	32.57	18.89	12.07	5.30	1.02	100.00	PROW
	0.62	3.74	4.75	4.59	5.34	5.69	3.56	4.37	PCOL
	136.52	1840.74	4163.79	6356.55	8423.47	8563.15	5913.40	4637.73	MEAN, INCOME
PUBLIC ADM.SOC SERV	51.8	4132.0	7435.1	6063.7	3598.5	1196.6	193.5	22671.1	COUNT
	0.23	18.23	32.80	26.75	15.87	5.28	0.85	100.00	PROW
	0.60	2.61	5.48	7.45	8.05	6.50	3.41	5.01	PCOL
	351.67	1731.21	3202.55	3431.85	4196.70	5273.67	2107.31	3246.97	MEAN, INCOME
PUBLIC INSTRUCTION	34.2	5984.7	9878.4	5877.3	3079.0	1230.3	560.0	26643.8	COUNT
	0.13	22.46	37.08	22.06	11.56	4.62	2.10	100.00	PROW
	0.39	3.79	7.28	7.22	6.89	6.68	9.86	5.89	PCOL
	1037.79	1692.94	3326.05	4876.30	5143.39	4750.10	8571.41	3684.24	MEAN, INCOME
PERSNL & DOMESTIC SERV	4906.3	37040.7	13292.1	8464.9	4595.1	1706.5	611.1	70516.7	COUNT
	6.82	52.53	18.85	12.00	6.52	2.42	0.87	100.00	PROW
	55.42	23.44	9.79	10.40	10.30	9.27	10.76	15.58	PCOL
	199.98	419.35	763.19	924.45	983.82	759.53	643.46	576.81	MEAN, INCOME
TOTAL	8672.7	159039.1	135730.0	81370.9	44634.8	10415.0	5681.2	452504.5	COUNT
	1.92	34.92	29.99	17.98	9.87	4.07	1.26	100.00	PROW
	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	PCOL
	366.62	914.44	2105.12	2856.75	3486.15	3534.97	3380.53	1999.00	MEAN, INCOME
NO INFO	3583.4	96014.4	96302.8	55077.9	28971.4	11514.8	3873.9	295398.6	COUNT
	1.21	32.50	32.62	18.65	9.81	3.90	1.31	100.00	PROW
	.	.	.	.	.	.	.	.	PCOL
	376.87	953.83	1527.00	1614.00	1999.96	1720.27	1464.60	1430.91	MEAN, INCOME

occupations show similarly steep age-income profiles. In contrast, the peak income for maids is only one-fourth higher than the average starting incomes. The cross-tabulation by industry, presented in Table 7, demonstrates that incomes increase more with age in commerce, finance, and public instruction than in agriculture, manufacturing, construction, or personal and domestic service. Although the industries with larger experience effects tend to be higher-paying, the correlation is not very great.

7. Questions: a) How do the distributions of workers among sectors of residence differ by age? b) Does income rise more with age in some residential areas than in others? (Table 8)

Answers: a) Higher income sectors have older workers on average. b) Income rises more with age in higher income sectors in the cross section.

The data in Table 8 reveal that disproportionately more older workers reside in high income sectors. For example, 21.0% of the workers living in the highest income sector (Sector 8) are more than 45 years of age, as compared with 14.8% of all workers in that age category. The most likely explanation for this pattern is that, as their incomes increase with age, workers tend to move into better neighborhoods; lower life expectancy among residents of poor neighborhoods is also a possible explanation. Regarding the question of age-income profiles, they clearly do differ across sectors.

TABLE 8.

CROSS-TABULATION: SECTOR OF RESIDENCE BY AGE

	(12,14)	(15,24)	(25,34)	(35,44)	(45,54)	(55,64)	(65,99)	TOTAL	
	294.4	7131.7	6013.2	3969.5	2867.8	1463.3	521.4	22261.3	COUNT
SECTOR 1	1.32	32.04	27.01	17.83	12.88	6.57	2.34	100.00	PROW
	2.40	2.81	2.59	2.91	3.89	4.89	5.46	2.98	PCOL
	269.1	852.8	1765.3	1865.9	1970.8	1945.0	1318.7	1499.1	MEAN, INCOME
	2007.3	45052.2	40270.7	22412.9	11587.3	4498.6	1427.1	127256.0	COUNT
SECTOR 2	1.58	35.40	31.55	17.61	9.11	3.54	1.12	100.00	PROW
	16.38	17.73	17.35	16.43	15.73	15.03	14.93	17.01	PCOL
	237.1	780.1	1216.9	1318.3	1299.4	1117.8	942.1	1065.6	MEAN, INCOME
	2559.4	60144.3	58344.1	31758.2	16559.6	5745.2	1719.8	176830.8	COUNT
SECTOR 3	1.45	34.01	32.99	17.96	9.36	3.25	0.97	100.00	PROW
	20.88	23.67	25.14	23.27	22.48	19.20	18.00	23.64	PCOL
	319.6	891.1	1535.6	1702.0	1629.3	1403.1	881.8	1325.8	MEAN, INCOME
	944.6	24469.3	23391.4	13439.7	6261.6	2217.0	468.5	71182.2	COUNT
SECTOR 4	1.33	34.38	32.85	18.88	8.80	3.11	0.66	100.00	PROW
	7.71	9.63	10.07	9.85	8.50	7.41	4.90	9.52	PCOL
	272.1	939.2	1711.4	2041.1	2132.4	1958.6	1962.7	1535.5	MEAN, INCOME
	893.4	17749.4	17933.6	10451.2	4691.5	2250.1	941.0	54910.3	COUNT
SECTOR 5	1.63	32.32	32.66	19.03	8.54	4.10	1.71	100.00	PROW
	7.29	6.99	7.73	7.66	6.37	7.52	9.85	7.34	PCOL
	251.5	985.8	1776.9	2398.3	2354.9	1881.4	1215.9	1658.7	MEAN, INCOME
	2234.6	43242.3	39001.4	24335.8	12411.0	4158.7	1254.5	126648.3	COUNT
SECTOR 6	1.76	34.14	30.80	19.22	9.80	3.28	1.00	100.00	PROW
	18.23	17.02	16.80	17.84	16.85	13.89	13.23	16.93	PCOL
	269.2	902.4	1620.1	2276.6	2208.4	1594.9	1196.2	1530.0	MEAN, INCOME
	1953.5	35006.6	30256.0	18265.7	11136.9	5469.5	1934.1	104032.4	COUNT
SECTOR 7	1.88	33.65	29.09	17.56	10.71	5.26	1.86	100.00	PROW
	15.94	13.78	13.04	13.39	15.12	18.27	20.24	13.91	PCOL
	227.3	1117.8	2759.8	3772.7	4765.0	4217.1	3255.1	2638.2	MEAN, INCOME
	1369.0	21257.6	16882.5	11815.7	8140.5	4127.9	1278.5	64871.8	COUNT
SECTOR 8	2.11	32.77	26.02	18.21	12.55	6.36	1.97	100.00	PROW
	11.17	8.37	7.27	8.66	11.05	13.79	13.38	8.67	PCOL
	295.3	1065.6	3354.0	5463.1	7466.2	7436.6	8946.5	3939.9	MEAN, INCOME
	12256.2	254053.5	232092.8	135448.8	73656.3	29930.5	9555.1	747993.1	COUNT
TOTAL	1.64	33.96	31.03	18.24	9.85	4.00	1.28	100.00	PROW
	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	PCOL
	269.6	929.4	1865.1	2435.9	2896.5	2836.8	2603.8	1775.1	MEAN, INCOME

Comparison of average incomes among 45-54 years olds with the average incomes among 15-24 year olds yields the following results:

Sector Number	Average Income	Average Income of 15-24 year-old residents	Average Income of 45-54 year-old residents ÷ Average Income of 15-24 year-old residents
2	1066	780	1.66
3	1327	891	1.83
1	1499	853	2.31
6	1530	902	2.45
4	1536	939	2.27
5	1659	986	2.39
7	2638	1118	4.26
8	3940	1066	7.00

The observed pattern (i.e., income increases more with age in the high income sectors) is consistent with the hypothesis that workers residing in poor neighborhoods have fewer opportunities for training and occupational upgrading. If this were correct, it would be worrisome and would suggest various policy interventions: among the possibilities are subsidies for public transport, establishment of local offices of a public employment service, creation of industrial parks in low income areas, and construction of worker housing near employment opportunities in higher income areas. It is also consistent with a more positive scenario: that many residents of poor neighborhoods do experience income growth over time and they can therefore afford to move to better neighborhoods, as the age distribution of workers by sector suggests. We thus confront an ambiguity of causality:

Sector of the city is both a determinant of success in the labor market and a reflection of success in the labor market. The consequent ambiguity of interpretation cannot be resolved with cross sectional data from censuses or surveys. Only imaginative use of longitudinal data -- on workers who *ex ante* were in different sectors of the city -- can possibly distinguish among these alternative views.

8 and 9. Questions: Do natives of Bogota earn more than in-migrants because a) natives are disproportionately in better occupations and industries than migrants? b) natives earn more than migrants within any given occupation or industry? or c) both? (Tables 9 and 10)

Answers: a) yes. b) as often as not, no.

The distribution of occupations and industries is somewhat better for natives than for migrants. The data in Table 9 show that migrants comprise 76 % of Bogota's total population, yet 91% of the maids, 86% of persons in other service occupations, and fewer than 70% of professional and technical workers, administrators and managers, and clerks and typists are migrants. The differences in

TABLE 9.

CROSS-TABULATION: OCCUPATION BY MIGRANT STATUS

	MIGRANT	NON MIGRANT	TOTAL	
	37175.	16836.	54011.	COUNT
PROFESS	68.83	31.17	100.00	PROW
& TECH	7.49	10.49	9.22	PCOL
	5042.5	4871.2	4989.1	MEAN, INCOME
	7147.	3177.	10324.	COUNT
ADMIN &	69.22	30.78	100.00	PROW
MANAGER	1.44	1.98	1.57	PCOL
	9199.1	7990.8	8827.2	MEAN, INCOME
	55070.	28402.	83472.	COUNT
CLERK &	65.97	34.03	100.00	PROW
TYPISTS	11.09	17.68	12.70	PCOL
	1949.2	1987.9	1962.4	MEAN, INCOME
SALES MA	33902.	8564.	42466.	COUNT
NAG.PROP	79.83	20.17	100.00	PROW
RIETOR	6.83	5.33	6.46	PCOL
	2869.8	3614.1	3019.9	MEAN, INCOME
	41020.	13942.	54961.	COUNT
OTHER	74.63	25.37	100.00	PROW
SALES	8.26	8.68	8.36	PCOL
	1637.1	1657.4	1642.2	MEAN, INCOME
SERV	53354.	8680.	62033.	COUNT
WORK.NOT	86.01	13.99	100.00	PROW
MAID	10.74	5.40	9.44	PCOL
	1086.3	1249.2	1109.1	MEAN, INCOME
	62864.	6202.	69066.	COUNT
MAIDS	91.02	8.98	100.00	PROW
	12.66	3.86	10.51	PCOL
	376.3	338.2	372.8	MEAN, INCOME
	7478.	1284.	8762.	COUNT
AGRICULT	85.34	14.66	100.00	PROW
URE	1.51	0.80	1.33	PCOL
	2276.1	5273.3	2715.4	MEAN, INCOME
	22748.	7183.	29931.	COUNT
PROD SUP	76.00	24.00	100.00	PROW
ERVISORS	4.58	4.47	4.55	PCOL
	1193.1	1244.1	1205.3	MEAN, INCOME
	105872.	43607.	149479.	COUNT
PROD	70.83	29.17	100.00	PROW
WORKERS	21.32	27.15	22.74	PCOL
	1167.8	1216.3	1181.9	MEAN, INCOME
CONSTRUC	34355.	12833.	47187.	COUNT
T WORKER	72.80	27.20	100.00	PROW
S	6.92	7.99	7.18	PCOL
	940.8	1033.4	966.0	MEAN, INCOME
TRANSPOR	28618.	7758.	36376.	COUNT
T WORKER	78.67	21.33	100.00	PROW
S	5.76	4.83	5.53	PCOL
	1393.6	1370.1	1388.6	MEAN, INCOME
	6968.	2172.	9140.	COUNT
OTHER	76.24	23.76	100.00	PROW
	1.40	1.35	1.39	PCOL
	747.0	553.1	700.9	MEAN, INCOME
	496568.	160640.	657209.	COUNT
TOTAL	75.56	24.44	100.00	PROW
	100.00	100.00	100.00	PCOL
	1715.4	2021.3	1790.1	MEAN, INCOME

.	65735.	25050.	90785.	COUNT
NO INFO	72.41	27.59	100.00	PROW
	-	-	-	PCOL
	1572.2	1913.7	1666.4	MEAN, INCOME

TABLE 10.
CROSS-TABULATION: INDUSTRY BY MIGRANT STATUS

	MIGRANT	NON MIGRANT	TOTAL	
	6487.5	1257.6	7745.1	COUNT
AGRICULTURE	83.76	16.24	100.00	PROW
	1.90	1.13	1.71	PCOL
	3387.2	6354.1	3559.0	MEAN, INCOME
	1643.0	499.1	2142.1	COUNT
MINING	76.70	23.30	100.00	PROW
	0.48	0.45	0.47	PCOL
	3669.1	5329.7	4056.0	MEAN, INCOME
FOOD PROD.BEV. TABAC	18074.6	4506.9	22581.5	COUNT
	80.77	19.23	100.00	PROW
	5.54	4.04	5.17	PCOL
	1523.8	1633.0	1544.9	MEAN, INCOME
TEXTILES & FOOTWEAR	37335.1	11051.9	48387.0	COUNT
	77.16	22.84	100.00	PROW
	10.95	9.90	10.69	PCOL
	1283.5	1433.1	1317.7	MEAN, INCOME
	9468.8	4012.1	13480.9	COUNT
LUMBER & WOOD	70.24	29.76	100.00	PROW
	2.78	3.59	2.98	PCOL
	1341.8	1228.6	1308.1	MEAN, INCOME
PAPER, PRINTING, PUBLISH	6758.3	4182.4	10940.7	COUNT
	61.77	38.23	100.00	PROW
	1.98	3.75	2.42	PCOL
	1848.7	1982.4	1899.8	MEAN, INCOME
	4343.2	1800.6	6223.7	COUNT
MINERAL PROD	69.78	30.22	100.00	PROW
	1.27	1.63	1.38	PCOL
	1452.5	1581.2	1491.4	MEAN, INCOME
INDUS CHEM PETRO	11024.8	3890.7	14915.5	COUNT
	73.92	26.08	100.00	PROW
	3.23	3.49	3.30	PCOL
	2338.7	2944.1	2496.7	MEAN, INCOME
	19483.9	8834.4	28318.3	COUNT
METAL INDUSTRY	68.80	31.20	100.00	PROW
	5.71	7.92	6.25	PCOL
	1796.8	1894.0	1827.1	MEAN, INCOME
	14061.7	5652.0	19713.5	COUNT
OTHER INDUSTRY	71.33	28.67	100.00	PROW
	4.12	5.06	4.35	PCOL
	1754.7	2110.9	1856.9	MEAN, INCOME
	2576.6	1144.9	3721.5	COUNT
UTILITIES	69.24	30.76	100.00	PROW
	0.76	1.03	0.82	PCOL
	2305.4	2893.7	2486.4	MEAN, INCOME
	38184.8	14991.0	53175.8	COUNT
CONSTRUCTION	71.82	28.18	100.00	PROW
	11.20	13.42	11.75	PCOL
	1181.9	1519.0	1276.9	MEAN, INCOME
WHOLE SALE TRADE	6377.8	2607.8	8985.4	COUNT
	70.98	29.02	100.00	PROW
	1.87	2.34	1.99	PCOL
	3234.5	3877.6	3421.2	MEAN, INCOME
	26189.5	8009.9	34199.4	COUNT
RETAIL TRADE	76.58	23.42	100.00	PROW
	7.68	7.18	7.56	PCOL
	2136.8	2045.7	2115.3	MEAN, INCOME
	15389.5	4524.9	19914.4	COUNT
OTHER COMMERCE	77.28	22.72	100.00	PROW
	4.51	4.05	4.40	PCOL
	3118.5	3339.7	3168.8	MEAN, INCOME
TRANS & COMMUNICATION	12970.6	4771.5	17742.1	COUNT
	73.11	26.89	100.00	PROW
	3.80	4.27	3.92	PCOL
	2599.3	2519.5	2577.8	MEAN, INCOME
	12604.7	7181.9	19786.6	COUNT
FINANCIAL EST	63.70	36.30	100.00	PROW
	3.70	6.43	4.37	PCOL
	4403.5	5046.6	4637.7	MEAN, INCOME
PUBLIC ADM, SOC SERV	16947.9	5723.2	22671.1	COUNT
	74.76	25.24	100.00	PROW
	4.97	5.13	5.01	PCOL
	3234.0	3255.4	3247.0	MEAN, INCOME
PUBLIC INSTRUCTION	18663.9	7979.9	26643.8	COUNT
	70.05	29.95	100.00	PROW
	5.47	7.15	5.89	PCOL
	3705.4	3634.7	3684.2	MEAN, INCOME
PERSNL & DOMESTIC SERV	61593.2	8923.4	70516.7	COUNT
	87.35	12.65	100.00	PROW
	18.06	7.99	15.58	PCOL
	524.9	935.2	576.8	MEAN, INCOME
	340978.4	111616.0	452594.5	COUNT
TOTAL	75.34	24.66	100.00	PROW
	100.00	100.00	100.00	PCOL
	1865.2	2349.8	1993.8	MEAN, INCOME
	221324.9	74073.8	295398.5	COUNT
NO INFO	74.92	25.08	100.00	PROW
	-	-	-	PCOL
	1411.2	1489.9	1430.9	MEAN, INCOME

occupational mix of migrants compared with natives are significant but not substantial. Differences of similar magnitude appear in the industry breakdowns. Migrant/native income differences within occupations or industries are small. Natives earn more than migrants in seven occupational groups, migrants earn more in three occupational groups, and average incomes are within 30 pesos (about U.S. $1) of each other in four occupations. This suggests that migrants acquire income equality with natives in the same occupation within a fairly short time; whether they acquire occupational equality as well cannot be determined without an age breakdown.

10. <u>Questions:</u> a) <u>How do the distributions of workers among sectors of residence differ by migrant status?</u> b) <u>Is the native/migrant income ratio greater in some residential areas than in others?</u> (Table 11)

<u>Answers</u>: a) <u>Very little</u>. b) <u>Yes, greatest in the highest income sector.</u>

Migrants and natives do not differ much in their residential patterns. Of persons with identifiable sector of residence, 75.2% were migrants. The proportion of migrants in the eight residential sectors ranges from 72.8% to 79.0% with no apparent relationship to income level. The small size of these differences and the lack of a systematic relationship with income suggest that migrants become integrated into the Bogota labor market over time; whether recent migrants are equally well-integrated within a short time is not clear from the available data. Turning to income differentials

TABLE 11.

CROSS-TABULATION: SECTOR OF RESIDENCE BY MIGRANT STATUS

	MIGRANT	NON MIGRANT	TOTAL	
	16467.	5794.	22261.	COUNT
SECTOR 1	73.97	26.03	100.00	PROW
	2.93	3.12	2.98	PCOL
	1479.	1557.	1499.	MEAN, INCOME
	95577.	31679.	127256.	COUNT
SECTOR 2	75.11	24.89	100.00	PROW
	17.00	17.06	17.01	PCOL
	1047.	1120.	1066.	MEAN, INCOME
	133904.	42927.	176831.	COUNT
SECTOR 3	75.72	24.28	100.00	PROW
	23.81	23.12	23.64	PCOL
	1315.	1365.	1327.	MEAN, INCOME
	56173.	15009.	71182.	COUNT
SECTOR 4	78.92	21.08	100.00	PROW
	9.99	8.08	9.52	PCOL
	1471.	1777.	1536.	MEAN, INCOME
	43349.	11561.	54910.	COUNT
SECTOR 5	78.95	21.05	100.00	PROW
	7.71	6.23	7.34	PCOL
	1633.	1755.	1659.	MEAN, INCOME
	92227.	34421.	126648.	COUNT
SECTOR 6	72.82	27.18	100.00	PROW
	16.40	18.54	16.93	PCOL
	1489.	1639.	1530.	MEAN, INCOME
	77072.	26961.	104032.	COUNT
SECTOR 7	74.08	25.92	100.00	PROW
	13.71	14.52	13.91	PCOL
	2500.	3034.	2638.	MEAN, INCOME
	47534.	17338.	64872.	COUNT
SECTOR 8	73.27	26.73	100.00	PROW
	8.45	9.34	8.67	PCOL
	3602.	4866.	3940.	MEAN, INCOME
	562303.	185690.	747993.	COUNT
TOTAL	75.17	24.83	100.00	PROW
	100.00	100.00	100.00	PCOL
	1699.	2007.	1775.	MEAN, INCOME

by sector of residence, the ratio of natives' incomes to migrants' incomes rises monotonically with income. One possible explanation is that Bogota natives have the advantages from birth of better public health conditions, higher-quality and more plentiful schooling opportunities.

11. Question: Do better-educated workers in Bogota earn more because: a) they are disproportionately in higher-paying occupations? b) they earn more within any given occupation? or c) both? (Table 12)

Answer: Both, with substantial components due to each.

As compared with those with no schooling, workers with primary education earn nearly twice as much, those with secondary education three times as much, and those with higher education twelve times as much. The data in Table 12 reveal that the differences in occupational composition across educational groups are considerable. For example, persons with higher education are more than 100 times as likely as persons with no education to be in professional and technical occupations. On the other hand, more than 40% of workers with no education were in service occupations as compared with only 1% of persons with higher education. We also find that within occupations, better-educated persons earn quite a bit more, e.g., the ratio of incomes of workers with higher education to the incomes of persons with no education is nearly five to one in professional and technical occupations, eleven to one in sales jobs, four to one in production, and eight to one in construction.

TABLE 12.

CROSS-TABULATION: OCCUPATION BY EDUCATION

	NONE	PRIMARY	SECONDARY	HIGHER	TOTAL	OTHER	
PROFESS & TECH	183.0	3969.6	22069.3	26730.3	52952.2	1059.0	COUNT
	0.35	7.50	41.68	50.48	100.00	-	PROW
	0.43	1.12	10.97	56.62	8.18	10.38	PCOL
	1553.9	1749.9	2706.2	7405.3	5002.7	4310.9	MEAN, INCOME
ADMIN & MANAGER	18.1	1308.1	3922.9	4748.6	9997.7	326.4	COUNT
	0.18	13.08	39.24	47.50	100.00	-	PROW
	.425E-01	0.37	1.95	10.06	1.55	3.20	PCOL
	278.6	2974.5	6584.4	12313.7	8821.9	8990.0	MEAN, INCOME
CLERK & TYPISTS	556.5	17311.9	55512.1	8186.9	81567.4	1904.8	COUNT
	0.69	21.22	68.06	10.04	100.00	-	PROW
	1.31	4.86	27.58	17.34	12.61	18.67	PCOL
	780.5	1160.1	1912.7	4013.5	1956.1	2229.1	MEAN, INCOME
SALES MANAG,PROPRIETOR	2393.5	21382.0	15928.8	2267.3	41971.5	494.3	COUNT
	5.70	50.94	37.95	5.40	100.00	-	PROW
	5.63	6.01	7.91	4.80	6.49	4.84	PCOL
	880.2	1705.0	4344.1	8351.0	3018.5	3136.8	MEAN, INCOME
OTHER SALES	3155.5	26772.8	21645.8	2542.6	54116.8	844.6	COUNT
	5.83	49.47	40.00	4.70	100.00	-	PROW
	7.42	7.52	10.75	5.39	8.36	8.28	PCOL
	532.7	925.2	2194.1	6008.2	1648.7	1229.4	MEAN, INCOME
SERV WORK,NOT MAID	5894.3	42884.2	11775.3	609.8	61163.6	869.7	COUNT
	9.64	70.11	19.25	1.00	100.00	-	PROW
	13.86	12.05	5.85	1.29	9.45	8.52	PCOL
	562.4	899.9	1909.6	6265.2	1115.3	677.2	MEAN, INCOME
MAIDS	12811.2	51088.4	3709.1	0.0	67608.8	1457.3	COUNT
	18.95	75.56	5.49	0.00	100.00	-	PROW
	30.13	14.35	1.84	0.00	10.45	14.28	PCOL
	324.7	391.4	434.1	-	373.5	340.7	MEAN, INCOME
AGRICULTURE	1262.7	5340.4	1493.0	518.8	8614.8	147.3	COUNT
	14.66	61.99	17.33	6.02	100.00	-	PROW
	2.97	1.50	0.74	1.10	1.33	1.44	PCOL
	490.4	1070.2	6245.9	14862.2	2712.8	2969.9	MEAN, INCOME
PROD SUPERVISORS	1394.5	19399.1	8361.2	392.1	29546.9	383.8	COUNT
	4.72	65.66	28.30	1.33	100.00	-	PROW
	3.28	5.45	4.15	0.83	4.57	3.76	PCOL
	779.7	980.9	1637.3	3619.9	1206.3	1132.2	MEAN, INCOME
PROD WORKERS	5948.2	96859.1	44167.4	990.0	147964.8	1513.6	COUNT
	4.02	65.46	29.85	0.67	100.00	-	PROW
	13.99	27.21	21.94	2.10	22.87	14.84	PCOL
	787.0	1084.4	1403.4	3259.3	1182.2	1156.7	MEAN, INCOME
CONSTRUCT WORKERS	5948.9	35830.7	4600.6	154.8	46535.1	652.3	COUNT
	12.78	77.00	9.89	0.33	100.00	-	PROW
	13.99	10.06	2.29	0.33	7.19	6.39	PCOL
	790.1	910.8	1460.4	6379.5	967.9	831.0	MEAN, INCOME
TRANSPORT WORKERS	1162.5	27103.3	7664.4	71.0	36001.3	375.0	COUNT
	3.23	75.28	21.29	0.20	100.00	-	PROW
	2.73	7.61	3.81	0.15	5.56	3.68	PCOL
	893.7	1334.5	1661.8	2049.7	1391.4	1120.2	MEAN, INCOME
OTHER	1785.8	6761.3	418.3	0.0	8965.5	174.3	COUNT
	19.92	75.41	4.67	0.00	100.00	-	PROW
	4.20	1.90	0.21	0.00	1.39	1.71	PCOL
	625.8	723.4	750.2	-	705.2	483.8	MEAN, INCOME
TOTAL	42514.7	356011.1	201268.1	47212.4	647006.3	10202.3	COUNT
	6.57	55.02	31.11	7.30	100.00	-	PROW
	100.00	100.00	100.00	100.00	100.00	100.00	PCOL
	593.5	993.5	2174.7	7218.4	1788.9	1869.5	MEAN, INCOME
NO INFO	4917.7	46041.9	31637.3	6365.0	88961.9	1822.6	COUNT
	5.53	51.75	35.56	7.15	100.00	-	PROW
	-	-	-	-	-	-	PCOL
	694.9	908.2	2047.3	6076.3	1671.3	1430.0	MEAN, INCOME

12. Question: Concerning the relationship between education and industry in Bogota: a) Within an industry, do better-educated workers earn more? b) Within an educational group, does the average income depend on industry? (Table 13)

Answers: a) Yes, a great deal more.

b) Yes, but relative to the inter-education group differences, the inter-industry differences are much smaller.

For those individuals for whom industry information is available, the ratio of incomes of the highly-educated to the incomes of those with no education is twelve to one. The income ratios in various industries are of the same order of magnitude: twenty-five to one in agriculture, twelve to one in textiles; thirteen to one in construction, eleven to one in retail trade, eight to one in transport and communications, and so on. By comparison, inter-industry differences are a great deal smaller, though by no means trivial. Particularly noteworthy is the pattern of incomes for workers with primary school education, who comprise 54% of the Bogota labor force: the dispersion of industry averages around the overall average is remarkably small, with two outliers standing out (utilities on the high end, personal and domestic service on the low end).

TABLE 13.

CROSS-TABULATION: INDUSTRY

BY EDUCATION

	NONE	PRIMARY	SECONDARY	HIGHER	TOTAL	OTHER	
AGRICULTURI	832.5	3848.7	2010.9	946.9	7639.0	106.1	COUNT
	10.90	50.38	26.32	12.40	100.00	-	PROW
	3.01	1.59	1.46	2.43	1.71	1.56	PCOL
	518.3	1315.1	5775.4	13136.0	3867.7	3961.4	MEAN, INCOME
MINING	242.3	887.2	495.5	463.2	2088.1	53.9	COUNT
	11.61	42.49	23.73	22.18	100.00	-	PROW
	0.88	0.37	0.36	1.19	0.47	0.79	PCOL
	2401.4	1140.8	3967.9	10704.1	4079.0	3163.8	MEAN, INCOME
FOOD PROD.BEV TABAC	1579.4	15349.7	5156.4	936.9	23022.4	359.1	COUNT
	6.86	66.67	22.40	4.07	100.00	-	PROW
	5.71	6.35	3.76	2.40	5.16	5.28	PCOL
	783.0	1015.8	2403.5	6909.8	1550.5	1186.4	MEAN, INCOME
TEXTILES & FOOTWEAR	1286.1	29770.2	15963.7	897.0	47917.1	469.9	COUNT
	2.68	62.13	33.32	1.87	100.00	-	PROW
	4.65	12.31	11.63	2.30	10.75	6.91	PCOL
	776.2	991.9	1508.2	9289.0	1313.5	1745.1	MEAN, INCOME
LUMBER & WOOD	496.0	9036.8	3682.3	123.8	13338.7	142.2	COUNT
	3.72	67.75	27.61	0.93	100.00	-	PROW
	1.79	3.74	2.68	0.32	2.99	2.09	PCOL
	1363.7	1198.5	1509.8	3472.1	1311.7	976.6	MEAN, INCOME
PAPER, PRINTING, PUBLISH	116.0	4628.9	5584.6	559.9	10889.5	51.2	COUNT
	1.07	42.51	51.29	5.14	100.00	-	PROW
	0.42	1.91	4.07	1.44	2.44	0.75	PCOL
	1433.5	1191.9	2117.0	5775.4	1904.6	887.7	MEAN, INCOME
MINERAL PROD	563.2	3944.8	1238.8	382.6	8109.5	114.2	COUNT
	9.22	64.57	20.29	5.94	100.00	-	PROW
	2.04	1.63	0.90	0.93	1.37	1.68	PCOL
	998.8	938.4	1537.7	7946.5	1480.5	2072.4	MEAN, INCOME
INDUS CHEM PETRO	315.8	6709.8	5856.2	1826.8	14707.5	207.9	COUNT
	2.15	45.61	39.82	12.42	100.00	-	PROW
	1.14	2.77	4.27	4.68	3.30	3.08	PCOL
	780.1	1124.8	2223.6	8592.5	2482.4	3503.7	MEAN, INCOME
METAL INDUSTRY	770.9	14727.3	10995.7	1625.3	28119.2	199.2	COUNT
	2.74	52.37	39.10	5.78	100.00	-	PROW
	2.79	6.09	8.01	4.17	6.31	2.93	PCOL
	863.0	1224.0	2002.6	6372.6	1816.2	3366.0	MEAN, INCOME
OTHER INDUSTRY	594.1	10747.7	7225.1	862.4	19429.3	284.5	COUNT
	3.06	55.32	37.19	4.44	100.00	-	PROW
	2.15	4.44	5.26	2.21	4.36	4.18	PCOL
	739.4	1107.5	2352.6	7722.3	1852.9	2123.6	MEAN, INCOME
UTILITIES	133.4	1607.6	1459.5	473.4	3673.9	47.7	COUNT
	3.63	43.76	39.73	12.89	100.00	-	PROW
	0.48	0.66	1.06	1.21	0.82	0.70	PCOL
	1400.3	1560.8	2329.2	6443.1	2489.3	2260.2	MEAN, INCOME
CONSTRUCTION	6334.7	38069.8	6090.5	1888.7	52383.8	782.1	COUNT
	12.09	72.67	11.63	3.61	100.00	-	PROW
	22.91	15.74	4.44	4.84	11.75	11.50	PCOL
	719.2	907.9	1789.4	9079.0	1282.2	922.5	MEAN, INCOME
WHOLE SALE TRADE	270.4	2956.8	4160.2	1339.0	8726.2	259.2	COUNT
	3.10	33.88	47.68	15.34	100.00	-	PROW
	0.98	1.22	3.03	3.43	1.96	3.81	PCOL
	665.3	1208.8	3707.8	7593.9	3363.1	5375.4	MEAN, INCOME
RETAIL TRADE	1941.1	16501.5	13693.4	1608.8	33744.8	453.6	COUNT
	5.75	48.90	40.58	4.77	100.00	-	PROW
	7.02	6.82	9.97	4.12	7.57	6.67	PCOL
	610.3	1196.8	2899.9	6698.3	2119.5	2029.6	MEAN, INCOME
OTHER COMMERCE	891.6	9558.0	7709.4	1431.9	19591.0	323.4	COUNT
	4.55	48.79	39.35	7.31	100.00	-	PROW
	3.22	3.95	5.61	3.67	4.39	4.76	PCOL
	609.4	1422.5	4499.1	9684.0	3200.0	1277.0	MEAN, INCOME
TRANS & COMMUNICATION	471.0	8740.7	7022.3	1316.8	17551.4	190.7	COUNT
	2.69	49.80	40.01	7.50	100.00	-	PROW
	1.71	3.61	5.11	3.38	3.94	2.80	PCOL
	860.6	1498.9	3192.0	7183.4	2585.6	1858.6	MEAN, INCOME
FINANCIAL EST	100.8	3025.4	9915.4	6306.5	19348.1	438.5	COUNT
	0.52	15.64	51.25	32.59	100.00	-	PROW
	0.36	1.25	7.22	16.16	4.34	6.45	PCOL
	546.8	1468.4	3269.3	8231.5	4591.0	6701.4	MEAN, INCOME
PUBLIC ADM.SOC SERV	501.0	6887.3	9743.1	5020.7	22152.1	519.0	COUNT
	2.26	31.09	43.98	22.66	100.00	-	PROW
	1.81	2.85	7.10	12.87	4.97	7.63	PCOL
	968.6	1472.6	2562.8	7179.6	3234.2	3792.5	MEAN, INCOME
PUBLIC INSTRUCTION	311.2	3523.9	11587.8	10754.7	26177.6	466.2	COUNT
	1.19	13.46	44.27	41.08	100.00	-	PROW
	1.13	1.46	8.44	27.57	5.87	6.86	PCOL
	1596.8	1160.6	2067.0	6323.2	3688.0	3473.2	MEAN, INCOME
PERSNL & DOMESTIC SERV	9899.0	51311.0	7709.5	268.6	69107.0	1329.7	COUNT
	14.31	74.16	11.14	0.39	100.00	-	PROW
	35.80	21.22	5.62	0.69	15.52	19.56	PCOL
	333.3	495.1	1320.4	4116.1	578.0	515.4	MEAN, INCOME
TOTAL	27650.0	241831.9	137300.4	39014.0	445796.3	6798.1	COUNT
	6.20	54.25	30.80	8.75	100.00	-	PROW
	100.00	100.00	100.00	100.00	100.00	100.00	PCOL
	629.1	992.0	2472.2	7510.1	1995.8	2262.7	MEAN, INCOME
NO INFO	19782.4	160221.1	95605.0	14563.3	290171.9	5226.8	COUNT
	6.82	55.22	32.95	5.02	100.00	-	PROW
	-	-	-	-	-	-	PCOL
	568.9	971.2	1705.4	5937.9	1435.0	1204.9	MEAN, INCOME

13. Questions: a) How do the distributions of workers among sectors of residence differ by educational level? b) Does income rise with education more in some sectors of the city than in others?

Answers: a) The best-educated workers are concentrated in the highest-income neighborhoods; b) Yes, highest gains in the highest-income neighborhoods.

Differences in residential patterns across educational groups are considerable (Table 14). For instance, 7% of workers in the Bogota labor force have higher education; of residents of the highest income sector (sector 8), however, 25% have higher education. At the other end of the income distribution, the poorest sector (sector 2) contains 22% of the people with no education compared with 5% of the people with higher education. If we turn our attention to income-education profiles within residential sectors, we find: i) income rises with education in the cross section more among residents of some parts of the city than among others; ii) the largest income gains are found in the highest income sectors;[1/] and iii) all of the difference, however, comes at the secondary and higher education levels; among workers with lower levels of education, residence in a high income sector is not associated with a higher income. Once again, interpretation problems are paramount: are the lower incomes received by workers with secondary and higher education who reside in low income neighborhooods due to limitations imposed by the location, or is it that the unsuccessful among the better-educated have little choice but to live in poor neighborhoods? And still, the alternative views cannot be distinguished with the available data.

1/ Cf. Mohan (1979, p. 41).

TABLE 14.

CROSS-TABULATION: SECTOR OF RESIDENCE BY EDUCATION

	NONE	PRIMARY	SECONDARY	HIGHER	TOTAL	OTHER	
	1815.6	11160.1	7232.8	1605.3	21815.5	445.7	COUNT
SECTOR 1	8.33	51.16	33.15	7.36	100.00	-	PROW
	3.83	2.78	3.11	3.00	2.96	3.71	PCOL
	484.3	901.5	1915.4	4968.5	1502.3	1342.6	MEAN, INCOME
	10582.6	79817.6	31925.1	2745.5	125070.8	2185.2	COUNT
SECTOR 2	8.46	63.82	25.53	2.20	100.00	-	PROW
	22.31	19.85	13.71	5.12	16.99	18.17	PCOL
	621.1	884.5	1449.5	3737.8	1069.1	866.2	MEAN, INCOME
	8950.3	97364.0	61978.7	6210.4	174543.4	2287.4	COUNT
SECTOR 3	5.15	55.78	35.51	3.56	100.00	-	PROW
	18.95	24.22	26.61	11.59	23.72	19.02	PCOL
	613.4	1039.3	1653.3	3654.2	1329.4	1200.5	MEAN, INCOME
	3243.7	37633.9	25983.3	3399.7	70265.7	916.6	COUNT
SECTOR 4	4.62	53.56	36.99	4.84	100.00	-	PROW
	6.84	9.36	11.16	6.35	9.55	7.62	PCOL
	661.6	1158.5	1862.3	4073.3	1536.9	1428.7	MEAN, INCOME
	3319.8	28838.7	17924.6	3834.9	53998.1	922.2	COUNT
SECTOR 5	6.15	53.42	33.33	7.10	100.00	-	PROW
	7.00	7.17	7.73	7.16	7.34	7.67	PCOL
	554.7	1042.7	1985.2	5738.8	1660.4	1557.3	MEAN, INCOME
	8565.7	70789.7	38466.3	6811.7	124633.4	2014.9	COUNT
SECTOR 6	6.87	56.80	30.86	5.47	100.00	-	PROW
	18.05	17.61	16.52	12.71	16.93	16.76	PCOL
	694.9	999.5	1896.8	6001.6	1528.9	1597.4	MEAN, INCOME
	6020.3	46438.1	34214.7	15304.2	101977.1	2055.3	COUNT
SECTOR 7	5.90	45.54	33.55	15.01	100.00	-	PROW
	12.69	11.55	14.69	28.56	13.86	17.09	PCOL
	489.1	943.9	3005.4	7789.1	2636.0	2747.4	MEAN, INCOME
	4893.6	30010.8	15105.1	13664.8	63674.2	1197.6	COUNT
SECTOR 8	7.69	47.13	23.72	21.46	100.00	-	PROW
	10.32	7.46	6.49	25.50	8.65	9.96	PCOL
	571.7	846.1	5294.2	10435.3	3938.1	4034.4	MEAN, INCOME
	47432.5	402053.0	232905.4	53577.4	735968.2	12024.9	COUNT
TOTAL	6.44	54.63	31.65	7.28	100.00	-	PROW
	100.00	100.00	100.00	100.00	100.00	100.00	PCOL
	604.0	983.7	2157.4	7082.7	1774.7	1802.9	MEAN, INCOME

B. The Single-Equation Non-Interactive Approach

Beyond simple tabulations, the most frequently used test for labor market segmentation is a multiple regression earnings function relating a worker's earnings to socioeconomic and employment characteristics. Among the personal characteristics commonly included are education, age or experience, sex, migrant status, etc. Job characteristics may include size of firm, capital intensity, worker productivity, among others. A test of segmentation which is commonly employed is the following: If, after controlling for personal characteristics, we still find that job characteristics are significant determinants of income, then the labor market is said to be segmented. This test of segmentation corresponds to Definition (ii): workers with "equal" human capital are rewarded differently depending on the segment of the labor market in which they work.

Earnings functions have been run for a large number of countries. The evidence Psacharopoulos (1978) has synthesized covers the earnings functions for 16 less developed countries.1/ In general, earnings functions estimated on LDC data are found to perform well. Education and age systematically appear as important explanatory variables. The effects of education are quantitatively large as well, each year of education adding from 5% to 17% to one's annual earnings.

1/ The countries covered are Brazil, Colombia, Cyprus, Iran, Kenya, Malaysia, Mexico, Morocco, Nigeria, Peru, Singapore, Taiwan, Thailand, Turkey, Vietnam, and Yugoslavia.

Colombia, too, also offers numerous multiple regression earnings functions dating back a decade (see Table 15). Education consistently has an important positive effect on income. Age or experience are also found to be related positively to income. Other variables, such as city of residence, family background, and employer characteristics, although statistically significant determinants of income, are not very important in magnitude. Finally, these studies explain up to fifty percent of the variance in individual incomes.

What of wage differences for seemingly "comparable" workers depending upon their sector of employment? An illustrative empirical test is offered by the work of Bourguignon (1979), using the following variables:

Y = income,

EDUC = years of schooling,

EXP = labor market experience,

EXPSQ = " " " squared,

WORKTIME = hours per week

D = dummy variable for modern sector employment.[1/]

Following Souza and Tokman (1976) and Webb (1974), Bourguignon (p. 47) distinguishes between traditional sector employment (productive units with five or fewer workers) and modern sector employment (those with six or more workers). All persons with university education and all government employees are considered members of the modern sector regardless of firm size, while all domestic servants are included in the traditional sector.

1/ In empirical work, Bourguignon used the logarithm of D. It is unclear how he has taken the logarithm of a 1/0 dummy variable.

TABLE 15

Principal Results of Studies Using Microeconomic Survey Data to

Construct Earnings Functions in Colombia

AUTHOR	YEAR OF DATA AND SOURCE	GEOGRAPHICAL COVERAGE	SAMPLE SIZE	DEPENDENT VARIABLE	STATISTICALLY SIGNIFICANT INDEPENDENT VARIABLES	R^2
Schultz (1968)	1965 Survey of Employment and Unemployment (CEDE)	Bogotá	1,000 individuals both sexes	Logarithm of wage adjusted for a 48 hour work week	Educational level, age, other family income (women only)	.17 - .24
Gonzáles (1971)	1967-68 Survey of Family Bud- gets and Expenditures (CEDE)	Bogotá	918 individuals both sexes	Income	Educational level, age, income source (capital, independent work, mixed or salaried), sex	.38
Musgrove (1974)	1967-68 Survey of Family Bud- gets and Expenditures (CEDE)	Bogotá Barranquilla, Cali, Medellin	2,949 families	Logarithm of imputed "relative long term income" of family	Interactive variables involving educational level and age of family head, head's marital and family status, presence of capital income, number of workers in family, city	.49
Urrutia (1974)	1967 Survey of Occupational and Geograph- ical Mobility (CEDE)	Bogotá Bucaramanga, Manizales, Medellin	331 individuals both sexes	Income	Educational level age, sex	Approx- imately .45

continued on next page

TABLE 15. Continued

AUTHOR	YEAR OF DATA AND SOURCE	GEOGRAPHICAL COVERAGE	SAMPLE SIZE	DEPENDENT VARIABLE	STATISTICALLY SIGNIFICANT INDEPENDENT VARIABLES	R^2
Kugler (1975)	1970 National Household Survey (DANE)	National	607 individuals both sexes	Logarithm of income	Educational level and experience level of individual, parents' income	.50
Fields (1976)	1967 Survey of Occupational and Geographical Mobility (CEDE)	Bogotá Bucaramanga, Manizales, Medellín	331 individuals, both sexes	Logarithm of income	Educational level, experience, sex, city of residence, occupation, parents' education and income	.55
Fields and Schultz (1977)	1973 Census	National	860,000 individuals	Logarithm of income	Educational level, age, department, rural/urban, employer/employee	Up to .35
Fields (1978a)	1967-68 Survey of Family Budgets and Expenditures (CEDE)	Bogotá Barranquilla, Cali, Medellin	877 manufacturing workers, both sexes	Logarithm of income	Educational level, age, sex, industry, of employment	.41
Bourguignon (1979)	1974 Household Survey (DANE)	Barranquilla, Bogotá, Bucaramanga, Cali, Manizales, Medellín, Pasto	4,700 salaried workers, both sexes	Logarithm of income	Educational level, experience, work time, modern/traditional sector	Up to .38

The regression evidence he presents (p. 66, reg. 1.a) for males in Bogota is: 1/

$$\text{Log } Y = \underset{}{5.266} + \underset{(.004)}{.145}\ \text{EDUC} + \underset{(.003)}{.074}\ \text{EXP} - \underset{(.000)}{.001}\ \text{EXPSQ} + \underset{(.040)}{.196}\ \text{WORKTIME}$$

$$+ \underset{(.021)}{.123} \log D,\ R^2 = .316,\ n = 3713,$$

All coefficients are statistically significant at the 1% level. Bourguignon himself interprets the significance of the modern-traditional variable as evidence of a degree of dualism in the Bogota labor market (though he later argues that the degree of dualism is not great).

Some new evidence for the workers of Bogota appears in this and the several subsequent sections. The data set used for the econometric work presented here is the Public Use Sample from the 1973 Census, the same source used in the tabulations of Section A, but with certain restrictions. Only the male sample was used, and it was further limited to workers who had an income and who reported that they were employed.

The explanatory variables used in the regressions are education, age, industry, and occupation. The migrant variable is omitted due to its insignificance in past studies of urban Colombia (Fields, 1976; Jaramillo, 1979). The sector of residence is omitted in keeping with the simplifying assumptions stated on page 25.

1/ Standard errors are given in parentheses.

The first regressions were run on the entire sample and are reported in Table 16. Regression (1) expresses the logarithm of income as a function of education categories and age. The four education dummies correspond respectively to primary education (some or all), and some education level not ascertained. Thus, the omitted category is no education. Age and age squared are measured in years, the latter to allow the curvilinear effects.

We find in this sample of male workers that education and age do indeed contribute significantly to the explanation of income, the coefficients being many times their standard errors. The estimated values are quite reasonable in magnitude. The R^2 is .41, a highly respectable figure that compares well with the explanatory levels found in the other studies reviewed above (cf. Table 15).

Regression (2) of Table 16 adds a series of industry and occupation categories to the education and age variables and estimates the full set using Ordinary Least Squares. Performance of the industry and occupation is poor: the estimated magnitudes are not very large; many of the estimated effects are statistically insignificant, which in a sample of 44,000 cases indicates really weak performance; and the contribution of these variables to the proportion of variance explained is only 2%, though still statistically significant by standard F tests.

From this evidence, we might draw the following inference about labor market segmentation in Bogota based on job type:

> <u>If labor market segmentation is defined as a statistically significant effect of sector of employment on income for seemingly-comparable workers, the evidence is weak but nonetheless statistically significant that by this definition the Bogota labor market is segmented.</u>

Table 16

Regressions on Full Sample

	Regression (1)		Regression (2)	
	Regression Coefficient	Standard Error	Regression Coefficient	Standard Error
EDUC1 (Primary, some or all)	0.437	(0.015)	0.405	(0.015)
EDUC2 (Secondary, some or all)	1.022	(0.016)	0.908	(0.016)
EDUC3 (Higher, some or all)	2.060	(0.020)	1.717	(0.022)
EDUC4 (Some education, level not ascertained)	1.301	(0.051)	1.113	(0.050)
AGE	0.110	(0.001)	0.108	(0.001)
AGESQ	-0.001	(0.00002)	-0.001	(0.00002)
IND1 (Agriculture and mining)			-0.155	(0.028)
IND2 (Construction)			-0.210	(0.015)
IND3 (Commerce)			0.065	(0.016)
IND4 (Services)			0.020	(0.014)
IND5 (Other non-manufacturing)			-0.108	(0.009)
OCC1 (Professional, technical, managerial)			0.505	(0.028)
OCC2 (Clerical)			0.119	(0.027)
OCC3 (Sales)			0.114	(0.026)
OCC4 (Production)			0.020	(0.025)
OCC5 (Construction and transport)			0.024	(0.026)
OCC6 (Other non-service)			0.002	(0.025)
CONSTANT	4.224		4.343	
R^2	0.41		0.43	
SEE	0.710		0.695	
n	41,307		41,307	

Actually, the evidence is so weak that I would prefer to say:

> Only weak support is found for the proposition that the Bogota labor market is segmented by sector of employment.

C. Inequality Within and Between Groups

In Section B, weak effects for industry and occupation were found in an earnings function which also inclueded education and age. Although these weak results might be symptomatic of model misspecification, I would suggest that the cause for the weak occupation and industry results appears to lie elsewhere. When one looks in Table 17 at the extent of correlation between income, industry, and occupation, a deeper empirical problem becomes evident: Income is not very highly correlated with the broad industry or occupational categories used. Even the highest correlation (between LOGY and OCC1) implies that just 14% of the variance in LOGY is associated with knowledge that the worker is in a professional, technical, or managerial occupation or not. Although it might be argues that the categorization used is too broad or that measurement errors in the Census are severe, it is also possible that incomes of Bogota's workers are not determined primarily by the industry or occupation of employment.

What I just said has important implications for the degree of labor market segmentation in Bogota. Any test of segmentation should recognize differences within groups as well as differences between them. Dual economy theorists hyphotesize that the labor market is divided into a primary and a secondary segment (or modern and traditional). If the dualists are right, earnings in the two

TABLE 17

Correlation Coefficients

Industry of Employment	Coefficient of Correlation Between Log of Income and:
(Agriculture and Mining)	-.015
(Construction)	-.145
(Commerce)	.072
(Services)	.191
(Other Non-Manufacturing)	-.053
Occupation	
(Professional, technical, managerial)	.373
(Clerical)	.060
(Sales)	.047
(Production)	-.122
(Construction and Transport)	-.118
(Other Non-service)	-.073

segments should be rather distinct. Two alternative possibilities are depicted in Figure 3. The frequency distributions in Panel A are quite consistent with labor market duality. In that case, the sector of employment is rather decisive in predicting an individual's income. Such a finding would suggest that differential access to jobs in the various sectors is an important source of inequality. Further research into employers' hiring practices might prove particularly fruitful in understanding why the labor market rewards different persons differently. However, if the data were as in Panel B, with much income dispersion within each of the sectors and much overlap between them, it would be much harder to claim a dualistic labor market.

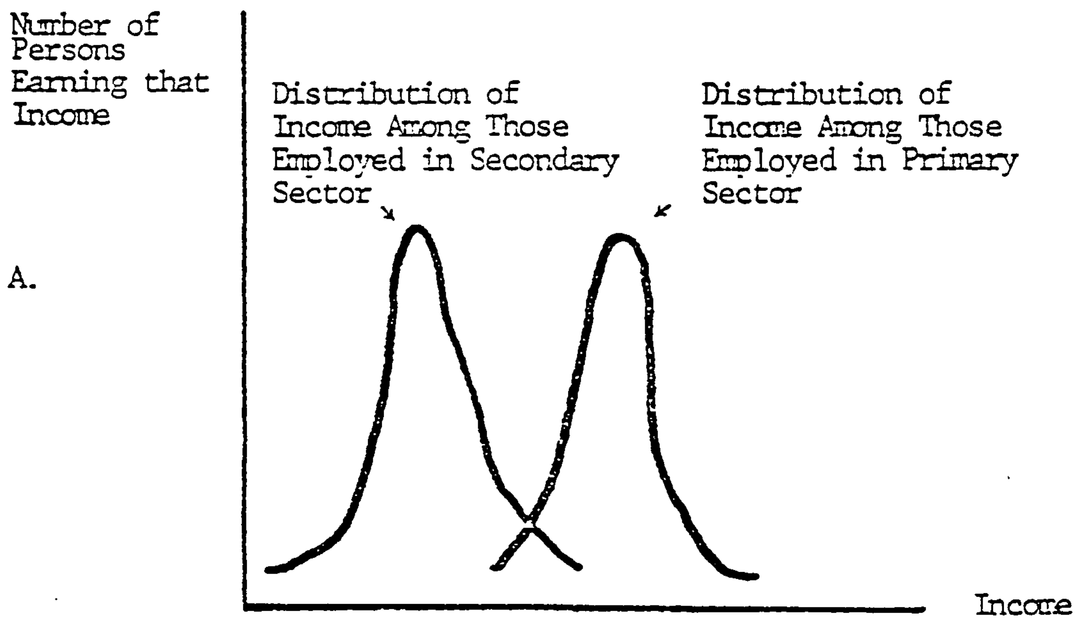
Tabulations like those presented in Section A seem to show that workers with various personal characteristics or employed in various kinds of jobs receive quite different returns in the Bogota labor market. But I would caution readers to treat these data carefully before inferring that labor markets are segmented, since no evidence on intra-group income variability is presented in those sorts of tables.

Studies conducted in a number of LDC labor markets, including that of Bogota, have shown that despite large differentials in average incomes between one labor force group and another -- where groupings are by education, industry, or other income-determining characteristics -- the great bulk of income inequality is <u>within</u> the groupings. Simply put, no one variable, nor set of explanatory variables combines, is decisive in predicting income with a high degree of precision.

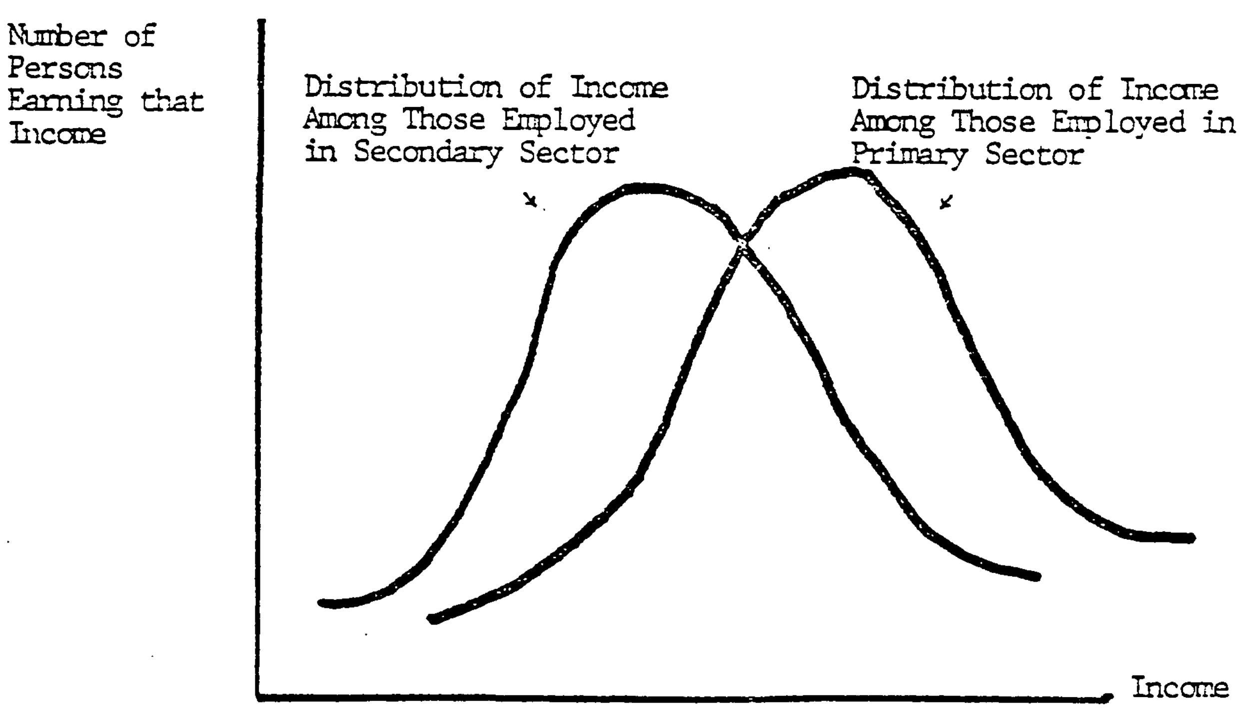
Figure 3

DISTRIBUTION OF INCOME WITHIN AND BETWEEN LABOR MARKET SECTORS

A.



B.



In the four major cities of Colombia including Bogota, the following income differences have been observed:

Group	Mean Income (in pesos per three months)*
All urban manufacturing workers	6,570
Education breakdown:	
Primary	3,820
Secondary	8,020
Higher	16,180
Sector breakdown (selected industries):	
Clothing	4,100
Transportation	5,920
Foodstuffs	6,730
Textiles	8,200
Elec. Machinery	8,240
Chemicals	12,320

Although this may at first seem convincing evidence of labor market segmentation, Figures 4 through 6 demonstrate that there is a great deal of overlap between one education or industry group and another, especially in the industry plots, and no sign of bimodality. Given the more disaggregated presentation of the available data in Figures 4-6, we should be much less willing to conclude that the labor market in urban Colombia is segmented, at least in these dimensions.

* Fields (1978a), derived from 1967/68 family budget data from CEDE.

FIGURE 4

DISTRIBUTION OF (LOG) INCOME, MANUFACTURING WORKERS, URBAN COLOMBIA, FULL SAMPLE.

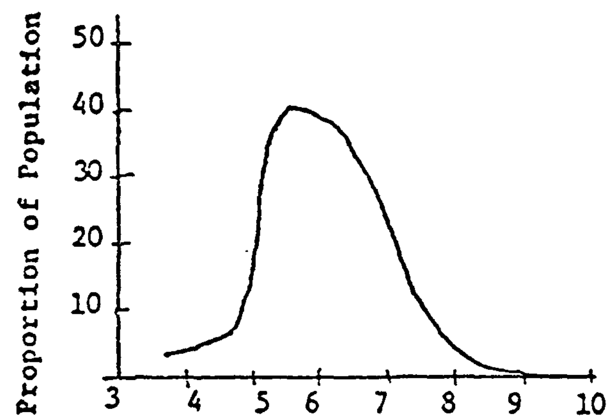


FIGURE 5

DISTRIBUTION OF (LOG) INCOME BY EDUCATION GROUP

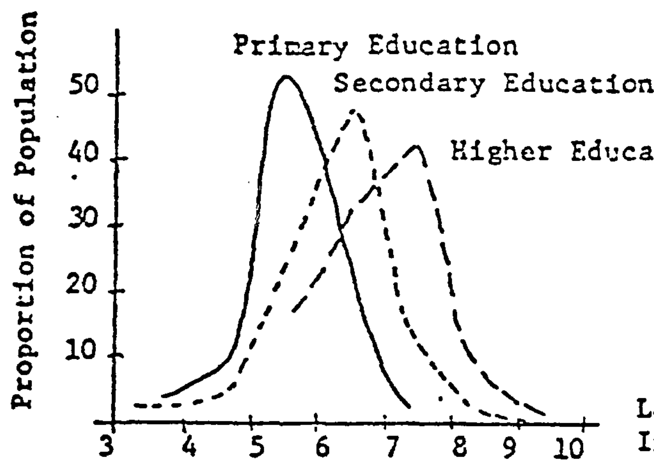
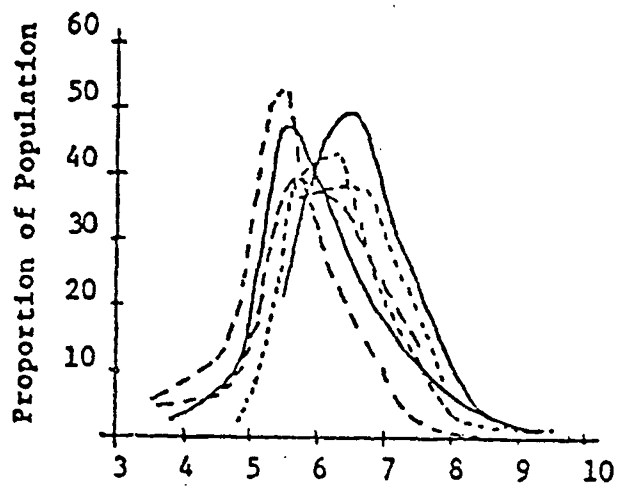


FIGURE 6

DISTRIBUTION OF (LOG) INCOME BY INDUSTRY GROUP



Key: ___ Foodstuff ___ Chemicals
.... Textiles ... Elec. Machinery
--- Clothing --- Transportation

Source: Fields (1978a)

We have thus reached a partial answer to the title question:

The Bogota labor market is not sharply segmented if, by "labor market segmentation," we mean large income differences between workers in various occupations, industries, or other labor force divisions as compared to variations within those groupings.

D. Segmentation Schemes

A somewhat different notion of segmentation arises, one that requires a different kind of test. It may be that the earnings functions themselves depend on the segment of the labor force in which an individual works. Accordingly, some researchers have proposed stratifying the labor force into various segments and examining the determinants of income within each. With few exceptions, however, these studies have largely ignored the causal structure of the labor market, i.e., no attention is paid to how the segmenting variables enter the income determination process.1/ Some, like sex and race, are given attributes of the individual. Others, such as firm size and public/private sector employment, reflect the choices made by individuals in the pursuit of higher economic status and the constraints imposed upon those choices. A third kind of segmenting variable sometimes used is income itself.

1/ See, for example, Psacharopoulos (1978), where segmentation by income, occupation, race, and sex are treated identically.

Once these different kinds of segmentation are recognized, they are readily seen to fit in with the causal structure of the labor market. The first kind of segmentation (e.g., sex, race) is by exogenous income-determining factors; the second (e.g., firm size kind of employment) is by endogenous income-determinig factors; and the third is by the dependent variable (income itself).

In the next three sections, I shall show that the validity of various segmentation schemes depends critically on how the segments are defined. To summarize the results, I claim:

Type of Segmentation	Validity of Intra-Segment Earnings Functions
Type-1: Segmentation by Exogenous Independent Variable	Valid
Type-2: Segmentation by Endogenous Independent Variable	Questionable
Type-3: Segmentation by Dependent Variable	Invalid

These points are developed at length in Sections E-G.

E. Segmentation by Exogenous Income-Determining Factors (Type-1)

Some factors are clearly exogenous to the income-determination process. Without question, these include sex, age, race, and family background; somewhat less certainly exogenous, but usually treated as such, are migrant status, education, and religion. What all these factors have in common is that for all practical purposes they are unalterable, i.e., in the pursuit of higher economic status, the individual cannot do anything about these factors.

The key conclusion about Type-1 segmentation (by exogenous independent variables) is that meaningful results are obtained when the labor force is segmented in this way. 1/ More precisely:

> Segmentation by exogenous variables produces unbiased estimates of the parameters of the earnings function for workers in each segment.

By this, I mean that an undistorted estimate of the earnings function is obtained for each group. For example, for both men and women in the labor force, income (Y) is partly determined by education (X). Figure 7 depicts the pattern found in the raw data for men and women, denoted respectively by M and W, and the fitted regression lines (Table 18). The line in the center is fit to the whole sample; Segmenting the sample into men's and women's observations, we obtain the upper and lower lines. These two lines respectively give unbiased estimates of the income which a man or woman with the specified education would be expected to receive. It is apparent that the predicted values for the two sexes straddle the line fit to the entire sample. Put differently:

> The regression fit to the whole sample is not a good predictor of income for anyone: it systematically overstates predicted income for women and understates predicted income for men.

1/ This same conclusion holds for the U.S. literature on differences in male-female and black-white earnings functions.

FIGURE 7

STRATIFICATION BY EXOGENOUS INCOME-DETERMINING FACTOR

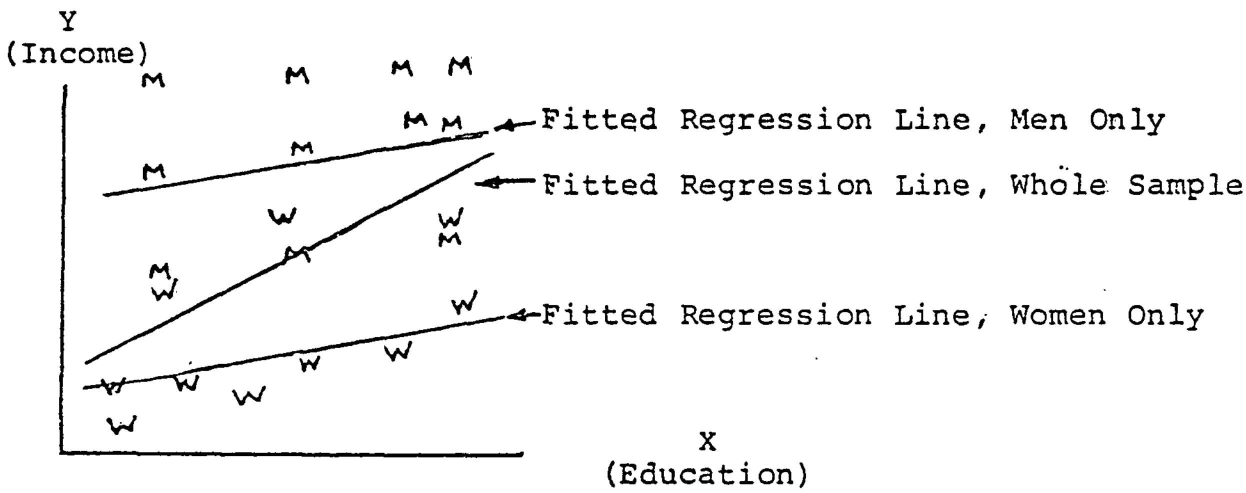


TABLE 18.

Separate Earnings Functions for Men and Women in Bogota

Dependent Variable: Logarithm of Income

Independent Variables	Salaried Men	Salaried Women
Education	.135 (.004)	.094 (.006)
Experience	.075 (.003)	.024 (.003)
Experience Squared	-.001 (.000)	-.000 (.000)
Hours per week	.098 (.045)	.050 (.046)
Modern Sector Employment	.182 (.025)	.017 (.029)
Constant	5.625	6.683
R^2	.384	.180
Number of Observations	2761	1986

Note: Standard errors in parentheses
Source: Bourguignon (1979, p.66)

In addition, the regression coefficients (as illustrated by the slopes of the lines in the figure), we see something even stranger:

> The regression fit to the whole sample systematically overstates the effect of an extra year of education on income for both men and women.

The message, very simply, is that when different groups in the labor force receive different incomes, when these incomes are generated by different underlying earnings function, and when the groupings are based on an exogenous characteristic, the sample should be stratified and separate earnings functions run for each segment.

In summary:

> If labor market segmentation is defined as a situation where workers in different groups have different earnings functions, and if it is believed that the labor market is segmented according to exogenous independent variables, unbiased estimates of the parameters of the earnings function may be obtained by stratifying the sample by these alleged segmentation variables. Empirical evidence shows that by this definition, the Bogota labor market is segmented by sex.

F. Segmentation by Endogenous Income-Determining Factors (Type-2)

Endogenous independent variables are those income-determining factors which result from choices made by and opportunities open to workers in their quest for an improved economic position. These variables include: occupation; industry of employment; characteristics of the occupation, industry, or firm; and place of work. The unifying feature is that incomes vary from one occupation/industry/firm/work place to the next, even for workers with identical personal characteristics. In Bogota, as elsewhere, workers presumably prefer the occupation/industry/firm/work place combination which pays best.

When earning functions differ significantly from one occupational, industrial, or other group to the next, the result is usually taken as evidence of labor market segmentation. This is compatible with definitions of segmentation that emphasize income differences. The empirical evidence is incomplete, however, in that the rules determining access of individuals to various occupations or industries remain unexamined.

A review of the literature turns up many studies where earnings structures have been compared for workers in separate occupations, industries, firm size categories, and places of work of residence. Included among the research studies on Colombia are papers by Kugler et al. (1979), Altimir and Pinera (1977), Mohan (1979), and Bourguignon (1979).

How valid are within-group regressions when the groups are defined according to endogenous income-determining factors? The answer has three parts:

When the labor force is grouped according to endogenous income-determining factors, if there is no mobility between groups, and if the labor force is homogeneous with respect to omitted variables, then within-group regressions are valid. Under these assumptions, intra-group regressions provide meaningful estimates to questions such as: Does education pay off more in the modern sector than in the traditional sector? Given one's education, does income vary with occupation? The stated assumptions imply a completely-segmented labor market, i.e., one in which otherwise identical workers do in fact receive different wages depending solely upon the segment of the labor market in which they are first employed, with no opportunity to move to better segments.

<u>When the labor force is grouped according to endogenous income-determining factors and there is intergroup mobility, however, within-group regressions are invalid</u>. Any degree of mobility between segments means that some of those who start in group i move up to group j. This mobility is ignored in within-group regressions. The result is sample selectivity bias: looking only at the incomes of those individuals who <u>end up</u> in group i underestimates the incomes expected by individuals who <u>started</u> in that occupation or industry or who <u>at some time</u> have worked in it. This bias occurs even if upward mobility takes place without regard to the individual's race, sex, or other characteristics.

<u>When the labor force is grouped according to endogenous</u> income-determining factors, the labor force is heterogeneous with respect to omitted variables, and if the effects of these unmeasured variables are ignored, then within-group regressions are also invalid. In labor economics, the likely omitted variable is ability. In earnings functions, the coefficients on variables such as education that are correlated with ability are biased <u>upward</u>, since part of the estimated return attributed to education is in fact a return to

superior ability. [1] If one stratifies by variables correlated with ability and runs separate earnings functions within each stratum, however, the likely effect is to reduce the apparent contribution of education in determining earnings in the lower strata even, in extreme cases, producing an apparent negative relationship between education and earnings. This small or negative relationship is erroneous since it is the (unmeasured) low ability rather than the (measured) high education which results in low income. For example, the low incomes of college graduates working as street vendors more probably reflect the unmeasured physical and mental limitations of those individuals more than it does the lack of skills acquired during 16 years of schooling.

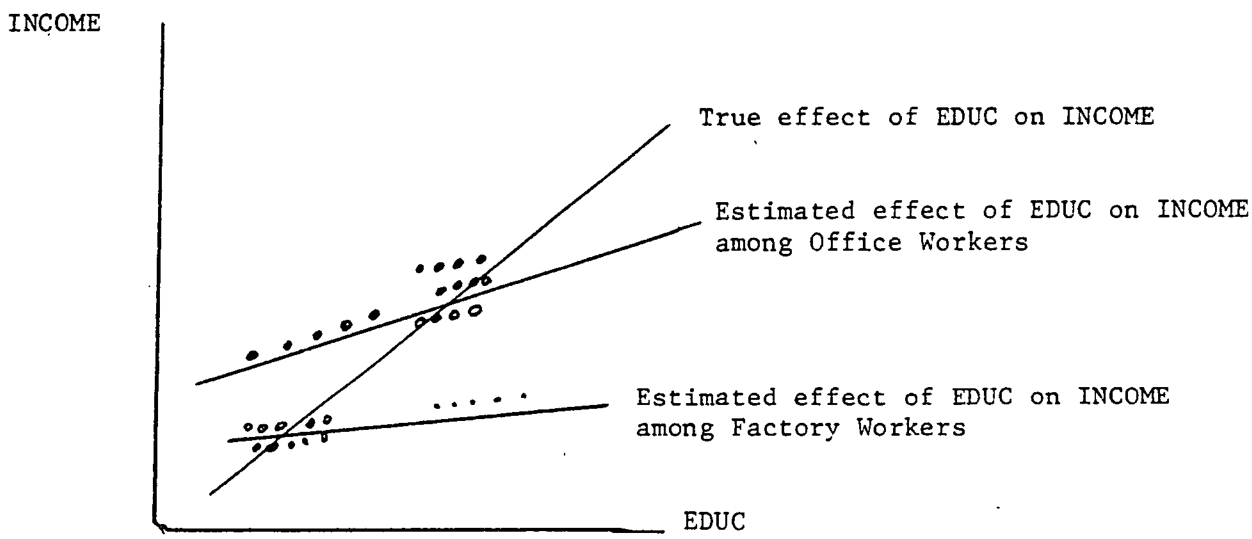
Stratifying a sample by endogenous income-determining factors thus yields invalid results except under strong assumptions that do not hold. In each case, the problem is a form of selectivity bias: education tends to raise people's incomes by moving them out of lower occupational categories into higher ones, and this effect is missed when income functions are estimated within occupations. Estimates of income determination from intra-occupation regressions thus are conditional on remaining in that occupation, and as such are biased downward. An ordinary factory worker who acquires one more year of education is less likely to remain a factory worker, so adverse selection determines the sample.

1/ See, for example, Griliches (1975).

Figure 8 illustrates these relationships:

FIGURE 8

Segmentation by Endogenous Income-Determining Factor



Let us now turn to the empirical results. Intra-industry and intra-occupation regressions for the 1973 Census sample of workers in Bogota are presented in Tables 19 and 20. These regressions results are subject to an unknown degree of sample selectivity bias.

It is clear by inspection that income structures within industries and occupations are not the same from one to the next. Indeed, by the standard Chow test, these differences are highly statistically significant at all tabulated levels. Comparisons of the regression coefficients suggest that:

(1) The effect of education on income is larger in agriculture and mining and commerce than in the other industries.

(2) Somewhat offsetting the pattern in (1), commerce which has a small slope is the industry with the highest intercept.

Table 19

Regressions Within Industries

	IND1	IND2	IND3	IND4	IND5	IND6
	Agriculture and Mining	Construction	Commerce	Services	Other Non-Manufacturing	Manufacturing
EDUC1	0.558 (0.109)	0.279 (0.031)	0.666 (0.069)	0.280 (0.069)	0.427 (0.023)	0.350 (0.033)
EDUC2	1.802 (0.124)	0.741 (0.043)	1.455 (0.070)	0.963 (0.070)	0.933 (0.024)	0.836 (0.034)
EDUC3	3.076 (0.144)	2.395 (0.074)	2.270 (0.085)	1.899 (0.071)	1.858 (0.031)	1.955 (0.046)
EDUC4	3.099 (0.656)	0.774 (0.215)	2.149 (0.229)	1.695 (0.125)	1.014 (0.074)	0.964 (0.103)
AGE	0.066 (0.012)	0.082 (0.004)	0.133 (0.006)	0.127 (0.005)	0.106 (0.002)	0.119 (0.003)
AGE^2	-0.0005 (0.00015)	-0.0009 (0.00005)	-0.0013 (0.00007)	-0.0013 (0.00006)	-0.0012 (0.00003)	-0.0013 (0.00004)
CONSTANT	4.368	4.803	3.520	4.034	4.353	4.231
R^2	0.560	0.303	0.431	0.573	0.331	0.392
SEE	0.920	0.672	0.821	0.679	0.693	0.655
n	673	4342	3308	4024	18982	9978

Table 20

Regressions Within Occupations

	OCC1	OCC2	OCC3	OCC4	OCC5	OCC6	OCC7
	Professional Technical, Managerial	Clerical	Sales	Production	Construction and Transport	Other Non-Service	Service
EDUC1	-0.160 (0.147)	0.251 (0.083)	0.502 (0.049)	0.316 (0.027)	0.382 (0.026)	0.499 (0.031)	0.469 (0.108)
EDUC2	0.409 (0.144)	0.751 (0.082)	1.236 (0.050)	0.683 (0.028)	0.724 (0.032)	1.131 (0.034)	1.021 (0.114)
EDUC3	1.194 (0.144)	1.322 (0.085)	2.041 (0.067)	1.298 (0.071)	1.425 (0.156)	2.160 (0.047)	2.171 (0.199)
EDUC4	0.826 (0.172)	1.120 (0.141)	1.515 (0.187)	0.701 (0.091)	0.467 (0.161)	1.325 (0.129)	1.623 (0.546)
AGE	0.125 (0.006)	0.127 (0.004)	0.122 (0.004)	0.112 (0.002)	0.099 (0.003)	0.096 (0.003)	0.113 (0.011)
AGE^2	-0.0012 (0.00008)	-0.0013 (0.00006)	-0.0012 (0.00005)	-0.0012 (0.00003)	-0.0011 (0.00004)	-0.0009 (0.00004)	-0.0011 (0.00015)
CONSTANT	4.811	4.187	3.923	4.444	4.545	4.309	3.982
R^2	0.426	0.483	0.346	0.239	0.192	0.372	0.413
SEE	0.739	0.566	0.828	0.637	0.637	0.730	0.758
n	3266	3780	5944	12472	7117	7885	843

(3) Although age-earnings profiles are steeper in some industries (commerce services and manufacturing) than in others, these differences are not systematically related to the education-earnings relationships.

(4) Turning from industries to occupations, we observe that education-earnings profiles are steepest for sales and service workers.

(5) As an offsett to the pattern of education-earnings slopes, the occupations with the smallest slopes are those with the largest intercepts (professional, construction, and production workers).

(6) The age-earnings profiles do not differ among occupations in any large or systematic way.

(7) Intra-industry and intra-occupation earnings functions vary in explanatory power (as measured by R^2); no systematic pattern emerges.

To summarize these results:

> Significantly different earnings functions are found for workers in different industrial and occupational groupings. This might be interpreted as evidence of labor market segmentation in Bogota, at least according to some of the more common definitions.

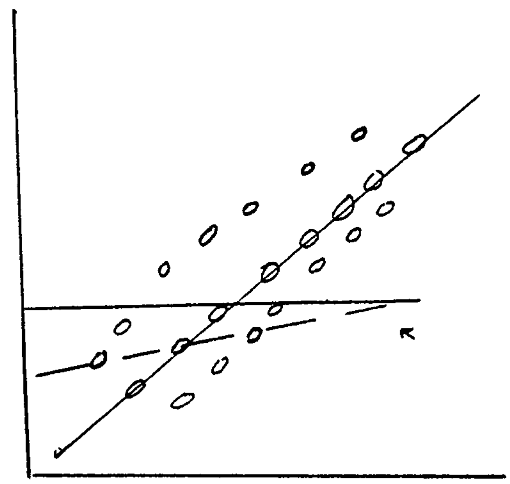
I should repeat: I have my reservations about these results which cloud the interpretation. Workers in Bogota do not remain in the same industry or occupation throughout their lifetimes; that many change categories is reflected in the age compositions of occupations and industries in Tables 6 and 7. Cross section regressions like those in tables 19 and 20 cannot take adequate account of these changes, so I hesitate to give much weight to these results. Perhaps in the future, once we know the income profiles of individuals who started out in particular industries or occupations, we will be better able to assess the effect of occupation or industry or employment on workers' life chances.

G. Segmentation by Dependent Variable (Type-3)

The dependent variable in this study is (the logarithm of) income. Some earlier work has actually or in effect stratified by the dependent variable and run separate earnings functions for each. To do so is methodologically inappropriate.

Segmentation by the dependent variable results in severe truncation bias.. Truncation occurs when a sample is limited to include only those cases within a particular range of values. When samples are truncated by the dependent variable, in this case income, the result is a misestimated regression coefficient which is biased toward zero. In particular, this means that when income functions are estimated on a sample of low income workers, they tend incorrectly to find little or no apparent effect of education on income, as illustrated in the following figure:

FIGURE 9
ILLUSTRATION OF TRUNCATION BIAS 1/



The essence of the truncation bias is adverse sample selectivity. Intuitively, the reason that bias is introduced when a sample is truncated by income is that one of the effects of education is to raise people's incomes and hence remove them from the sample. It is evident that education has an effect on income even at the lowest levels but this effect is distorted because of truncation.

The literature offers many examples of tests for labor market segmentation which suffer from truncation bias. Several authors have looked at the determinants of income for low income workers and inferred from the small magnitudes of regression coefficients or analysis or variance effects that income is not affected by education (i.e., direct segmentation by the dependent variable). Nothing can

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1/ Source: Cain (1976)

be learned about labor market segmentation from such invalid "evidence." Equally invalid are similar tests conducted within low income occupations (e.g., among small farmers in poor countries) or within low income neighborhoods (e.g., in urban ghettos or squatter settlements).

A direct examination of truncation bias in the case of Bogota is highly revealing. I divided the workers into two groups -- those with incomes above and below 1,000 pesos per month -- and ran separate regressions within each of the two groups. The results, presented in Table 21 and Figure 10, are actually quite extraordinary: in the sample as a whole, incomes rise steadily with education; however, within the higher income sample, the income gain is attenuated, because low income workers are systematically excluded; and in the low income sample, the apparent effect of education on income is even smaller and becomes <u>negative</u> for higher education! To reiterate, these estimated relationships are totally biased and ought not to be believed because of adverse sample selectivity and the resultant truncation bias.

To infer from invalid evidence that the human capital model does not apply to the poor is bad enough just as a matter of social science. But the policy implications of that conclusion are far more serious. It would be disastrous if a policy-maker were to back away from educational investments because of evidence like this. This confirms my worst fears: that policies deleterious to the interests

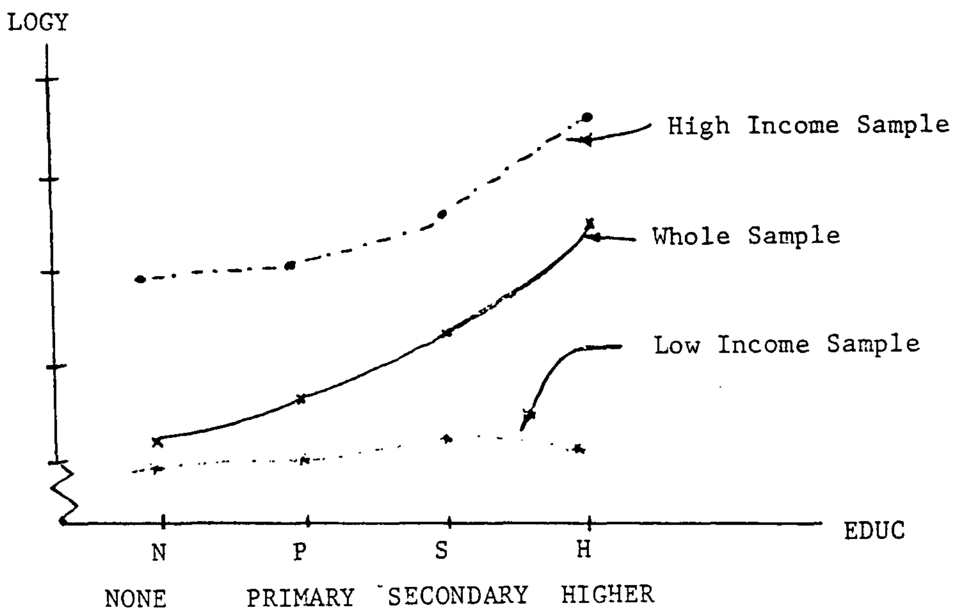
TABLE 21

REGRESSIONS WITHIN INCOME GROUP

	WHOLE SAMPLE	INCOME ≥ 1,000	INCOME < 1,000
EDUC1 (Primary)	0.437 (0.015)	0.1109 (0.022)	0.183 (0.015)
EDUC2 (Secondary)	1.022 (0.016)	0.509 (0.022)	0.343 (0.018)
EDUC3 (Higher)	2.060 (0.020)	1.370 (0.024)	0.143 (0.081)
EDUC4 (Level Unknown)	1.301 (0.051)	0.783 (0.047)	0.141 (0.106)
AGE	0.110 (0.001)	0.060 (0.002)	0.048 (0.002)
AGE^2	-0.001 (0.00002)	-0.003 (0.00002)	-0.006 (0.00002)
CONSTANT	4.224	5.872	5.338
R^2	0.410	0.371	0.061
SEE	0.710	0.555	0.568
N	41.307	24.693	1.6614

FIGURE 10

PREDICTED VALUES FOR WHOLE SAMPLE AND TRUNCATED SAMPLES



of the poor may be promulgated from a basis of ill-designed research findings. Many times, it is better to take on a small problem and do it right rather than to take on a larger problem and do it wrong.

H. Group Determination and Inter-Group Mobility

In Sections D-G, we examined the determinants of income for different groups of workers. That kind of analysis did not address the determination of group membership. Let us now indicate how that gap might be filled in future work.

The preceding sections distinguished between segmentation by exogenous income-determining factors, by endogenous income-determining factors, and by income itself. It is not of much interest to social scientists to predict sex, race, or other exogenous characteristics with one exception: predicting educational attainments by family background and local opportunity variables *is* of interest. We have ample evidence from Colombia and other countries that educational attainments are closely-linked across generations (i.e., the children of highly-educated, well-off parents are themselves more likely to achieve higher schooling levels) and by location (i.e., where there are more schools, more children attend).1/ For a limited group of workers in Bogota -- namely, those who live with their parents the 1973 Census data could be used to relate the

1/ The Colombia evidence includes studies by Rama (1969), Parra (1973), Urrutia (1974), Kugler (1975) and Fields (1976).

worker's income to his/her own education and the education, occupation, and income of the parents;[1] but I would not advise such a research undertaking since the sample of workers who live with their parents cannot be thought to be representative of the labor force as a whole.

Turning our attention to endogenous income-determining factors, this study has identified industry and occupation as such factors. Tabular evidence is available on the characteristics of workers in different occupations and industries (cf. Section A above and the references cited therein); but these efforts have not proceeded to the point of formal modeling of occupational/industrial outcomes, in Colombia or in other LDCs.

Finally, on the determination of membership in the poverty group (i.e., segmentation by the dependent variable), the studies by Mohan (1979), Bourguignon (1979), and earlier works cited therein give a clear picture of who the poor of Bogota are. I need not go further into poverty profiles at this time.

There remains the question of inter-group mobility or lack thereof. Up to now, no researcher has had access to data on changes in economic status over time. Consequently, we have been unable to gauge the extent to which today's poor were also yesterday's poor or whether different persons have taken their place. In addition, it

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1/ That is what Kugler (1975) did using an earlier national statistical office (DANE) sample.

has been impossible to look at changes over time in occupation, industry, and other measures of labor market status. Even fine microeconomic cross sectional data sets like the Census sample cannot be used for dynamic purposes.

Fortunately, new kinds of data sets are being generated. It would be particularly useful in these new data sets to solicit retrospective cross section information and/or longitudinal panel data to answer questions about inter-group mobility. We could, if we had such data, move ahead toward assessing the degree of mobility in the Bogota labor market, relate the observed inmobility to labor market barriers, and thereby move even further toward determining the degree of segmentation in the Bogota labor market.

Studies such as the ones outlined above would help clarify the proximate causes of poverty. The root causes of poverty in Bogota remain to be understood.

IV. CONCLUSIONS

A. Conceptual Conclusions

Four criteria for defining labor market segmentation were articulated: the definition should not be equivalent to the phenomena to be explained; a satisfactory definition must distinguish actions by segmenters which lead to labor market inequality from "justifiable" differences among workers; the definition should in principle permit identification of how the segmenter effects segmentation. The existing definitions never fulfill and seldom approach these criteria.

Five definitions commonly used in the segmentation literature were reviewed. These are:

(i) Heterogeneity of outcome.

(ii) Heterogeneity of outcomes among "comparable" workers as a function of group in the labor market (e.g., occupation or industry).

(iii) Heterogeneity of labor market functioning in various submarkets.

(iv) Limited access to good jobs.

(v) Non-random access to the available jobs.

Taken together, Definitions (ii) and (v) are the most helpful concepts of labor market segmentation yet devised. Jointly, they direct our attention toward the actual wage - and employment - determination mechanisms in labor markets. They take the first step toward explaining _why_ intergroup labor market differentials exist by showing _that_ intergroup market differentials exist in particular dimensions.

Eight statistical models for empirical estimation of a segmented labor market were presented. The available data set for Bogota affords measurement of income, sector of residence, education, age, migrant status, industry and occupation of employment, and average incomes in the several industries and occupations. The workings of the Bogota labor market suggest a model with four equations in four endogenous variables -- income, industry, occupation, and sector of residence. None of the eight models which have been applied in the literature fully capture the interrelationships among the variables. Hence, one cannot simply borrow an established procedure developed in some other context and apply it as is to Bogota.

Upon further consideration, some econometric models appear more justified by the underlying labor market conditions than do others. These econometric issues condition the interpretation of the empirical evidence, discussed below.

B. Empirical Conclusions

In answer to the empirical question of how segmented Bogota's labor market is, the following results were found:

1. There are differences in income among various groups of workers. The sample of workers in Bogota was divided according to sex, age, education, migrant status, industry, occupation, and sector of residence in the city. For each such grouping, differences among groups were evident, both in the simple tabulations (Table 2) and in the cross-tabulations (Tables 3-14).

2. None of these characteristics decisively segments the labor force. We find much inequality within each group and much overlap between the groups. The data exhibit neither a clear duality nor any sign of bimodality (Figures 4-6).

3. Among male workers in Bogota, there are significant differences in income given education and age for workers in different industries and occupations. (Table 16) However, not all differences are economically significant in magnitude or statistically significant in sign. Thus:

4. Overall, only a weak correlation appears between income and occupation or industry of employment. While there are tendencies for workers with the same education and age to earn higher incomes in one industry or occupation rather than another, these tendencies are not at all pronounced. (Table 17).

5. Segmenting the labor force according to exogenous explanatory variables results in significantly different earnings functions for different labor force groups; these groupings are statistically valid. Earnings functions estimated separately for men and women are significantly different from one another (Table 18).

6. Segmenting the labor force according to endogenous explanatory variables results in significantly different earnings functions for different industrial and occupational groups; these groupings are only approximately valid. The earnings functions are noticeably different for workers in various industries (Table 19) and occupations (Table 20). This kind of segmented earnings function with the segments chosen according to

endogenous explanatory variables would be exactly valid if labor market segmentation were complete (i.e., no worker who starts working in a low-paying segment is able to enter a higher-paying segment subsequently) and if the distributions of abilities among workers in the various segments were identical. Since these assumptions presumably do not hold in the Bogota labor market, however, selectivity bias occurs in the within-industry and within-occupation regressions, rendering the estimated earnings functions only approximately valid.

7. Segmenting the labor force according to income results in significantly different earnings functions for the poverty and non-poverty groups; inferences of labor market segmentation drawn from these groupings are totally invalid: When separate regressions were run for poverty and non-poverty groups, there appears to be a positive relationship between income and education for the non-poverty group only; for the poverty group, a weak relationship between income and education appears in the lower educational categories and a negative relationship is found between income and education at the higher educational levels. (Table 21) These results are completely biased due to the adverse sample selectivity and consequent downward truncation bias which is introduced when a sample is chosen on the basis of the dependent variable. Income and education are in fact positively related throughout the entire range of observations (Table 16) and hence the slopes of the earnings functions estimated for both the poverty and the non-poverty groups are biased downward (Figure 10).

C. Needs for Future Research

The empirical work presented in this paper used a particular kind of data (microeconomic Census data on individuals) and focused on a particular kind of question (segmented earnings functions). The needs for future research fall into three general areas: doing a better job on the same kind of question with the same kind of data, addressing a broader range of questions, and using different kinds of data. These are neither mutually exclusive nor jointly exhaustive.

Perhaps the least expected empirical result reported here is the weak effect of the industry and occupation on income. The weakness of these variables is open to a variety of interpretations, most prominently: a genuinely integrated labor market or mismeasurement. Further work on segmentation by type of employment needs to establish which is the better explanation.

There is value in moving beyond data based solely on cross sections of individuals. We need to look at household data on changes over time changes in wages, in kind of employment, in labor force participation rates and and their relationships to education, sex, occupation, initial income, and the other variables considered in this paper. We need also to examine differences in firms wage structures, employment decisions, hiring practices, and promotion policies. We need to observe information and misinformation, mobility and immobility, access and barriers to access, and stratification in the labor market. And we need to integrate these different kinds of information and relate them to poverty, inequality, and development.

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