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The Mystery of Discrimination in Latin America

Conventional wisdom holds that Latin America is a highly discriminatory society. This belief is hardly surprising given the history of ethnic and class conflicts in the region and the plethora of anecdotal evidence reinforcing this notion. However, whereas it cannot be argued that many societies in the region do, in fact, discriminate, the crucial questions have barely been broached. Understanding the extent of such discrimination and exploring the channels through which it operates deserve special attention.

How widespread is discrimination in Latin America? The primary opinion survey in the region, Latinobarómetro, explores discriminatory perceptions for representative samples of the population of eighteen countries.[1] As shown in figure 1, when individuals were asked in 2001 who they think suffers the most from discrimination, they consistently and overwhelmingly highlighted the poor, followed by indigenous peoples and Afro-descendants. This pattern is consistent across countries in the region. In all the countries surveyed, poverty is perceived as being the main driver of discrimination, with responses varying from 14 percent in the case of Panama to 49 percent in the case of Nicaragua. Figure 2 illustrates these results for the countries surveyed.

These results, however, are not entirely consistent with the answers to a similarly worded question asked only a few years later. Starting in 2004, the same Latinobarómetro survey asked Latin Americans why they think people

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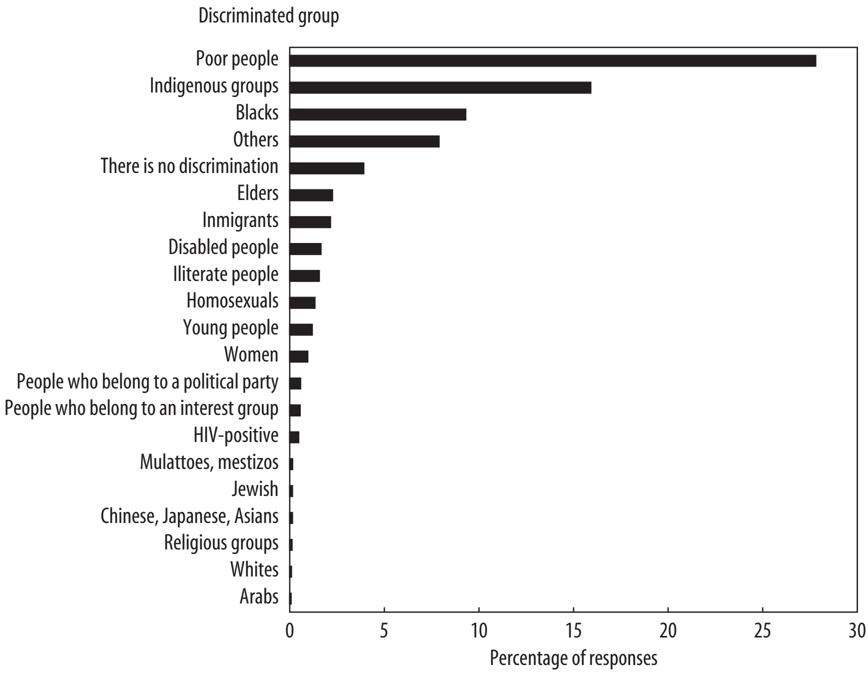
1. The countries surveyed by Latinobarómetro are Argentina, Bolivia, Brazil, Colombia, Costa Rica, Chile, the Dominican Republic, Ecuador, El Salvador, Guatemala, Honduras, Mexico, Nicaragua, Panama, Paraguay, Peru, Uruguay, and Venezuela. For more information on the Latinobarómetro Corporation and its surveys, see its website (www.latinobarometro.org).

FIGURE 1. Groups Affected by Discrimination in Latin America, 2001[a]

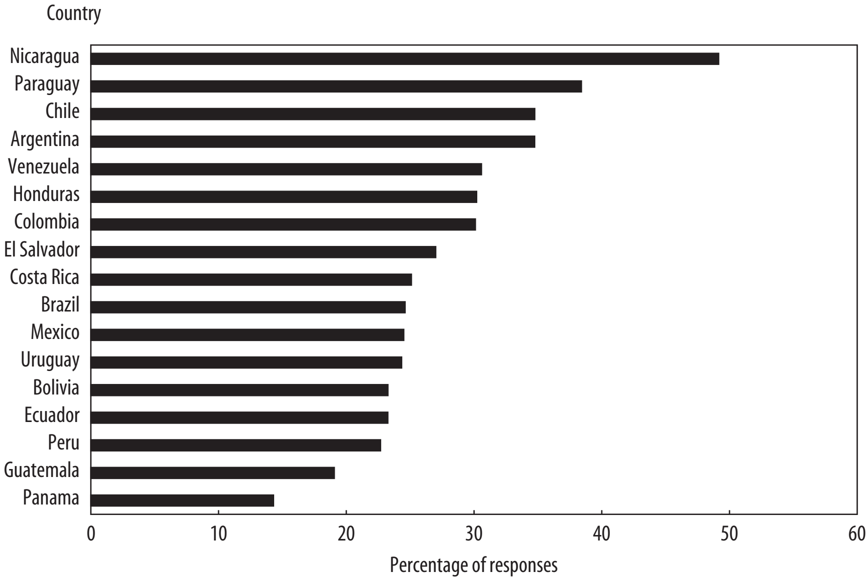


Source: Latinobarómetro (2001).

a. The figure reports responses to the following 2001 Latinobarómetro survey question: "From what you have known or heard, which groups do you think experience the most discrimination, or do you think that there is no discrimination?"

in their country are not treated equally. One out of every three Latin Americans pointed to poverty as the basis for unequal treatment, but in a departure from the earlier poll, individuals did not identify ethnic and racial characteristics as the second and third top reasons for discrimination. Rather, they cited lack of education and lack of connections as the basis for unequal treatment. One interpretation of these results is that Latin Americans now consider economic factors more important than social factors in explaining unequal treatment, although responses vary by country. Figure 3 shows the ranking of reasons for the whole region, and figure 4 shows how the perceived reasons for unequal treatment vary from one country to another. While poverty is considered the number one cause of discrimination in the Dominican Republic and Nicaragua, lack of education tops the list of reasons in Guatemala. Lack of connections, which ranks third in the region overall, is viewed as the most important reason for unequal treatment in Mexico, Colombia, and Panama.

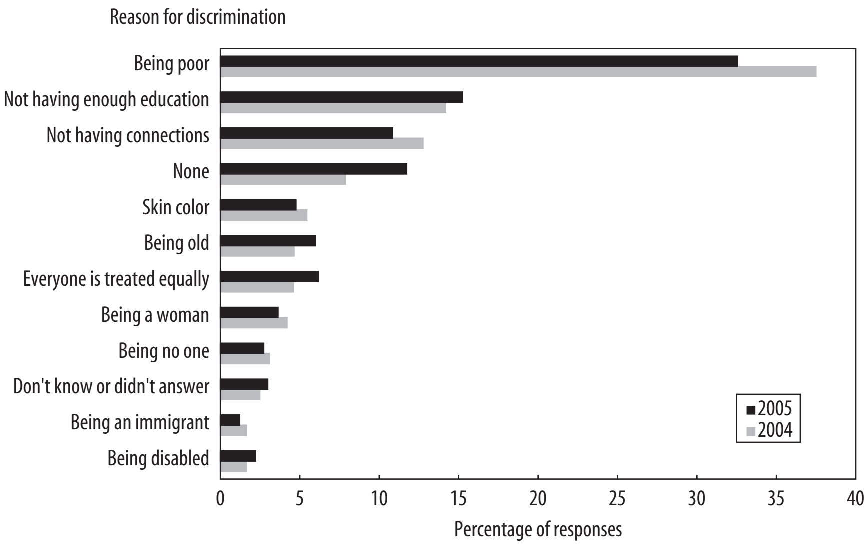
FIGURE 2. Perceptions of Discrimination by Poverty, by Country[a]



Source: Latinobarómetro (2001).

a. For each country, the figure reports that percentage of Latinobarómetro respondents in 2001 who think that poverty is the main reason that people are not treated equally.

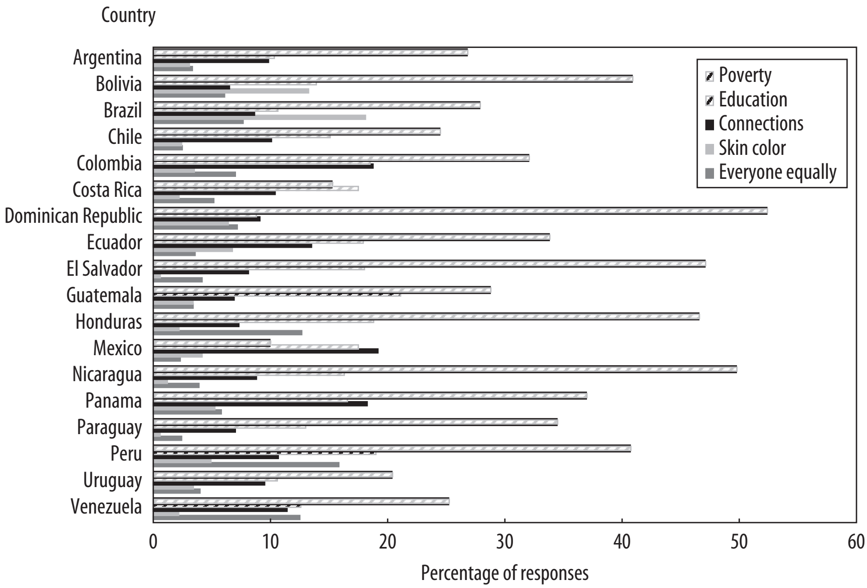
FIGURE 3. Reasons for Discrimination in Latin America, 2004 and 2005[a]



Source: Latinobarómetro (2004, 2005).

a. The figure reports responses in 2004 and 2005 to the following Latinobarómetro survey question: “Of all the reasons for which people are not treated equally, which one affects you the most?”

FIGURE 4. Reasons for Discrimination, by Country[a]



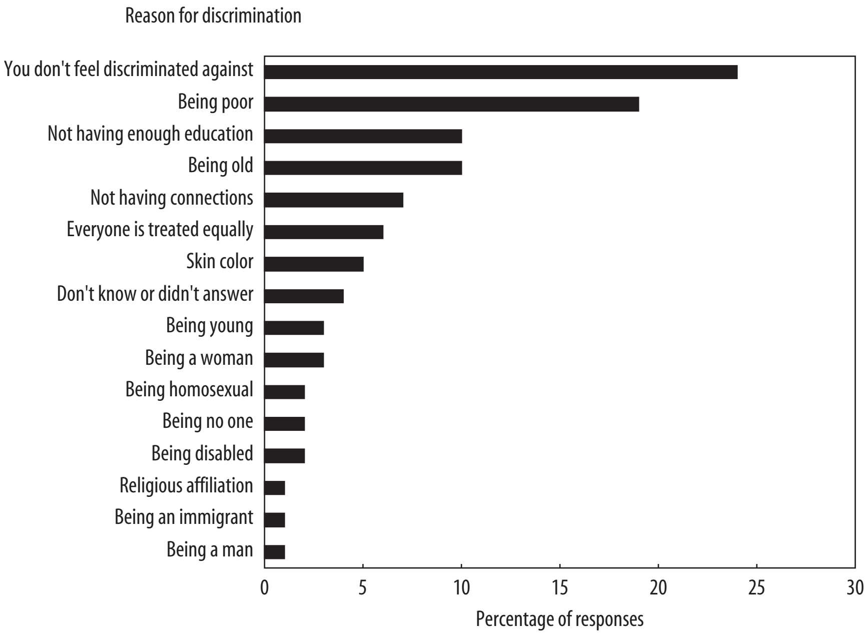
Source: Latinobarómetro (2005).

a.–For each country, the figure reports responses to the following 2005 Latinobarómetro survey question: "Of all the reasons for which people are not treated equally, which one affects you the most?"

Skin color raises important concerns in Brazil and, to a lesser extent, Bolivia. The percentages of respondents who felt that everyone is treated equally in their country varies from 16 percent in Peru to 2 percent in Mexico, Paraguay, and Chile. The cases of Paraguay (35 percent) and Chile (25 percent) are interesting, as none of the reasons cited for unequal treatment are assigned great importance. Nonetheless, very few people in these countries state that everyone is treated equally there. This suggests that the subtleties of discrimination are not well captured by the survey in these two countries.

The most recent Latinobarómetro survey, for 2006, further complicates the picture. In addition to the reasons for unequal treatment cited in the 2004 and 2005 surveys, a new option allowed individuals to state that they did not feel discriminated against at all. Nearly 24 percent of the surveyed individuals chose this response, making it the new top answer. The relative ranking of the rest of the reasons for unequal treatment remained almost unaltered since the 2005 survey. The only exception is that being old ranked ahead of not having connections for the first time. As before, skin color, gender, and

FIGURE 5. Reasons for Discrimination in Latin America, 2006[a]



Source: Latinobarómetro (2006).

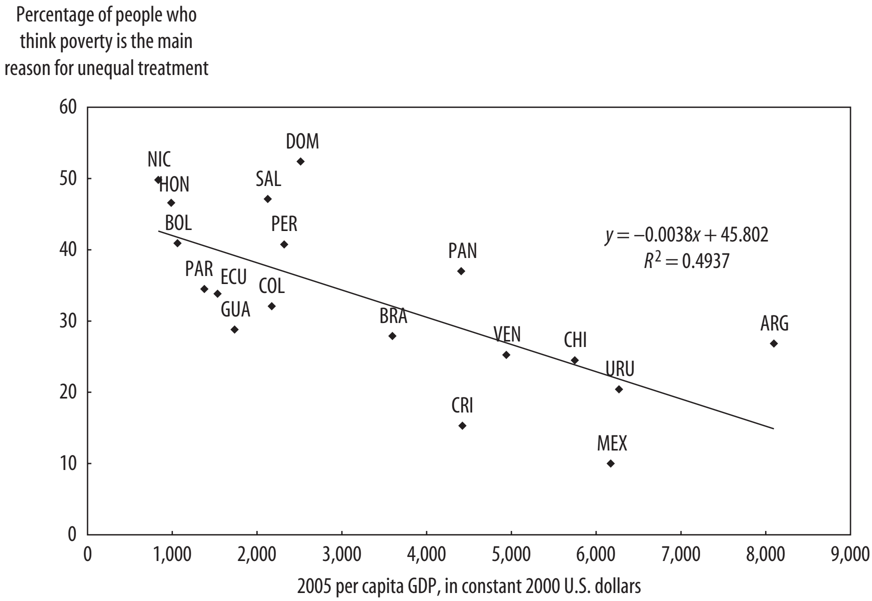
a. The figure reports responses to the following 2006 Latinobarómetro survey question: "Of all the reasons for which people are not treated equally, which one affects you the most?"

disabilities were not ranked high as characteristics triggering discriminatory behaviors. These results are shown in figure 5.[2]

The fact that the social characteristics typically linked to discrimination register low on the opinion surveys in most countries in Latin America is, in itself, quite remarkable. Perhaps societies in the region do not discriminate on the basis of ethnicity, race, or gender as much as conventional wisdom would

2. In Europe, the characteristics that the population perceives as being the drivers of discrimination (or disadvantaged treatment) are more social than economic in nature. Eurobarometer, the European opinion survey, dedicated a recent special issue (European Commission 2007) to exploring discriminatory perceptions in the twenty-five member countries of the European Union. The four groups ranked by surveyed respondents as the most disadvantaged were the disabled, the Roma (gypsies), people over fifty years of age, and people of a different ethnic group than the rest of the population. These characteristics come closer to what conventional wisdom would dictate in terms of groups that experience discrimination.

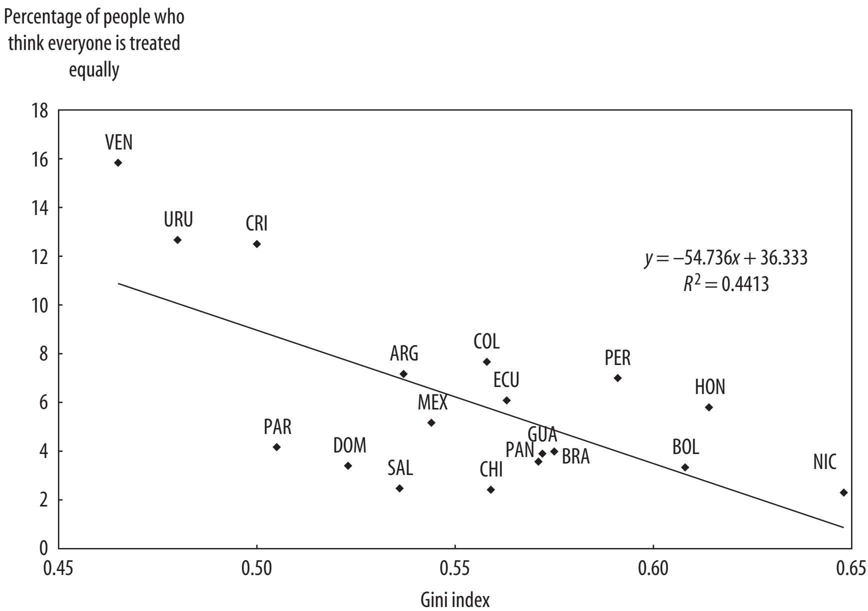
FIGURE 6. Size of the Economy and Perceptions of Discrimination by Poverty



Source: Latinobarómetro (2005); World Bank, *World Development Indicators* database.

suggest. Alternatively, perhaps the individuals surveyed are reluctant to reveal their true beliefs for fear of retaliation or for concerns about being perceived as politically incorrect. Another problem may be that the factors indicated in opinion polls as being the most common reasons for discrimination are categories that do not capture poverty per se, but characteristics that respondents associate with it. In fact, the perception of discrimination by poverty may be highly correlated with other variables such as the general economic condition of the population or social characteristics that are more traditionally linked to discriminatory practices. The perception of poverty as a key discriminatory problem is fairly low in countries that are relatively homogeneous in terms of race. For instance, only about 20 percent of respondents link discrimination with poverty in Uruguay. By the same token, respondents in countries that are more racially diverse indicate that poverty is a crucial discriminatory issue. In Peru, for example, nearly 41 percent of respondents cite poverty as the most important reason for unequal treatment. Figures 6 and 7 present scatter plots and simple correlations between basic economic variables and perceptions of discrimination. Figure 6 shows that the perception of discrimination by

FIGURE 7. Inequality and Perceptions of Nondiscrimination



Source: Latinobarómetro (2005); World Bank, *World Development Indicators* database.

poverty is accentuated in smaller economies. Conversely, figure 7 suggests that people in more equal societies are more apt to view their environment as nondiscriminatory.

Given the above, some countries in the region have recently undertaken efforts to gain more precise knowledge about the perception of discrimination. For example, researchers in Peru have adapted the discrimination scales of the 1995 Detroit Area Study; they find that 88 percent of a representative sample of Peruvians report having experienced at least one situation of discrimination.[3] In Mexico, the results of the First National Survey of Discrimination show that nine out of every ten individuals with certain characteristics (such as disabilities, an indigenous background, homosexual orientation, advanced age, or membership in religious minorities) think discrimination exists in their country.[4] The Survey of Perceptions of Racism and Discrimination in Ecuador

3. The National Survey of Exclusion and Social Discrimination; see DEMUS (2005).
4. SEDESOL (2005).

reveals that while 62 percent of Ecuadoreans agree that there is racial discrimination in their country, only 10 percent admit to being openly racist; Afro-descendants are the group perceived to suffer the greatest discrimination in Ecuador.[5] These are three prominent examples of how countries have used ad hoc surveys to explore local perceptions of discrimination. However, most of these and related surveys, while specialized, suffer from potentially confusing biases similar to those described above.[6]

The perceptions of discrimination in Latin America are also reflected in the public discourse. Soruco, Piani, and Rossi document the intricacies of discriminatory attitudes in the media regarding migrants (or their families) in Cuenca and San Fernando, Ecuador.[7] They find considerable discriminatory discourse in the content of newspaper articles referring to migration in September 2005 and February 2006 (the period of their study). They highlight that the traditional discrimination against peasants and indigenous population has taken a new form, as discriminatory attitudes have been extended to migrants who, after returning home from abroad, bring back westernized attitudes and behaviors.

This panorama of perceptions and public discourse about discrimination in Latin America represents an important step toward understanding the magnitude of the problem, but it is not particularly useful for understanding the mechanisms through which discrimination occurs and the associated welfare costs. Nonetheless, as figures 6 and 7 suggest, the perception of discrimination (or the lack thereof) may be associated with economic outcomes such as the size of the economy and income distribution. An economic analysis of discrimination that moves beyond perceptions is greatly needed. A thorough understanding of the mechanisms through which discrimination occurs and the economic implications of related processes is essential for effective policy design.

Beyond Opinion Polls

Analyzing discrimination from an economic perspective requires more than information on individual perceptions. These data are informative only to the extent that they influence individuals' economic decisions, actions, and outcomes. It is precisely in relation to outcomes that the economic literature sheds

5. Secretaría Técnica del Frente Social (2004).
6. Bertrand and Mullainathan (2001).
7. Soruco, Piani, and Rossi (2007).

light on discrimination, so we start by outlining a few working definitions of discrimination from the international economic literature for purposes of clarity and providing perspective on the studies described in this and subsequent sections.

Discrimination can take place under different circumstances or in different markets, and it can be based on different discriminatory characteristics such as race, ethnicity, gender, disability, and migratory condition, to name a few. Altonji and Blank define discrimination in labor markets as “a situation in which persons who provide labor market services and who are equally productive in a physical or material sense are treated unequally in a way that is related to an observable characteristic such as race, ethnicity, or gender. By ‘unequal’ we mean these persons receive different wages or face different demands for their services at a given wage.”[8] This definition can be summarized as unequal treatment for the same productivity, which outside of labor markets would read unequal treatment for the same characteristics. As mentioned earlier, some characteristics are harder to observe than others. One avenue to better understanding discrimination along these lines would be to design studies aimed at uncovering the unobservables as much as possible. Before delving into this further, it is useful to distinguish between preference-based discrimination (people treating members of certain groups differently simply because they do not like them) and statistical discrimination (people using group membership as a proxy measure for unobserved characteristics). The latter corresponds to the popularly held notions of stigmatization or stereotyping. For instance, employers who assume that Afro-descendants have the ability to perform certain manual tasks but are not necessarily capable of fulfilling more intellectual responsibilities may not offer many opportunities for white-collar jobs to Afro-descendants. Consequently, an Afro-descendant might not even get in the door for an equal assessment of observable human capital characteristics. Stigmatization in this sense constitutes a form of discrimination that complements the notion of unequal treatment for the same characteristics.

The literature in the region tries to quantify discriminatory outcomes by means other than opinion polls. The topics of interest range from income differences to limited participation in labor markets (including limited access to human capital, segregation, differences in returns to human capital characteristics, limited access to jobs, and informality), limited access to health care services, education, and physical infrastructure and housing, and lack of political

8. Altonji and Blank (1999).

representation, social protection, and security (victimization). Gandelman, Ñopo, and Ripani, for example, document the literature on Latin America, addressing differences in the topics mentioned above with respect to race, ethnicity, migratory condition, disabilities, and gender.[9]

In this paper we focus on a particular family of studies, namely, wage gaps decompositions. Numerous efforts have focused on documenting earnings differentials between females and males, indigenous and nonindigenous people, or Afro-descendants and whites. As the pieces of the literature that we survey in this section show, comparisons of hourly labor earnings (wages or self-employment income) suggest the existence of notorious gaps. However, nonindigenous (or male) workers exhibit human capital characteristics that are, on average, more desirable than those of indigenous (or female) workers. Examples of those characteristics include education, labor market experience, and field of specialization. To attribute the whole earnings gap to the existence of labor market discrimination would therefore be misleading. At least a component of the gap can be attributed to differences in observable human capital characteristics that the labor market rewards and, hence, is not attributable to the existence of discrimination. Blinder and Oaxaca were the first to explore this avenue of research, in which the profession has been able to identify, to some extent, the magnitude of this component.[10]

To summarize the basic idea behind this approach, we denote the two comparison groups as A and B. We can then estimate a Mincer equation for each group:

$$y_i^A = \boldsymbol{\beta}^A \mathbf{x}_i^A + \varepsilon_i^A$$

and

$$y_i^B = \boldsymbol{\beta}^B \mathbf{x}_i^B + \varepsilon_i^B,$$

where y is the logarithm of hourly wages, $\mathbf{x}$ the vector of observable characteristics, $\boldsymbol{\beta}$ the vector of their corresponding rewards, and ε the residuals. The wage gap, which is the difference between the average logarithms of hourly wages of the comparison groups, can be computed as

$$\text{Gap} = \overline{y}^A - \overline{y}^B = \hat{\boldsymbol{\beta}}^A \overline{\mathbf{x}}^A - \hat{\boldsymbol{\beta}}^B \overline{\mathbf{x}}^B,$$

9. Gandelman, Ñopo, and Ripani (2007).
10. Blinder (1973); Oaxaca (1973).

which, in turn, after some algebraic manipulation can be expressed as

$$\text{Gap} = \hat{\boldsymbol{\beta}}^A\left(\overline{\mathbf{x}}^A - \overline{\mathbf{x}}^B\right) + \left(\hat{\boldsymbol{\beta}}^A - \hat{\boldsymbol{\beta}}^B\right)\overline{\mathbf{x}}^B.$$

We next denote the first component as $\Delta_{\mathbf{x}}$ and the second as Δ_0, so we can write the equation as a two-component sum:

$$\text{Gap} = \Delta_{\mathbf{x}} + \Delta_0.$$

The first component, $\Delta_{\mathbf{x}}$, captures the part of the wage gap that can be attributed to the existence of differences in average observable characteristics between the two comparsion groups. The second component, Δ_0, is what remains unexplained and can be attributed to the existence of elements that play a role in the determination of wages in labor markets but that the econometrician cannot observe (one of those elements being discrimination). The literature includes various extensions of this basic setup, including correction for selection into active labor market participation, the use of quantile regressions instead of ordinary least squares (OLS), additional explorations of the distribution of the gaps, microsimulations, and matching comparisons. Tables 1 and 2 summarize some of the literature for the region that applies the Blinder-Oaxaca approach (and its extensions) to the analysis of racial and gender wage gaps, respectively.

The unexplained gaps reported in the tables are those that remain after controlling for different sets of observable characteristics (presented in the last columns).[11] They are computed as percentages of the average hourly wages of the groups with lower earnings (namely, females, Afro-descendants, and indigenous). The results summarized in the tables suggest more similarities than differences in the literature, especially for gender gaps. The discrepancies in the literature on racial gaps mostly depend on the differences of the racial groups that each paper compares and the methods employed. Work in this area is lacking for many Latin American nations, however.[12]

For this study, we use the most recent surveys available, together with the Harmonized National Household Surveys assembled by the Inter-American Development Bank's Research Department, to perform comparable wage gap decompositions by race for five countries and by gender for seventeen of them. Table 3 presents information on the surveys used for each country.

11. That is, they correspond to Δ_0, according to the notation introduced above.

12. Tables 1 and 2 do not represent exhaustive lists of the research on wage gaps in the region, but they are as comprehensive as possible within the context of the present study.

TABLE 1. Decompositions, by Race

Study	*Data source* [a]	*Coverage*	*Comparison groups*	*Unexplained wage gap (percent)*	*Methodology and control variables*
Arcand and d'Hombres (2004)	PNAD (1998)	Brazil	Whites vs. browns	17	Blinder-Oaxaca with quantile regressions; sample selection corrected with controls for experience, schooling, self-evaluation of health, family status, region of residence, location (urban or rural), signature of a formal labor contract, and occupation
			Whites vs. blacks	27	
Arias, Yamada, and Tejerina (2002)	PNAD (1996)	Brazil	Whites vs. blacks	33	Blinder-Oaxaca with quantile regressions adjusting for differences in education and work experience
Barrón (2005)	ENAHO (May 2003–April 2004)	Lima, Peru	Born in Lima vs. born in other provinces	5–9	Propensity score matching with controls for gender, mother's education, age, schooling, private and public education, formal and informal employment, and potable water
Campante, Crespo, and Leite (2004)	PNAD (1996)	Brazil	Whites vs. blacks and browns	14	Blinder-Oaxaca with controls for education, experience, formal employment, sector, public and private job, regional characteristics, and mother's education
De Ferranti and others (2004)	Household surveys: Brazil (1996); Bolivia (1999); Guatemala (2000); Guyana (1999)	Bolivia	White vs. nonwhite men	37	Blinder-Oaxaca with controls for education, area, age, and other individual and labor market characteristics
		Brazil		15	
		Guatemala		28	
		Guyana		5	
Gallardo (2006)	EMEDINHO and ENEMDUR (2000)	Ecuador	White vs. mestizo men[b]	17	Blinder-Oaxaca with 2SLS using as controls: experience, education, area, and formal occupation
			White vs. mestizo women[b]	44	
			White vs. mestizo men[c]	18	
			White vs. mestizo women[c]	40	

Garcia-Aracil and Winter (2006)	ECV (1999)	Ecuador (excl. Amazon)	Nonindigenous vs. indigenous	59	Blinder-Oaxaca with controls for education and residence
Guimarães (2006)	PNAD (2002)	Brazil	Whites vs. blacks and browns	16	Blinder-Oaxaca with controls for education, experience, sex, household chief, sector, type of contract, and region
Larrea and Montenegro (2006)	ECV (1998)	Ecuador (excl. Amazon)	Nonindigenous vs. indigenous	57	Blinder-Oaxaca with controls for education and labor market
Leite (2005)	PNAD (1996)	Brazil	Whites vs. blacks and browns	19	2SLS with IV for ability bias and controls for mother's and father's education; quantile regression for schooling
Ñopo and others (2007)	LSMS (2000) and an additional racial module	Peru	Whites vs. indig. (self-employed)	13–19	Blinder-Oaxaca with controls for education and experience, personal and family characteristics, and labor market
			Whites vs. mestizos (self-empl.)	5–8	
			Mestizos vs. indig. (self-empl.)	3–7	
			Whites vs. indigenous (waged)	11–14	
			Whites vs. mestizos (waged)	0–12	
			Mestizos vs. indig. (waged)	6–13	
Soares (2000)	PNAD (1998)	Brazil	White vs. black and brown men	116	Blinder-Oaxaca with controls for experience, education, sector, type of labor contract, and region

a. ECV: *Encuesta de Condiciones de Vida;* EMEDINHO: *Encuesta de Medición de Indicadores de la Niñez y los Hogares;* ENAHO: *Encuesta Nacional de Hogares;* ENEMDUR: *Encuesta de Empleo, Desempleo y Subempleo en el Area Urbana y Rural;* LSMS: Living Standards Measurement Study (World Bank); PNAD: *Pesquisa Nacional por Amostra de Domicílios.*

b. Mestizos are self-identified.

c. Mestizos are identified by primary language.

TABLE 2. Decompositions, by Gender

Study	*Data source* [a]	*Coverage*	*Unexplained wage gap (percent)*	*Methodology and control variables*
Aguilar and Dresdner (2000)	CASEN (1987, 1990, 1992, 1994, 1996, 1998)	Chile	9–21	Blinder-Oaxaca with correction for selection bias
Brown, Pagan, and Rodríguez-Oreggia (1999)	ENEU (1987, 1993)	Mexico 1987	18	Blinder-Oaxaca with controls for age, education, experience, occupation, and other individual characteristics
		1993	17	
Contreras and Puentes (2000)	EOD (1966–96)	Chile	10–20	Blinder-Oaxaca with correction for selection bias
De Ferranti and others (2004)	Household surveys: Brazil (1996); Bolivia (1999); Guatemala (2000); Guyana (1999)	Bolivia	36	Blinder-Oaxaca with controls for education, area, age, and other individual and labor market characteristics
		Brazil	53	
		Guatemala	78	
		Guyana	55	
Deutsch and others (2005)	EHPM (1989, 1993, 1997)	Costa Rica 1989	24	Blinder-Oaxaca with Fluckiger and Silber methodology (occupational segregation) and controls for education, experience, number of children, occupation, and other labor market characteristics
		1993	12	
		1997	20	
	EPED (1997)	Ecuador	20	
	ECH (1989, 1992, 1997)	Uruguay 1989	26	
		1982	20	
		1997	20	
Fuentes, Palma, and Montero (2005)	CASEN (1990, 1992, 1994, 1996, 1998, 2000, 2003)	Chile 1990	59	Blinder-Oaxaca and Ransom with controls for education
		1992	49	
		1994	25	
		1996	29	
		1998	25	
		2000	22	
		2003	28	
Gonzales and Rossi (2002)	ECH (1986, 1990, 1994, and 1997)	Uruguay 1986	25	Blinder-Oaxaca and Ransom with correction of selection bias and controls for age, education, marital status, and labor market
		1990	26	
		1994	18	
		1997	13	
Khandker (1990)	ENNIV (1984)	Peru	17	Blinder-Oaxaca with correction for selection bias

Montenegro (2001)	CASEN (1990, 1992, 1994, 1996, 1998)	Chile 1990	24	Blinder-Oaxaca with quantile regressions and controls for education and experience
		1992	24	
		1994	21	
		1996	22	
		1998	19	
Ñopo (2008)	ENAHO (1999)	Lima, Peru	23	Matching (nonparametric decomposition) with controls for age, schooling, work experience, and formality
	Encuesta Especializada de Empleo (1986, 1987, 1989–95); ENAHO (1996–2000)	Lima, Peru	29	Matching (nonparametric decomposition) with controls for age, schooling, marital status, and migratory condition
Ñopo (2007)	CASEN (1992–2003)	Chile	10–20 at the bottom of the wage distribution; 40–80 at the top of the wage distribution	Matching (nonparametric decomposition) with controls for education, age, marital status, occupation, and other labor market characteristics
Psacharopoulos and Tzannatos (1992)	Household surveys of each country	Colombia 1979	15–20	Blinder-Oaxaca with and without correction for selection bias
		Mexico 1984	15–20	
		Peru 1990	15–20	
		Argentina 1985	40–50	
		Bolivia 1989	40–50	
		Ecuador 1987	40–50	
		Jamaica 1989	40–50	
Santos and Saba (2005)	PNAD (1982–90 and 1992–99)	Brazil 1982–90	30	Blinder-Oaxaca and Ransom, with controls for education, age, race, household head, formal labor relation, urban region, and metropolitan area
		1992–99	28	
Tenjo, Ribero, and Bernat (2005)	Household surveys of each country (1998)	Argentina	9	Blinder-Oaxaca with selectivity correction and controls for education and experience
		Brazil	32	
		Colombia	8	
		Costa Rica	10	
		Honduras	19	
		Uruguay	22	

a. CASEN: *Encuesta de Caracterización Socioeconómico Nacional;* ECH: *Encuesta Continua de Hogares;* EHPM: *Encuesta de Hogares de Propósitos Múltiples;* ENAHO: *Encuesta Nacional de Hogares;* ENEU: *Encuesta Nacional de Empleo Urbano;* ENNIV: *Encuesta Nacional de Hogares sobre Medición de Niveles de Vida;* EOD: *Encuesta de Ocupación y Desocupación de la Universidad de Chile;* EPED: *Encuesta Periódica sobre Empleo y Desempleo;* PNAD: *Pesquisa Nacional por Amostra de Domicílios.*

TABLE 3. Countries Used and Their Surveys

Country	*Survey*	*Year*	*No. observations*
Argentina	Encuesta Permanente de Hogares Continua (EPHC)	2005	29,336
Bolivia	Encuesta de Hogares—Programa MECOVI	2002	6,884
Brazil	Pesquisa Nacional por Amostra de Domicilios (PNAD)	2003	140,042
Chile	Encuesta de Caracterización Socioeconómica Nacional (CASEN)	2003	79,261
Colombia	Encuesta Continua de Hogares (ECH)	2003	40,468
Costa Rica	Encuesta de Hogares de Propósitos Múltiples	2004	13,891
Dominican Rep.	Encuesta Nacional de Fuerza de Trabajo (ENFT)	2003	9,864
Guatemala	Encuesta Nacional sobre Condiciones de Vida	2002	3,900
Honduras	Encuesta Permanente de Hogares de Propósitos Múltiples	2003	9,591
Mexico	Encuesta Nacional de Ingresos y Gastos de los Hogares (ENIGH)	2002	23,694
Nicaragua	Encuesta Nacional de Hogares sobre Medición de Nivel de Vida	2001	5,808
Panama	Encuesta de Hogares	2003	17,636
Peru	Encuesta Nacional de Hogares (ENAHO)—Condiciones de Vida y Pobreza	2003	23,536
Paraguay	Encuesta Permanente de Hogares (EIH)	2003	10,571
El Salvador	Encuesta de Hogares de Propósitos Múltiples del Programa MECOVI	2002	18,547
Uruguay	Encuesta Continua de Hogares (ECH)	2005	20,557
Venezuela	Encuesta de Hogares por Muestreo	2004	47,888

The wage gap decompositions presented here follow the approach developed by Ñopo using matching comparison techniques instead of Mincer equations.[13] The introduction of matching to the analysis of wage gaps raises a point that is commonplace in the impact evaluation literature (which developed matching), but has been absent from the gap decomposition discussion. Namely, a proper account of the differences in characteristics must take into consideration that the supports of the comparison groups' observable characteristics do not overlap completely. Matching naturally moves the analysis toward such a comparison of supports, as well as toward the distribution (and not just the average) of the comparison groups' observable characteristics. As a result, the matching estimators deliver more accurate measures of the decompositions of wage gaps than Mincer equations. Empirical comparisons of decompositions made with matching techniques and with traditional OLS reveal that the latter tends to overestimate the unexplained component of the gap by 2 to 8 percent points. Additionally, decompositions based on matching deliver estimators for two components of the wage gaps that are attributable to the existence of uncommon supports and provide interesting insights for the analysis of the gaps. One of those components, denoted Δ_M in the appendix, accounts for the fact that males attain combinations of observable characteris-

13. Ñopo (2004). See the appendix for a brief discussion of the decomposition method.

TABLE 4. Racial Wage Gaps after Controlling for Observable Characteristics[a]
Percent

	Relative racial gaps and controlled differences			
		Controls		
Country	*Hourly wage gap of whites relative to natives*	*Gender, age, and education*	*Gender, age, education, and marital status*	*Gender, age, education, marital status, and residence in the capital city*
Bolivia	38.2	22.5	24.3	24.3
Brazil	88.1	31.1	n.a.	n.a.
Chile	51.8	16.1	15.3	11.3
Guatemala	98.9	36.2	40.0	16.5
Paraguay	84.3	42.7	38.6	38.9

n.a. Not available.

a. Wage is equal to the hourly monetary labor income from the main occupation. The sample only includes people with incomes higher than zero.

tics that females do not. For the case of gender wage gap decompositions, this corresponds to individuals in their mid-40s, with a college degree or more, married, with kids, and working in managerial occupations. That is, this corresponds to the typical profile of corporate middle and upper managers, a clearly male-dominated segment of the labor markets. The second component, denoted Δ_F in the appendix, accounts for the reverse situation, in which females in labor markets attain certain combinations of characteristics that males do not. This corresponds to cases of working individuals in their early 30s, with a high school diploma or less, single, with kids, and born outside the capital city. That is, this corresponds to the typical profile of domestic servants, a clearly female-dominated segment of the labor markets.

We were able to compute racial wage gaps only in the five countries where we found a variable for racial self-identification. This corresponds to quechuas, aymaras, guaraníes, chiquitaños, and mojeños in Bolivia; pretos and pardos in Brazil; people who state that they belong to an indigenous group in Chile; people from around fifteen different indigenous groups in Guatemala; and guaraníes in Paraguay. We are aware of the limitations of the self-identification approach to determining racial groups in the region, but it allows us to compare the most number of countries under the same basis.[14]

Table 4 shows racial wage gaps in hourly wages with and without controls for different sets of observable characteristics. That is, according to the nota-

14. Telles and Lim (1998) and Ñopo, Saavedra, and Torero (2007) discuss the limitations of the self-identification approach.

TABLE 5. Components of the Racial Wage Gap Stemming from Uncommon Supports
Percent

	Controls					
	Gender, age, and education		Gender, age, education, and marital status		Gender, age, education, marital status, and residence in the capital city	
Country	*Whites*	*Natives*	*Whites*	*Natives*	*Whites*	*Natives*
Bolivia	0.4	0.2	−2.2	2.4	2.6	−2.0
Brazil	0.0	0.0	n.a.	n.a.	n.a.	n.a.
Chile	5.5	0.0	9.7	0.1	22.5	0.2
Guatemala	51.9	1.0	50.1	5.0	68.8	2.5
Paraguay	28.1	0.8	28.4	2.6	33.7	2.3

n.a. Not available.

tion introduced above, we report the values of the gap and Δ_0 for different sets of control characteristics. The gaps have been computed using information only from individuals who reported positive labor earnings in their main occupation in the surveys. The gaps are reported as percentages of the average hourly wages in the main occupation of the group with lower wages.

The highest racial wage gaps, between 90 and 100 percent, are found in Brazil and Guatemala. However, after we control for gender, age, education, marital status, and residence in the capital city (in three different sets of variables), the remaining gaps are less than half the original values. Two of the decompositions could not be performed for Brazil because their survey did not include information on marital status. In the other countries, we obtain similar results when we control for gender, age, and education and when we control for these three characteristics plus marital status and residence in the capital city.

Table 5 shows the components of the wage gaps that are attributable to the lack of common support on the distribution of observable characteristics of whites and natives, for the three sets of control characteristics. The results show that the existence of unmatched whites (or whites out of the common support) contributes notably to the total racial wage gaps, especially in Guatemala and, to a lesser degree, Paraguay and Chile. This is the result of two factors: a sizable share of the working population of whites and natives differs in their observable characteristics, and whites with characteristics out of the common support earn hourly wages in the top percentiles of the wage distribution.

We computed gender wage gap decompositions for seventeen countries. Following a similar approach to that used in the racial decompositions, we also computed unexplained wage gaps for three sets of controlling characteristics:

TABLE 6. Gender Wage Gaps after Controlling for Observable Characteristics[a]
Percent

	Relative gender gaps and controlled differences			
		Controls		
Country	Hourly wage gap of males relative to females	Age and education	Age, education, and marital status	Age, education, marital status, and residence in the capital city
Argentina	2.0	15.3	15.2	14.8
Bolivia	6.7	4.4	5.3	7.3
Brazil	19.6	46.3	n.a.	n.a.
Chile	12.9	32.7	28.3	27.5
Colombia	8.0	14.6	10.9	11.3
Costa Rica	–6.2	13.1	11.2	10.0
Dominican Republic	12.0	29.5	29.0	n.a.
Guatemala	27.3	17.4	16.2	22.5
Honduras	–6.2	3.4	1.9	2.1
Mexico	9.9	12.8	11.3	13.4
Nicaragua	3.8	21.0	17.9	16.4
Panama	–2.8	25.1	22.4	23.4
Peru	31.1	27.6	28.9	31.9
Paraguay	17.9	23.5	18.5	20.4
El Salvador	18.1	19.8	18.0	16.7
Uruguay	13.2	37.2	34.3	34.0
Venezuela	–1.5	13.2	12.0	11.9

n.a. Not available.

a. Wage is equal to the hourly monetary labor income from the main occupation. The sample only includes people with incomes higher than zero.

originally controlling for age and education only; adding marital status to the previous two; and adding residence in the capital city to the previous three. We report the unexplained components of the gender wage gaps in table 6 and the components attributable to the lack of common support in table 7.

The wage gap is negative in Costa Rica, Honduras, Panama, and Venezuela. That is, females earn more per hour than males, on average, in these four countries. However, when we control for the sets of characteristics mentioned above—in other words, when we compare males and females with the same characteristics—males earn more than their female counterparts. Other countries in the region similarly present higher controlled gaps than original gaps, which reflects the fact that females have surpassed males in schooling attainment in the region.[15] Regarding the components of the wage gap stemming

15. See Duryea and others (2007).

TABLE 7. Components of the Gender Wage Gap Stemming from Uncommon Supports
Percent

	Controls					
	Age and education		*Age, education, and marital status*		*Age, education, marital status and residence in the capital city*	
Country	*Males*	*Females*	*Males*	*Females*	*Males*	*Females*
Argentina	0.0	0.0	0.1	–0.5	0.7	–0.9
Bolivia	1.3	0.2	1.8	0.3	4.7	–1.3
Brazil	0.0	0.0	n.a.	n.a.	n.a.	n.a.
Chile	0.0	0.0	0.1	–0.5	0.2	–0.7
Colombia	0.2	0.0	0.4	–0.4	1.0	–1.0
Costa Rica	–0.1	0.1	–0.3	–2.1	0.9	–2.4
Dominican Republic	–0.2	–0.1	0.5	–2.2	n.a.	n.a.
Guatemala	9.9	–2.6	13.4	–2.9	17.7	–8.4
Honduras	2.7	–0.3	3.2	–6.2	6.6	–8.2
Mexico	0.4	0.0	1.1	–2.7	2.1	–2.1
Nicaragua	3.0	–0.6	4.0	0.3	9.5	–3.0
Panama	0.2	0.0	–0.4	–1.8	1.1	–3.0
Peru	0.2	0.1	0.1	0.8	1.2	–0.1
Paraguay	0.8	–0.4	2.0	–2.2	5.1	–3.2
El Salvador	0.4	0.0	1.2	–1.5	2.1	–1.9
Uruguay	–0.3	0.1	–0.7	–0.1	–1.5	–0.6
Venezuela	0.0	0.0	0.0	–0.5	0.2	–0.9

n.a. Not available.

from uncommon supports, the estimators suggest a sizable "upper management effect" only in Guatemala and, to a lesser degree, in Bolivia, Honduras, Nicaragua, and Paraguay.

The failure to explain the existent wage gaps on the basis of observable differences in human capital characteristics may lead to claims of discrimination in Latin American labor markets. This avenue for quantifying unexplained wage gaps, however, is subject to criticism. The most common involves the failure to truly identify discriminatory behaviors based on the presence of unobservable characteristics. That is, these studies typically can only analyze human capital characteristics that are easily observable (such as schooling, labor market experience, field of specialization, and sector choice), while other, less easily observed characteristics also help explain earnings gaps. Good examples of these unobservable characteristics include entrepreneurial attitudes, motivation, work ethic, commitment, and assertiveness. Researchers cannot capture such characteristics in a survey, but an employer or, more generally, the relevant actors in the labor market can observe them and act accordingly. If indigenous and nonindigenous workers (or females and males) demonstrate regular differences in some of these "unobservable characteristics," then the components of the earnings gap attributable to discrimination would be overestimated. The literature has moved toward incorporating different attempts to observe the unobservable, that is, to capture, with research methods, the richest possible information that the relevant actors in the markets face in making their decisions.

Observing the Unobservable

Very recent research, sponsored by the Inter-American Development Bank through its Latin American and Caribbean Research Network, finds mixed evidence for the unequal treatment definition of discrimination.[16] Further attempts to disentangle preference-based and statistical discrimination suggest that Latin Americans do not practice the former type of discrimination. Gutiérrez and Núñez assess social class discrimination based on the administrative records of alumni of a Chilean university, which provided school performance variables in addition to the traditional human capital variables that most studies use.[17] This allowed them to uncover some of the traditional unobservable elements of individual productivity. To assess class differences, they asked a pool of individuals to rate the extent to which they associated a surname with the upper or lower classes. Their results point to the existence of some sort of "classism" in Chile. Individuals with surnames perceived as belonging to the upper class earned significantly more than individuals with surnames perceived as being from the lower class, even after the authors controlled for human capital characteristics such as school-performance indicators. Bravo, Sanhueza, and Urzua similarly interviewed college alumni to study gender differences in labor market earnings among graduates of the business, law, and medicine schools of a single university; they find evidence

16. See Inter-American Development Bank's website "Network Study: Discrimination and Economic Outcomes" (www.iadb.org/res/network_study.cfm?st_id=86). See also Marquez and others (2007) for a comprehensive summary of the research network's results.

17. Gutiérrez and Núñez (2004).

of unjustified gender differences in earnings only in the legal profession.[18] The gender differences found in business and economics vanished after they controlled for family conditions. The gender differences among alumni of the medical school vanished when they controlled for hours worked, firm size, and geographic region.

In a separate study, Bravo, Sanhueza, and Urzúa replicated the standard hiring audit study in Santiago, Chile.[19] They mailed resumes of fictitious applicants to job postings that appeared in the largest Santiago newspapers. The "synthetic" resumes were created such that for each job posting they sent responses from female and male applicants, with upper- and lower-class surnames, and from wealthy and poor municipalities (neighborhoods). With these variations by gender, surname, and municipality, they randomly created human capital characteristics and labor market histories for their fictitious applicants. From March to August 2006, they sent out 6,300 resumes and recorded the callbacks received by their fictitious applicants. They found no systematic differences in callback rates by gender or surname or municipality. This surprising result contrasts with the findings of Bertrand and Mullainathan, who originally applied this methodological approach in Chicago and Boston and found substantial differences in callback rates for fictitious applicants with black-sounding and white-sounding names.[20] The result suggests that Chilean employers—or at least those who advertise their job vacancies in the newspapers—do not actively discriminate in the first rounds of their hiring process.

Moreno and others designed a field experiment to detect discrimination in hiring in Lima, Peru.[21] Instead of creating a sample of synthetic resumes to be sent in response to job postings, they monitored the functioning of the Ministry of Labor's job intermediation service. The enriched design improved on the traditional audit studies in that it measured actual job offers and not only callbacks. The authors detected no significant differences in job hiring by race or gender. Males and females, as well as white-looking and indigenous-looking applicants, were equally likely to receive job offers in the three occupations covered in the study: salesperson, secretary, and administrative or accounting assistant. The study design included interviewing the applicants

18. Bravo, Sanhueza, and Urzúa (2007b).
19. Bravo, Sanhueza, and Urzúa (2007a); see also Riach and Rich (2002).
20. Bertrand and Mullainathan (2004).
21. Moreno and others (2004).

before their job interview. In these interviews, the authors were able to capture a rich set of human capital characteristics that were used to control the study results. One of the aspects explored in the interview was expectations and motivations. When they asked individuals how much they wanted to earn at the job in question, they found no race differences but significant gender differences. Females asked for wages between 6 and 9 percent lower than their male competitors, even after the authors controlled for a rich set of observable characteristics. This reveals some sort of self-discrimination or self-punishment in labor markets.[22]

Another experimental approach to understanding discrimination was developed by Cárdenas and others, who applied a battery of games (such as dictator, distributive dictator, ultimatum, trust, and third-party punishment) to a sample of people involved in the provision of social services in Bogotá, Colombia, including both beneficiaries and public officials.[23] To properly measure the behavior of public officials, they also gathered information on nonpublic officials to generate counterfactuals. They used this setup to measure the extent to which individuals who provide social services to the poor discriminate against the beneficiaries of those services. Across the board, they found an interesting prosocial behavior on the part of the average player. Public officials stated having more prosocial norms than their nonpublic official counterparts, but when facing real economic incentives in the field, public officials showed lower levels of fairness—in the form of altruism, trust, and social punishment—than nonpublic officials. Both public officials and their control group favored women and households with lower education and more dependents (especially if the dependents were children), whereas former combatants in Colombia's political conflict, street recyclers, street vendors, and people living in common-law unions received less favorable treatment.

Castillo, Petrie, and Torero, in another experimental setup, uncover some stereotyping among a representative sample of young Lima residents, but the attitudes vanished after information about performance was publicly revealed.[24] Using a repeated linear public goods game, they measured the extent to which people trust each other and engage in reciprocal behavior. In the game, each subject was given an endowment of twenty-five tokens and asked to divide it between a private and a public investment, which had

22. For similar evidence in the United States, see Babcock and Laschever (2003).
23. Cárdenas and others (2007).
24. Castillo, Petrie, and Torero (2007).

different returns depending not only on the individual's decision, but also on the decisions of their peers. They found that people used personal characteristics to choose partners, showing evidence of stereotyping in favor of women, tall people, and white-looking people. However, when the individuals were given information about the past performance of other players, that information overrode the previously held stereotypical beliefs. In the presence of an information shortage, performance-optimizing individuals relied on observable characteristics as a proxy measure of performance, thereby stereotyping their peers. They stopped doing so whenever the stereotyping proved to be suboptimal for their performance-maximizing objectives.

Elías, Elías, and Ronconi performed a similar study, within a simplified setup, of group formation and popularity among adolescents in Argentina.[25] They asked students in a sample of classrooms in Buenos Aires and Tucumán to rank their classmates according to their preferences for forming a team. The students were also asked to assess the beauty of their classmates. This subjective information about students was complemented with administrative records on grades, disciplinary actions, participation in scholarship programs, and tenure at the school. The authors interpret the aggregate ranking of the students as a measure of popularity. The only factor that was important in determining popularity was academic performance, whereas ethnicity, skin color, and parental wealth and nationality played no role as explanatory factors. Beauty was only important in mixed schools. The authors also find preferences for assortative mating, in that the students' academic performance was strongly correlated with their corresponding top choice in the rankings. They find similar results for beauty, parents' education, and gender.

Finally, Gandelman, Gandelman, and Rothschild test the hypothesis of differential treatment in the courts on the basis of gender, using housing-related cases in Uruguay.[26] They analyze data for 2,437 cases involving foreclosure proceedings, annulment of purchase agreements, actions in rem (that is, proceedings against property), annulments of promissory purchase agreements, and evictions, to assess the effect of the gender composition of the defendant household on the duration of the process. They find a strong correlation between the presence of women and the granting of time extensions in the processes, after controlling for a set of covariates. Judges were more lenient with women across the board.

25. Elías, Elías, and Ronconi (2007).
26. Gandelman, Gandelman, and Rothschild (2007).

Conclusions

Discrimination is well-rooted in the Latin American collective mind. Most individuals in the region firmly believe that there is some sort of discrimination in the marketplace. When asked about the basis for this discrimination, however, most people in the region do not believe that it operates against the groups traditionally discriminated against (indigenous groups, Afro-descendants, and women, to cite the most prominent historical examples). Rather, they state that the poor suffer the worst discrimination, followed by the uneducated and those with weak social connections. These perceptions of the identity of the discriminated groups pose interesting and challenging questions for the research agenda, pointing toward the existence of discrimination on the basis of economic characteristics, rather than biological or sociological characteristics.

An economic analysis of discrimination requires not only information on perceptions, but also an exploration of economic decisions and their outcomes. The economic literature in the region has advanced toward an understanding of discrimination by analyzing outcomes. We have presented examples centered on the labor market (including, wages, occupations, and formality), access to public goods and services (such as education, health, and security), and political representation, among other areas, which provide well-documented outcomes by gender, race, and ethnicity. In this survey, we have provided comparative measures of gender and racial wage gaps, after controlling for observable characteristics, following the matching comparisons approach developed by Ñopo.[27] We have stressed the unfavorable situation of females and minority groups with respect to males and whites regarding wages. Additionally, the racial wage gap decompositions carried out with the matching comparisons approach uncover important differences not only in wages for comparable characteristics, but also in the access to those comparable characteristics (as revealed by the sizable components of the wage gap explained by the lack of common support). However, the documentation of differentiated outcomes is not necessarily proof of discrimination, as the presence of unobservable factors limits the possibility of assessing gender, racial, or ethnic discrimination. It is very difficult to properly identify discrimination, given the existence of innumerable unobservable elements; it is even more problematic to quantify its economic impact.

27. Ñopo (2008).

This paper also reviews very recent experimental research performed in the region, using tools to observe the unobservable. Many of the results obtained from controlled experimental setups seem to contradict the idea that Latin Americans act discriminatorily. The evidence points to the existence of stereotyping that vanishes when information is revealed. To some extent, there is also evidence that self-discrimination partially explains discriminatory outcomes. Both stereotyping and self-discrimination are behaviors that may simply result from equilibrium situations in which market agents present substantial differences in endowments. Under these circumstances, labor markets (or the other markets analyzed in this paper) simply amplify differences that exist in other spheres. These avenues merit further research to explore the mechanisms underlying these behaviors.

How can these generalized perceptions of discrimination coexist with the lack of evidence of discriminatory behavior? We close the paper by proposing two explanations to the apparent puzzle. First, many other transaction points or markets, not yet analyzed by the experimental literature, may present evidence of discriminatory behavior. The experimental literature has made great strides in obtaining a deeper understanding of the functioning of discriminatory behavior and increasing the ability to observe the unobservable, but the gains in specificity come at the cost of limiting the possibility of generalizing the results (that is, reduced external validity). The sample of studies outlined here does not exhaust either the set of relevant transaction points or the intergroup interactions. More research is needed, not only to analyze processes of discrimination in other markets or transaction points, but also to improve the external validity of the situations already analyzed.

Second, in their daily activities most Latin Americans observe substantial differences in human, physical, financial, and social assets that are associated with gender, racial, ethnic, and class distinctions. These differentiated outcomes do not necessarily emerge as a result of the discriminatory practices of Latin Americans today. Unfortunately, the confusion between differentiated outcomes and discrimination is commonplace in the academic and political discussion. This, in turn, has automatically translated to public discourse and collective memories, and the extremely unequal distribution of wealth and assets reinforces the generalized notion that there is discrimination in Latin America. An important step toward understanding the issues and designing good policies is to recognize the differences between these facts, as they require different responses from governments, states, and societies. It is important to clarify the discussion in order to move forward.

Appendix: A Simplified Version of the Decomposition of Wage Gaps Based on Matching

We start by defining the gap as the difference of expected values of earnings between males and females:[28]

$$\text{Gap} = E(Y|M) - E(Y|F).$$

More specifically, we use a subindex on the expectation symbol to clarify the distribution of characteristics under which the expected values are computed. Thus,

$$\text{Gap} = E_M(Y|M) - E_F(Y|F).$$

One of the constituent points of this decomposition is the explicit recognition that the supports for the distributions of characteristics for F and M do not overlap completely. Matching allows us to recognize the common support directly. Those observations that fall within the common support can be matched, and those that fall outside the common support cannot. To take this into account, we separate the expected values into two elements (using some properties of expected values and probabilities):

$$\begin{aligned} E_M(Y|M) = {} & \mu_M(\text{matched}) * E_M(Y|M,\text{matched}) \\ & + \mu_M(\text{unmatched}) * E_M(Y|M,\text{unmatched}). \end{aligned}$$

and

$$\begin{aligned} E_F(Y|F) = {} & \mu_F(\text{matched}) * E_F(Y|F,\text{matched}) \\ & + \mu_F(\text{unmatched}) * E_F(Y|F,\text{unmatched}), \end{aligned}$$

where μ_F and μ_M denote the probability distributions of characteristics under F and M, respectively. Using the fact that μ (unmatched) = 1 − μ (matched)

28. Detailed discussions of the implicit assumptions made within this appendix are presented in Ñopo (2008). For expositional clarity, we present the setup for gender wage gap decompositions only. Applying the approach to racial gap decompositions simply requires relabeling the compared groups.

under both probability distributions (F and M), the Gap can be rewritten, after some rearrangements, as

$$\begin{aligned}\text{Gap} = {} & \mu_M(\text{unmatched}) * \left[E_M(Y|M,\text{unmatched}) - E_M(Y|M,\text{matched})\right] \\ & + E_M(Y|M,\text{matched}) - E_F(Y|F,\text{matched}) \\ & + \mu_F(\text{unmatched}) * \left[E_F(Y|F,\text{matched}) - E_F(Y|F,\text{unmatched})\right].\end{aligned}$$

Using the Blinder-Oaxaca approach of adding and subtracting a counterfactual element, we add and subtract $E_F(Y|M$, matched):

$$\begin{aligned}\text{Gap} = {} & \mu_M(\text{unmatched}) * \left[E_M(Y|M,\text{unmatched}) - E_M(Y|M,\text{matched})\right] \\ & + E_M(Y|M,\text{matched}) - E_F(Y|M,\text{matched}) + E_F(Y|M,\text{matched}) \\ & - E_F(Y|F,\text{matched}) + \mu_F(\text{unmatched}) * \Big[E_F(Y|F,\text{matched}) \\ & - E_F(Y|F,\text{unmatched})\Big],\end{aligned}$$

or simply Gap = $\Delta_M + \Delta_X + \Delta_0 + \Delta_F$, where

$$\begin{aligned}\Delta_M &= \mu_M(\text{unmatched}) * \left[E_M(Y|M,\text{unmatched}) - E_M(Y|M,\text{matched})\right]; \\ \Delta_x &= E_M(Y|M,\text{matched}) - E_F(Y|M,\text{matched}); \\ \Delta_0 &= E_F(Y|M,\text{matched}) - E_F(Y|F,\text{matched}); \\ \Delta_F &= \mu_F(\text{unmatched}) * \left[E_F(Y|F,\text{matched}) - E_F(Y|F,\text{unmatched})\right].\end{aligned}$$

With this notation, Δ_M and Δ_F are the components of the wage gap that account for differences in the support of the distributions of observable characteristics. Δ_M measures the contribution to the wage gap of the fact that there are some combinations of observable characteristics that males reach and females do not (for instance, middle-aged individuals who are corporate managers and have many years of occupational experience). Δ_M is then the expected increase in the average female wage if females achieve those individual male characteristics that remain unattained by females. Analogously, Δ_F measures the contribution to the wage gap of the existence of certain human capital profiles that are exclusively female (for instance, recent migrants who are single, with children, with low schooling attainment and who work as domestic servants). Thus Δ_F measures the expected increase in average female wages if all females achieve characteristics that are comparable to those of males.

As in the traditional Blinder-Oaxaca decomposition, Δ_X measures the extent to which the wage gap can be explained by differences in observable characteristics between the comparison groups. In our setup, however, this refers not only to the difference in average characteristics, but also to differences in their distributions. Thus Δ_X accounts for the expected decrease in male wages when their individual characteristics follow the distribution of their female counterparts.

Finally, Δ_0 is left as the component of the wage gap that cannot be explained on the basis of differences in observable characteristics of the comparison groups. This can be explained as either discrimination in pay or the existence of gender differences in unobservable characteristics that are related to productivity (or a combination of both). The results reported in tables 4 and 5 in the paper refer to this component.