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Discriminating attitudes, employment decisions, and wage setting at the workplace: evidence from experimental vignettes in a developing country

Actitudes discriminatorias, decisiones de empleo y fijación de salarios en el lugar de trabajo: evidencia de viñetas experimentales en un país en desarrollo

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Abstract
Objective: We study how a worker's personal demographic characteristics affect wage setting and employment decisions among the personnel of a random sample of Mexico City's service sector firms.
Methodology: We use experimental vignettes and multivariate regression analysis.
Results: Net of an explicit productivity measure, we find a discriminatory employment penalty of 11% from Central and south America workers. There is also a penalty for workers with asymmetric faces of 9% that is present only when operatives take firing decisions. For wages, we find a wage penalty for workers with asymmetric faces of 2.6% in the operatives sample but not significant effect in the managers' sample.
Originality: A novel experimental vignettes design is used for analysis.
Conclusions: There is compelling evidence that wage setting and employment dismissal decisions are affected by discriminatory attitudes/prejudices in Mexico City's service sector.

Keywords: discrimination attitudes, wage setting, Mexico.

JEL Classification: J71, J31.

Resumen
Objetivo: Estudiamos cómo las características demográficas personales de un trabajador afectan la fijación de salarios y las decisiones de empleo entre el personal de una muestra aleatoria de empresas del sector servicios en la Ciudad de México.
Metodología: Utilizamos viñetas experimentales y análisis de regresión multivariada.
Resultados: Controlando por una medida explícita de productividad, encontramos una penalización discriminatoria en el empleo de 11% para trabajadores provenientes de Centro y Sudamérica. También existe una penalización del 9% para trabajadores con rostros asimétricos, la cual se presenta únicamente cuando los operativos toman decisiones de despido. En cuanto a los salarios, encontramos una penalización del 2.6% para trabajadores con rostros asimétricos en la muestra de operativos, pero ningún efecto significativo en la muestra de gerentes.
Originalidad: Se utiliza un novedoso diseño de viñetas experimentales para el análisis.
Conclusiones: Existe evidencia contundente de que la fijación salarial y las decisiones de despido están afectadas por actitudes o prejuicios discriminatorios en el sector servicios de la Ciudad de México.

Palabras clave: actitudes de discriminación, determinación salarial, México.
Clasificación JEL: J71, J31.

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Introduction

Ever since the seminal works of Becker (1957) and Arrow (1973), the study of discrimination in the labor market and how it affects individual welfare has been an important strand of the economics literature. Various approaches have been suggested, from observational to experimental. In the experimental branch, correspondence designs have been implemented successfully to study how an applicant's characteristics affect job-application callback probabilities. This approach has been used to detect discrimination against women (v.g., Riach and Rich, 2006; Petit, 2007; Booth and Leigh, 2010), ethnic minorities (v.g., Jowell and Prescott-Clarke, 1970; Bertrand and Mullainathan, 2004), migrants (v.g., Weichselbaumer, 2020; Ahmad, 2020), and other important minorities in developed and developing country settings (v.g., Baert, 2018; Arceo-Gomez and Campos-Vazquez, 2014; Maurer-Fazio, 2012; Banerjee et al., 2009; Galarza and Yamada, 2014).

While experimental evidence on how discrimination affects the hiring process (call-back prob- abilities) is relatively well established, experimental work on how discrimination affects wage setting is much thinner (Neumark, 2018), especially in a developing country setting; partly because in a correspondence study it is almost impossible to proceed all the way into the hiring process to observe a wage offer.[1] However difficult, understanding whether and how discrimination affects wage setting is important, as there are consequences of injustice and inefficiency in allowing persistent wage gaps to exist in the labor market that are not related to productivity differences –as it unduly lowers the welfare of important social groups as well as the welfare of society as a whole.

Despite wage and employment decisions are primarily taken at the workplace, and it is at firm level that most labor discriminatory practices happen, few field experimental studies exist exploring how discrimination attitudes affect wage setting and employment decisions in actual firms (the most relevant pieces of work on the topic are Dulleck et al., (2020) and Bokemper et al., (2019)).

This is so regardless employer, co-worker, and consumer discrimination, have been theoretically and empirically investigated as something that occurs at firm level since early in the labor discrimination literature (Becker 1957, Bodvarsson and Partridge 2001). Moreover, experimental inquiry about how an individual's position at work may moderate his/her discriminatory attitudes regarding wage setting and employment decisions is scant. The present paper contributes an study that intends to cover the knowledge gap.

In particular, we explore whether discriminatory effects differ between managers and operative workers. This comparison is substantively important because, although operative workers are not usually the formal decision-makers on hiring, dismissal, or pay, they often contribute informal but consequential assessments of co-workers' performance, suitability, and technical competence (see, for instance, Werner, 1994; Bamberger et al., 2005, Bol, 2011; Bandiera et al., 2009; Roscigno, 2019). In many workplaces, especially in tasks that are operationally specialized, appraisal is performed using a 360-degree feedback process where supervisors and managers depend at least partly on peer evaluations when forming judgments about retention, task allocation, promotion, and pay adjustments (see, for instance, Hazucha et al., 1993; Bamberger et al., 2005; Antonioni and Park, 2001; McCarthy and Garavan, 2001; Valle and Bozeman, 2002). At the same time, we expect heterogeneous effects across organizational positions for two reasons. First, managers

[1] As it is impossible to produce real persons for real job interviews matching the characteristics of randomly generated CVs.

usually have more hiring experience and more training in personnel evaluation than operative workers, and therefore may be more aware of what constitutes discrimination and why it may be costly for the firm. Second, managers often face stronger organizational incentives to avoid discriminatory decisions, since firm performance may affect their compensation or career prospects, whereas operative workers do not usually face equivalent incentives to refrain from co-worker discrimination (Rousseau, 1978; Adams, 1977; Graham, 1969; Mujica and Bridges, 2023). Thus, comparing managers and operative workers allows us to examine not only whether non-productivity characteristics affect labor-market judgments, but also whether the weight assigned to such characteristics varies systematically across organizational roles.

Accordingly, we derive three hypotheses:

H1. Higher observed productivity decreases the probability of dismissal and wage cuts, while increasing the probability of wage raises.

H2. Net of observed productivity, workers' demographic and identity characteristics have independent effects on employment and wage-setting decisions.

H3. Net of observed productivity, the effects of workers' demographic and identity characteristics on employment and wage-setting decisions are stronger among operative workers than among managers.

H1 assesses whether respondents use the explicit productivity information embedded in the vignette when making labor-market decisions. H2 evaluates whether, net of observed productivity, workers' demographic and identity characteristics still affect those decisions, and finally H3 examines whether such non-productivity effects are stronger among operative workers than among managers.

We use experimental vignettes (Fisher, 1941; Box et al., 2005; Rossi and Anderson, 1982) to study how a worker's personal demographic characteristics affect stated wage setting and employment decisions among personnel of a random sample of 560 Mexico City's service sector firms, net of a measure of individual productivity. Oesch et al., (2017), Neumark (2018), and McDonald (2019) have previously used an experimental vignette design to study wage setting decisions to overcome the fact that observing -let alone experimenting on- a real wage offer is almost impossible.

Unlike most papers in the literature, our study is done in a developing country context;[2] particularly in Latin America, which is unique in many ways. The Mexican context is important in at least two aspects: (a) the institutional framework (laws, judiciary procedures, administrative procedures) implementing policies aiming to avoid discrimination at the workplace in Mexico is rather weak; (b) more importantly, Mexican authorities do not exert any effort to enforce anti-discriminatory laws within firms. Hence, what is done, it is done by self-regulation.

Our paper contributes to the literature on this subject in at least four main areas. First, we shift the focus from the prevalent experimental studies on discrimination affecting call-back probabilities in job advertisements to examining how discrimination impacts wage setting in actual firms. Second, our methodological approach contrasts with traditional studies, as we employ experimental vignettes rather than correspondence studies, providing a more suitable framework for studying wage-setting mechanisms within firms. Third, we explore the role of an individual's position within a firm as a potential moderator of discriminatory attitudes

[2] The developing country literature is scant. Brown (2022) studies whether school principal's evaluations affect teacher's wage in Pakistan and finds that female teachers get 10% lower wages. Gatskova (2021) looks at the role of gender attitudes on the gender gap in Ukraine.

concerning wage setting and employment decisions. Fourth, our study stands out by providing insights from a developing country perspective, where, unlike in most previous research, anti-discriminatory laws are weak and not well enforced.

Results show compelling evidence that operative workers have a set of prejudices/attitudes that penalize workers with asymmetrical faces—a proxy of beauty—in terms of job dismissing probabilities by about 5% and wage cuts by about 2.6% in a context of difficult economic times. Such an effect is not detected among managers. Also, we find evidence of attitudes/prejudices that increase the dismissing probability of migrants from Central and South America in hard times; both among managers and operatives. The size of the effect is 16% among managers and 11% among operatives. In good times, when wage raises are considered, we find no evidence of any discriminatory attitudes/prejudices.

The rest of the paper is organized as follows. Section *Data* describes the data and refers the reader to the online appendix for further details. Next, section *Design of the experimental vignettes* discusses the experimental design implemented and section *Methods of analysis* gives detail on the methods of analysis employed. Finally, section *Results* and section Discussion and conclusions.

Data

We use experimental data from 560 employees in 344 medium and large service firms, drawn from a sampling frame based on Mexico's official statistical directory of economic units (DENUE) compiled by INEGI (2025).[3] These firms were interviewed as part of a survey that we designed for studying job market discrimination in the service sector of Mexico City. The sample is representative of the set of all medium and large service firms and their employees that were operating during the study time in Mexico City. Fieldwork spanned six months, starting in November 2017 and ending in May 2018. Because medium and large firms may be different in terms of the protocOLS they may have in place to address discrimination, we explicitly stratified into two groups: (1) medium enterprises; and (2) large enterprises. The aim was to be able to split the sample into these groups and perform inference with sufficient power at 5% of significance.

The sample has a probabilistic stratified two-stage cluster design, where firms are selected in the first stage (PSUs) and employees are selected in the second stage (SSUs). Two employees, one belonging to the management/human resources team and one belonging to the operative team, are selected within each firm drawn from the first stage.[4] Selection in the first stage is done using systematic sampling to implicitly stratify by geography to ensure the sample is well balanced across Mexico City counties(alcaldías).

We obtained a final response rate of 27.6% at firm level among contacted firms and an 81.4% response rate at individual level. The non-contact rate amounted to 34%; which is similar to the 32% one-year firm mortality rate reported by INEGI in the service sector for the country as a whole. Hence, the rate of non-response is broadly

[3] DENUE provides comprehensive information on the location and characteristics of firms across sectors. Additional details on the sampling design are provided in the online appendix.

[4] We define an operative employee as any employee who performs tasks that are not related to management and/or human resources within the company. Depending on the nature of the company, operational staff may include frontdesk personnel, warehouse workers, drivers, mechanics, secretaries (not in human resources), engineers, technicians, IT staff, cleaning staff, etc. It is important to note that some operational workers supervise other operational workers and are consulted regarding the performance of the staff under their supervision.

justified by the general mortality rate among Mexican firms. Our response rate of 27.6% is also broadly consistent with the typical response rate for surveys to enterprises in Latin America as reported by Mellahi and Harris (2016). Further details about the sampling design of the survey are offered in the online appendix.

In this paper we primarily report an analysis of the experimental component of the survey, where results depend upon experimental design and random assignment to treatment rather than upon the statistical properties of the sample. **Table 1** presents descriptive statistics of the final sample.

Design of the experimental vignettes

An experimental vignette consists of a hypothetical story that is presented to the person being interviewed (Rossi and Anderson, 1982; Alexander and Becker, 1978; Atzmüller and Steiner, 2010). The story corresponds to an event of interest and includes key elements (description of the characters, events, costs) that are experimentally changed. Using vignettes is a way of knowing true perceptions, attitudes and opinions of a given person when the situation or the topic are controversial and subject to potential desirability bias (Edwards 1953). Experimental vignettes have been used in the past to study discrimination in the labor market (for an excellent review of the field see Neumark, 2018) by gender (Kübler et al., 2018; Finseraas et al., 2016; Rosen and Jerdee, 1974), age (Weiss and Maurer, 2004; Rosen and Jerdee, 1977) and ethnic group (Blommaert et al., 2014).[5]

After presenting an experimental vignette, the interviewee is asked to report her/his impressions and attitudes toward the hypothetical person involved in the story and/or to take hypothetical decisions. The experiment consists of randomly, and independently, changing some characteristics of the hypothetical person or situation described in the vignette (Fisher, 1942; Box et al., 2005). Because variation occurs at random, any change in the response variable (e.g., perceptions, attitudes, behavior) induced by the experiment can be interpreted, without further identification assumptions, as a ceteris paribus or causal effect.[6]

For our study, we designed two experimental vignettes. In each vignette, the (real) interviewed manager or operational employee is asked to imagine that s/he is the director of the human resources department (HR) in the firm s/he works. A series of hypothetical worker profiles are presented—one by one—and, after each profile is seen, responders are asked to take hypothetical wage setting and dismissal decisions. Two profiles are shown in each vignette; hence, each respondent sees a total of four hypothetical worker profiles. Moreover, vignettes take into consideration an explicit measure of productivity as well as workers' demographic and identity characteristics. Two contexts (frames) are considered: (a) the hypothetical employee already works in the firm and is being considered for a pay cut and/or a dismissal, and (b) the worker already works in the firm and is being considered for a pay increase. In none of the vignettes, monetary or non-monetary incentives are used.

[5] Although participants are asked to evaluate a firm outsde their own economic sector, a large body of evidence in experimental economics and survey methodology shows that vignette-based designs can elicit consistent and comparable evaluations of behavior, even beyond respondents' immediate experience (Alexander and Becker, 1978; Hainmueller et al., 2014; 2015).

[6] Standard models of efficiency wages and asymmetric information suggest that wages may depend on factors beyond observed productivity when firms cannot directly observe worker effort or performance. In our experimental design, however, productivity is explicitly observed, randomly assigned, and orthogonal to all other worker characteristics. Because productivity is fully observable, there is no incentive for efficiency wages to arise in this setting, which helps isolate the role of non-productivity attributes in respondents' decisions.

It is important to say at this point that our vignettes are unable to establish whether attitudes and/or prejudices are motivated by personal preferences or by statistical discrimination.

Characteristics of the profile photographs that randomly change in all vignettes

The profile of the hypothetical worker contains a photograph which is subject to experimental digital variation. To build these digitally altered photographs five real person images were selected from the Chicago face database (Ma et al., 2015). We chose five baseline, real person, images that were amenable for making naturalistic digital alterations and may not be detected easily as being tampered—potentially giving away our experimental design—; See **Figure 2.**[7] Therefore, following the canons of good experimental design, we decided to privilege digital malleability over correctly perceived Mexican ethnicity; prioritizing internal validity over external validity to avoid introducing bias to the estimators of the structural parameters of interest (Levitt and List, 2007; Loewenstein, 1999; Smith, 1982; Starmer, 1999; Berkowitz and Donnerstein, 1982).

Three characteristics (or factors) change, independently, at random: 1) gender, 2) skin tone and hair color, and 3) face symmetry as a proxy for "beauty". Each factor takes on all its possible levels with equal probability. **Figure 1** shows examples of how the photographs changes when these three characteristics change.

In total, five different people may be displayed in each instance of the vignettes and there are four different instances: two from the first vignette and two from the second vignette. **Table 6** presents descriptive characteristics that change with the profile picture.

Vignette 1 text and characteristics that change randomly

The first vignette presents a firm that is facing economic difficulties and must cut wages or dismiss workers. The interviewee has to decide the percentage of the worker's wage that will be cut. The cut can range from 0% to 100%. **Tables 2** and **3** show the text of the two profiles used in the first vignette.

In addition to the profile picture, other experimental characteristics/factors are: 1) an explicit measure of productivity (high/low (control)), 2) birthplace (Mexico City (control)/ other place in Mexico/Central and South America/USA), 3) sexual orientation (homosexual / heterosexual (control)), and 4) political party affiliation (PAN/PRI/PRD/INE (control)). As before, each factor takes on all its possible levels with equal probability. **Table 6** presents descriptive characteristics that change with the vignette text.

The vignette contains an explicit measure of productivity. This is a relevant part of the experimental design. Economic theory predicts that, discarding information or market power problems, the wage of a worker is equal to his or her marginal productivity (see, for instance, Varian, 1992). Nothing besides marginal productivity should affect wage. Therefore, in our design we expect that, if there are not discriminatory attitudes/prejudices, decisions over wages should be based exclusively on productivity. If we detect that characteristics other than productivity affect a wage cut, then, decisions of the respondent are discriminatory.

Once a wage cut decision is made, the respondent is presented with the opportunity of dismissing the worker as an alternative to improve the firm's finances. At this point the percentage of personnel that need to be fired is

[7] Initially, it was attempted to manipulate pictures labeled as Latino in the database. However, transforming the skin tone, skin-color, symmetry, and gender of these images resulted in unnaturalistic images that respondents could easily detect as being tampered. Thus, the baseline images we use belong to individuals whose photos were the most amenable to digital alteration according to a trial-and-error process of image selection.

presented, which randomly varies, with equal probability, between 25% and 75% from profile to profile. Immediately after, the interviewee decides whether to dismiss the worker based on information given. The decision is binary (yes/no).

As with wage cuts, dismissal decisions should be based solely on productivity. If there are demographic or identity characteristics that affect whether a worker is fired, then, there is evidence of discriminatory attitudes/prejudices in the labor market that potentially affect behavior.

Vignette 2 text and characteristics that change randomly

The second vignette studies salary increases in good times. Here, decisions are somewhat happier. The person being interviewed must decide the percentage of salary rise for the hypothetical worker. The raise can go from 0 to 100%. **Tables 4** and **5** show the text used in the two profiles of vignette 2.

Methods of analysis

Dismissing probability (Vignette 1)

Let $dismiss_{ij}^{*}$ be a latent variable representing the random disutility the $i-th$ respondent gets by keeping the $j-th$ worker at work

$$dismiss_{ij}^{*} = \beta_1 + \beta_2 female_{ij} + \beta_3 skin\ tone_{ij} + \beta_4 symmetric\ face_{ij} + \beta_5 sexual\ orientation + \beta_6 high\ productivity_{ij} + \beta_7 need\ to\ fire_{ij} + u_{ij} \quad (1)$$

where u_{ij} is a random error. Let $\boldsymbol{x}$ the 1×7 vector of explanatory variables and β the 7×1 vector of associated coefficients. We do not observe directly $dismiss_{ij}^{*}$. What we observe is whether the $i-th$ respondent dismissed or not the $j-th$ worker; which occurs when the latent disutility crosses a given threshold (set at 0 without loss of generality)

$$dismiss_{ij} = \begin{cases} 1\ if\ dismiss_{ij}^{*} > 0 \\ 0\ otherwise \end{cases} \quad (2)$$

By design $D(u \mid \boldsymbol{x}) = D(u)$. As a consequence, all experimental explanatory variables are independent of the error term and, hence, strictly exogenous.

We estimate the average treatment effects (ATEs) using a linear probability model (LPM) fitted by pooled ordinary least squares (POLS), pooling profiles 1 and 2 of vignette 1 to gain efficiency. Robust standard errors are reported.

Using OLS for fitting linear probability models for binary response variables has been criticized in the past because it does not guarantee predicted probabilities that fall within the $[0,1]$ range. While this is indeed a disadvantage for prediction, this is not a mayor drawback when the main objective of the researcher is to estimate average partial effects. In fact, the LPM has been shown to provide a good approximation of the underlying response probabilities and to produce a consistent estimator of the conditional mean near the center of the distribution of the explanatory variables $\boldsymbol{x}$ without imposing restricting distributional assumptions; particularly when "...control variables are discrete and only take on few values" (Wooldridge, 2007; Angrist and Pischke, 2009). Moreover, the use of LPM to estimate ATEs of experimental treatments on binary outcomes has been strongly advocated in the literature because coefficients deliver direct estimators of the ATEs (Gomila 2021).[8]

As a robustness analysis it is possible to include an interviewee individual specific effect c in equation (1)

$$dismiss_{ij}^{*} = \beta_1 + \beta_2 female_{ij} + \beta_3 skin\ tone_{ij} + \beta_4 symmetric\ face_{ij} + \beta_5 sexual\ orientation + \beta_6 hihg\ productivity_{ij} + \beta_7 need\ to\ fire_{ij} + c_i + u_{ij} \quad (3)$$

[8] Results from logit models are available from the authors upon request. In all cases, marginal effects and their standard errors are very similar to those obtained from LPM.

and fit a correlated random effects POLS nominating a set of controls that enter $E(c_i \mid \boldsymbol{\chi}_i)$ (Mundlak, 1978; Chamberlain, 1980). For our analysis we allow age, gender, and education of the interviewee to enter $E(c_i \mid \boldsymbol{\chi}_i)$.

Wage reduction (Vignette 1)

For analyzing decisions on wage reduction we fit the following linear regression model:

$$wage\ cut_{ij} = \beta_1 + \beta_2 female_{ij} + \beta_3 skin\ tone_{ij} + \beta_4 symmetric\ face_{ij} + \beta_5 sexual\ orientation + \beta_6 hihg\ productivity_{ij} + u_{ij} \quad (4)$$

Where, $wage\ cut_{ij}$ represents the percentage of $j-th$ (hypothetical) worker's wage that is reduced by the $i-th$ respondent. We condition to an explicit measure of productivity. The model is estimated by pooled OLS, pooling profiles 1 and 2 of vignette 1. Robust standard errors are reported. As in the case of the dismissal probability, as a robustness check, it is possible to include an interviewee individual specific effect c in equation (4). Again, we allow age, gender, and education of the interviewee enter $E(c_i \mid \boldsymbol{\chi}_i)$. The CRE linear model is fitted by pooled OLS.

Wage increase (Vignette 2)

Similarly, for analysis of decisions on wage increments we fit the following linear regression:

$$wage\ raise_{ij} = \beta_1 + \beta_2 female_{ij} + \beta_3 skin\ tone_{ij} + \beta_4 symmetric\ face_{ij} + \beta_5 sexual\ orientation + \beta_3 high\ productivity_{ij} + u_{ij} \quad (5)$$

Where $wage\ raise_{ij}$ represent the percentage of wage increase for the $j-th$ hypothetical worker given by the $i-th$ respondent. As before, the model is fit by OLS pooling profiles 1 and 2 of vignette 2. Robust standard errors are reported. For the case of wage raise we also fit a CRE linear model as a robustness check, letting age, gender, and education of the interviewee enter $E(c_i \mid \boldsymbol{\chi}_i)$.

Results

Results are presented in **Table 7** for the whole sample, and in **Tables 8** and **9** for managers and operatives separately. It is important to underline that, in the following discussion, all regressions control for an explicit measurement of productivity.

First experimental vignette

The first vignette presents a negative scenario where the economy is performing bad and the firms are in need of cutting wages or firing part of their labour force. After giving information of the context, the experiment consists in participants reading two hypothetical profiles and taking wage cuts and dismissing decisions for each case.

Dismissing probability. The first column of **Tables 7**, **8** and **9** present estimates of the marginal effects for the dismiss probability as fitted by a POLS estimator. As expected, higher productivity is associated with a reduction in the probability of being fired of about −17 percentage points (denoted as p.p. hereafter). The effect is significant at 1%. This result is consistent with standard economic theory and suggests that respondents take productivity into account when making decisions in the experimental setting.

We find evidence that, net effect of productivity, people with symmetrical faces have a lower probability of being dismissed of about −4.3 p.p. This discriminatory "*beauty effect*" is interesting; statistically significant at 10% for the whole sample, non statistically significant for the managers' sample and statistically significant at 1% for the operatives' sample—the point estimate goes up to −8.9 p.p in the latter sample. A "*beauty effect*" has already been described by other authors in the literature of discrimination but to our knowledge never documented in Mexico (Hamermesh and Biddle, 1993), nor found to be absent among managers—who are probably trained for not discriminating during

the hiring and firing process—but present among operatives. Basically, the literature finds evidence that there is a tendency, or bias, for employers to hire attractive people over unattractive ones; other things held constant (Hamermesh and Biddle, 1993; Harper, 2000). Mobius and Rosenblat (2006) provide evidence of this effect in a laboratory experiment. On observational designs, the beauty effect may not be caused only by employer discriminatory attitudes but also reflect client preferences for being served by more attractive individuals -i.e., demand-side biases that are transmitted into the labor market as firms seek to maximize sales (Reingen and Kernan, 1993). However, in our experimental design the economic contribution of the employee to the firm (productivity) is explicitly observed and randomly assigned, and thus held constant across profiles. This feature shuts down the productivity channel, so that any remaining symmetry effect reflects evaluations that are independent of productivity.

Other important finding: workers who were born in Central and South America have a probability of being fired that is about 11 p.p. higher than workers who were born in Mexico City. The effect is statistically significant at 5% and is present in both the managers and the operatives samples.

Wage reduction. Results are presented in the second column of **Tables 7**, **8** and **9**. Here we test whether the offered wage cut offered is affected by personal characteristics other than productivity. A graph with the density of the wage cut is shown in **Figure 3**. The distribution is single-peaked and has a long right tail. The mean is located at 15% with an standard deviation of 16.6.

Marginal effects in the third column of **Tables 7** through **9** show similar results to those found for the dismissing probability. At 5% statistical significance, high productivity workers receive smaller cuts. The marginal effect is small, about −2%, but statistically different from zero at 5%.

As before, this result is consistent with standard economic theory and suggests that respondents incorporate productivity into their decision-making.

Net of productivity, results indicate that symmetrically-faced people receive wage cuts that are about −2% lower than workers with asymmetrical faces. Likewise, workers that were born in Central America and South America face wage reductions that are approximately 3% higher than workers who were born in Mexico City (the control group). However, both effects are significant, only 10%.

Investigating potential heterogeneous effects, we split the sample between managers and operatives. Among managers, the size of the beauty effect flattens by a 0.65 factor. In contrast, the migrant effect becomes steeper by a 0.1 factor. In both cases, however, marginal effects are not statistically significant at any conventional level. In fact, among managers, we do not detect evidence of any discriminatory attitudes/prejudices as nothing comes out statistically significant. However, the reader should be careful in interpreting this result as the halving of the sample size causes an important loss of precision and we may not have enough power to reject the null.

Moving to analyze results among operatives we find that symmetrically-faced workers get a wage cut −2.6% lower than non-symmetrically-faced workers; the marginal effect is statistically significant at 5%. Hence, our findings indicate that the beauty effect in the population is driven by the attitudes/prejudices of operative workers. The migrant positive marginal effect is 2.63 but insignificant at any conventional level of significance.

Second experimental vignette

The second vignette presents a positive scenario where the economy is performing well and firms are considering wage increments. After giving

information of the context, the experiment consists of participants reading two hypothetical worker profiles and taking wage increase decisions for each case.

Wage raise in good times. The wage increase density is shown in the **Table 3**. The mean of the wage increase is 23%, with a standard deviation of 17. The distribution is bi-modal and biased towards the right, with one mode around 10% and the other around 30%.

We find that high productivity workers are offered a pay rise of about 9.6% higher than workers of low productivity. This is consistent with theory. It is worth to mention that the productivity measure's effect is greater when the wage is increased than when it is reduced. Finding behavior asymmetries when individuals face negative and positive information has been well described in the behavior economics literature and is not surprising (see, for instance, Kahneman and Tversky, 1979).

There is weak evidence that white and blonde-hair workers get a pay rise that is 2% higher than blown and dark-hair workers. The marginal effects is, however, only significant at 10%. Migrants from central and south America receive a pay rise that is 2.63% lower than workers in the control group (born in Mexico City). But, again, the migrant effect is only significant at 10%. These findings are consistent with the presence of discriminatory attitudes/prejudices in the Mexican labor market that rewards white (Caucasian) workers and punishes migrant workers from central and south America when pay rise decisions are taken. However, the reader should be careful, these marginal effects are only marginally statistically significant.

With exception of the productivity indicator—which marginal effects remain significant and with the expected sign—, splitting the sample between managers and operatives renders all marginal effects statistically insignificant; probably due to loss of precision.

Testing the statistical difference of marginal effects across managers' and operatives' samples

Table 10 contains a series of hypotheses tests comparing marginal effects for each experimental variable in the managers' and operatives' samples. As we mentioned before, we find that with exception of 'Symmetric face' and 'Central/South America', most of the differences in coefficients across samples and characteristics are statistically zero at 5%.

For the case of 'Symmetric face' in the probability of dismissal, we reject the null hypothesis that the marginal effect in the managers and operatives' samples are jointly zero at 5%. So, the marginal effect is different from zero at least in one sample—actually, as we pointed out before, it is in the operatives' sample where we detect that a symmetric face reduces the probability of a dismissal. The zero effect in the managers' sample, however, is not estimated with high precision. This is why a test for the equality of the marginal effect in the managers' and operatives' samples is only rejected at 10%. In summary: we find evidence of heterogeneous effects for symmetric face in the probability of dismissal but only at 10% of significance.

For 'Central/South America' in the probability of dismissal, we reject the null hypothesis that the marginal effect in the managers and operatives' samples are jointly zero at 5%. That is, the marginal effect is different from zero at least in one sample—actually, it is different from zero in both samples. But the difference in the marginal effects in both samples is not statistically different from zero at any standard level of significance. That is, both are equally discriminant.

Notice, however, that we do find substantial heterogeneity for the effect of productivity in the probability of dismissal, as we reject the null hypothesis that the marginal effect in the managers and operatives' samples are jointly zero

at 5% as well as we reject that the difference in the marginal effects across samples is zero at 5%. In fact, inspecting **Tables 8** and **9** it is possible to conclude that managers dismiss high productivity persons at lower rates than operatives. These results of heterogeneous effects are important.

Correlated random effects models

As discussed in section methods of analysis, in all models considered in previous subsections, it is possible to include a interviewee fixed effect causing the Mundlak (1978) and Chamberlain (1980) device. Such, correlated random effects models are easy to implement by adding extra interviewee's controls into the regression and fitting the model by pooled OLS. In all cases, we let age, gender, and education of the interviewee enter $E(c_i \mid \mathbf{x}_i)$. Results are reported in section 2 of the appendix. In all cases, we obtain similar results to the ones we have already discussed. As a consequence, we do not comment further.

Discussion and conclusions

In this article, we present findings from two experimental vignettes examining the influence of individual discriminatory attitudes on wage determination and employment decisions among 560 employees in 344 service sector firms in Mexico City. Specifically, we explore how an individual's position at work, distinguishing between managers and operatives, affects these attitudes and prejudices. Notably, despite a long tradition in economic theory of differentiating between vertical (employer-based) and horizontal (coworker-based) discrimination, there is a lack of experimental inquiry on how one's position at work moderates discriminatory attitudes or prejudices. We aim to bridge this knowledge gap.

An experimental vignette is a story that is presented to a person (the respondent) that involves another hypothetical person (the *decoy* worker) whose characteristics are experimentally changed. After the story is told, the respondent takes decisions that affect the hypothetical person's welfare. Vignettes are a device for learning respondents' true opinions, attitudes, prejudices and perceptions when the situation or topic is controversial and subject to potential desirability bias. Using such a device we explore how, conditional on an explicit measure of productivity, a worker's demographic characteristics such as gender, sexual orientation, skin tone, face symmetry (a proxy for "beauty"), and country of birth, affect how much the respondent cuts from a worker's wage in a context of bad economic times. Additionally, still in a context of bad economic times, we investigate how a worker's demographic characteristics affect the probability of being dismissed (fired) by the respondent. Finally, we do the same in a context of good economic times when decisions to raise wages are taken.

Our findings speak to the three hypotheses stated in the introduction. First, results provide clear support for H1: higher observed productivity decreases the probability of dismissal and wage cuts, while increasing the probability of wage raises. In the bad-times vignette, high-productivity workers are less likely to be dismissed and receive lower wage cuts. In the good-times vignette, high-productivity workers are offered higher wage raises. These findings are consistent with standard economic theory and suggest that respondents do take productivity into account when making decisions in the experimental setting.

Second, results also provide support for H2. Net of observed productivity, some workers' demographic and identity characteristics do affect employment and wage-setting decisions. In particular, we find evidence that migrants from Central and South America face a discriminatory increase in the probability of being dismissed in hard times. We also find that employees with symmetrical facial features are less likely to be dismissed and receive lower wage cuts in hard

times. No other demographic characteristic (i.e. gender, sexual orientation and skin color) is found to cause consistent discriminatory differences on employment probabilities or wages- the expected nondiscriminatory result.

At the same time, the migrant effect in dismissal decisions does not differ significantly between managers and operatives. The size of the effect is substantively important in both groups, and a hypothesis test for the equality of the migrant effect among the managers' and operatives' samples fails to reject the null at any standard statistical level. Hence, empirical evidence suggests that both managers and operatives exert a similar level of discrimination towards Central and South America workers in dismissal decisions.

The evidence for H3 is less strong, but still important. Net of observed productivity, some discriminatory effects are stronger among operative workers than among managers. In particular, when operatives take decisions, we find that employees with symmetrical facial features are less likely to be dismissed compared to those with asymmetrical facial features. Among managers, however, no statistically significant "beauty" effect is found. A hypothesis test for the equality of the beauty effect among managers and operatives rejects the null at 10%, mainly because the null beauty effect among managers is not estimated with enough precision. This implies that there is marginal evidence of a heterogeneous beauty effect in the probability of dismissal.

Regarding wage setting, we find that nothing except productivity affects wage cuts and wage raises when decisions are taken by managers. Nonetheless, there are indeed discriminatory penalties when operatives take decisions. In particular, symmetric-faced workers are given wage cuts that are lower than those given to asymmetric-faced workers. The beauty penalty, however, in the managers' and operatives' samples cannot be rejected to be different at conventional levels of statistical significance, mainly because the zero effect in the managers' sample is estimated with low precision. This adds up to some, but weak, evidence of heterogeneous beauty effects for wage setting.

Beyond the hypotheses stated in the introduction, we find substantial heterogeneity in the effect of productivity itself on the probability of dismissal. The difference in the marginal effect of productivity across both groups is statistically different from zero at 5%. In fact, our results show that managers dismiss high-productivity employees at lower rates than operatives. This is an important heterogeneous result. It is consistent with our initial argument that managers have more hiring and evaluation experience and stronger incentives to align dismissal decisions with workers' productivity. Managers may also have more anti-discrimination training and more reasons to avoid arbitrary dismissals because, among other reasons, their salaries or bonuses are often tied to firm performance, which can be hurt by misallocation. Operatives, in contrast, do not usually have such training and incentives. Thus, this heterogeneous productivity result reinforces the idea that position in the workplace shapes how respondents process information and make labor decisions. While our estimates are derived from a hypothetical setting, a large body of economic research shows that wage and employment outcomes are central determinants of individual income and well-being (see, for instance, Easterlin 1974, Clark and Oswald 1994). In this sense, if similar discriminatory behaviors operate in real-world settings, our findings suggest potentially meaningfull consequences for both individual welfare and allocative efficiency (Becker 1957; Hsieh et al., 2019).

In terms of public policy, our study highlights the importance of monitoring and policing firms to avoid discrimination in the workplace. Effort needs to be made not only to fight against

employer (vertical) discrimination, but co-worker discrimination needs to be addressed also. This is particularly important because, even if operative workers are not usually the formal decision-makers on dismissals or pay, they may still contribute relevant informal assessments about co-workers' performance, suitability, and technical competence, and such assessments may influence managerial decisions in practice.

Two main actions may be taken to curb employer and co-worker discriminatory attitudes at the workplace: (1) to establish law and procedures that make it compulsory for firms to keep individual employment records of all workers, including data on salary changes and layoffs. Such records must be auditable so that authorities, interested individuals, and the public may monitor firms' anti-discriminatory law compliance; (2) to make it compulsory that firms provide employees with information about their rights and the steps to take action in cases where they are discriminated against. It is equally essential to offer adequate support and time frames to people who may experience pay losses or miss out on deserved pay increases.

These implications should be interpreted with caution, as our design identifies behavioral responses in a controlled setting; however, they are consistent with theoretical and empirical work linking discrimination to misallocation and welfare losses in labor markets (Becker 1957, Hsieh et al., 2019).

Further investigation is needed to determine if the discriminatory attitudes/perceptions that we find are explained by taste discrimination, statistical discrimination (Becker 1957), or by discriminatory strategic behavior. Also, because nearly half of the Mexican labor force is employed in the informal sector, future work is needed to explore how discriminatory attitudes and prejudices affect wage and employment decisions in the informal sector.

Table 1
Descriptive statistics of the analytical sample (interviewed firms and employees)

Variable	Obs.	Mean	SD	Min	Max	Description
strata	560	1.57	0.50	1	2	Strata
age	553	31.07	10.09	17	68	Age
female	560	0.42	0.49	0	1	Female
primary	560	0.00	0.06	0	1	Primary
secry	560	0.09	0.29	0	1	Secondary
prepa	560	0.37	0.48	0	1	Preparatory
tech	560	0.05	0.21	0	1	Technical/commercial
teacher	560	0.02	0.13	0	1	Teacher
degree	560	0.43	0.50	0	1	First degree
postgrad	560	0.03	0.17	0	1	Postgraduate
othedu	560	0.01	0.07	0	1	Other education
bthcdmx	560	0.74	0.44	0	1	Born in Mx City
eperla	558	3.50	1.58	1	8	PERLA skin color
emanager	560	0.48	0.50	0	1	Manager
lwage	452	9.00	0.67	7.17	10.34	log(wage)
foreign	560	0.21	0.40	0	1	Foreign firm
county	560	6.91	4.34	1	15	County

Source: own elaboration.

Table 2

Text of first profile of vignette 1. Elements in italics within curly brackets and separated by a forward-slash symbol change randomly with equal probability. PRI, PAN, and PRD are political parties currently active in Mexico.

In what follows, I will give you the tablet so that you can take decisions about some worker profiles. Before you do so, I would like to tell you about the context in which you should take such decisions.
RAPSIC is a Mexican fizzy drink corporation located in the state of Guanajuato. Last year the company suffered an important fall in profits. Its actions lost 30% of their value.
The company is shutting down two production plants and has no option but to cut wages for some of its employees.
Imagine you are the head of human resources and your work involves cutting wages to save the company.
In what follows I will give you the tablet. Please, carefully read each of the following two profiles and decide the wage cut that each employee should take.
Image: {Andrés / Andrea}
Post: sub-director of sells.
Age: 25.
Nationality: Mexican.
Place of birth: {San Salvador, El Salvador / Ciudad de México / Tuxtla Gutiérrez, Chiapas / San Francisco, California}.
Annual review: signed {20 / 30} contracts with retail stores and supermarkets. This performance is slightly {*below / above*} the performance of previous employees in the same post.
Previous experience: coordinated the 2015 electoral campaign "go out and vote" of the {PAN / PRI / PRD / INE} in the county of Cortazar.
Other: Lives with {boyfriend Manuel / girlfriend Manuela} in the north of the city of León.
Approximately, how much wage would you cut for this worker? Response options: (A) 0% – 25%, (B) 26% – 50%, (C) 51% – 75%, (D) 76% – 100%.
Follow-up question:
[Programming: if option A is chosen, ask] How much between 0% –25%? Response op- tions: (a) 0%, (b) 5%, (c) 10%, (d) 15%, (e) 20%, (f) 25%.
[Programming: if option B is chosen, ask] How much between 26% –50%? Response options: (a) 26%, (b) 30%, (c) 35%, (d) 40%, (e) 45%, (f) 50%.
[Programming: if option C is chosen, ask] How much between 51% –75%? Response options: (a) 51%, (b) 55%, (c) 60%, (d) 65%, (e) 70%, (f) 75%.
[Programming: if option D is chosen, ask] How much between 76% –100%? Response options: (a) 76%, (b) 80%, (c) 85%, (d) 90%, (e) 95%, (f) 100%.
Now suppose that instead of a wage cut, you are asked to fire {25% / 50% / 75%} of the labor force. What recommendation would you do regarding this worker? Response options: (1) To fire; (2) Not to fire.

Source: own elaboration.

Table 3

Text of second profile of vignette 1. Elements in italics within curly brackets and separated by a forward-slash symbol change randomly with equal probability. PRI, PAN, and PRD are political parties currently active in Mexico.

In what follows, I will give you the tablet so that you can take decisions about some worker profiles. Before you do so, I would like to tell you about the context in which you should take such decisions.
RAPSIC is a Mexican fizzy drink corporation located in the state of Guanajuato. Last year the company suffered an important fall in profits. Its actions lost 30% of their value.
The company is shutting down two production plants and has no option but to cut wages for some of its employees.
Imagine you are the head of human resources and your work involves cutting wages to save the company.
In what follows I will give you the tablet. Please, carefully read each of the following two profiles and decide the wage cut that each employee should take.
Image: Eric / Érica
Post: sub-director of purchases.
Age: 28.
Nationality: Mexican.
Place of birth: {Guatemala, Ciudad de México / Monterrey, Nuevo León / Chicago, Illinois}.
Annual review: Reduced firm's expenses in {15% / 40%}. This percentage is is slightly {*below / above*} the reduction in expenses attained by previous employees in the same post.
Previous experience: Worked in an car agency in México City.
Other: Lives with {*boyfriend Daniel / girlfriend Daniela*} in the south of the city of León, {*is member of a liberal group that advoc*ates *the depenalisation of abortion / is a member of conservative group against the depenalisation of abortion / is a member of a group of photography*.}
Approximately, how much wage would you cut for this worker? Response options: (A) 0% – 25%, (B) 26% – 50%, (C) 51% – 75%, (D) 76% – 100%.
Follow-up question:
[Programming: if option A is chosen, ask] How much between 0% -25%? Response options: (a) 0%, (b) 5%, (c) 10%, (d) 15%, (e) 20%, (f) 25%.
[Programming: if option B is chosen, ask] How much between 26% -50%? Response options: (a) 26%, (b) 30%, (c) 35%, (d) 40%, (e) 45%, (f) 50%.
[Programming: if option C is chosen, ask] How much between 51% -75%? Response options: (a) 51%, (b) 55%, (c) 60%, (d) 65%, (e) 70%, (f) 75%.
[Programming: if option D is chosen, ask] How much between 76% -100%? Response options: (a) 76%, (b) 80%, (c) 85%, (d) 90%, (e) 95%, (f) 100%.
Now suppose that instead of a wage cut, you are asked to fire {25% / 50% / 75%} of the labor force. What recommendation would you do regarding this worker? Response options: (1) To fire; (2) Not to fire.

Source: own elaboration.

Table 4

Text of first profile of vignette 2. Elements in italics within curly brackets and separated by a forward-slash symbol change randomly with equal probability. PRI, PAN, and PRD are political parties currently active in Mexico.

Again, I will give you the tablet so that you can take decisions about some worker profiles. Before you do so, I would like to tell you about the context in which you should take such decisions.
COMSA is a livestock feed firm located in the state of Yucatán. Last year the company had an important surge in its profits. Its actions raised 250% and two new production plants were open.
As incentive, the company has decided to increase the wage of some employees.
Imagine you are the head of human resources and your work involves deciding what wage increase should receive each employee without damaging the company.
In what follows I will give you the tablet. Please, carefully read each of the following two profiles and decide the wage raise each employee should have.
Image: {Eugenio / Eugenia}.
Post: production and quality control coordinator.
Age: 31.
Nacionality: Mexican.
Place of birth: {Tegucigalpa, Honduras / Ciudad de México / Culiacán, Sinaloa / San Francisco, California}.
Annual review: Increased production in {10% / 20%}. This performance is slightly below / above the performance of previous employees in the same post.
Previous experience: worked in a pharmaceutics distribution firm in the city of Campeche.
Other: until last year was a member of the {*youth action committee of the PRI / youth action committee of the PAN / youth action committee of the PRD*}. Lives with {*boyfriend Victor / girlfriend Victoria*} in the north of the city.
Approximately, how much would you raise? Response options: (A) 0% – 25%, (B) 26% – 50%, (C) 51% – 75%, (D) 76% – 100%.
Follow-up question:
[Programming: if option A is chosen, ask] How much between 0% – 25%? Response op- tions: (a) 0%, (b) 5%, (c) 10%, (d) 15%, (e) 20%, (f) 25%.
[Programming: if option B is chosen, ask] How much between 26% – 50%? Response options: (a) 26%, (b) 30%, (c) 35%, (d) 40%, (e) 45%, (f) 50%.
[Programming: if option C is chosen, ask] How much between 51% – 75%? Response options: (a) 51%, (b) 55%, (c) 60%, (d) 65%, (e) 70%, (f) 75%.
[Programming: if option D is chosen, ask] How much between 76% – 100%? Response options: (a) 76%, (b) 80%, (c) 85%, (d) 90%, (e) 95%, (f) 100%.

Source: own elaboration.

Table 5

Text of second profile of vignette 2. Elements in italics within curly brackets and separated by a forward-slash symbol change randomly with equal probability. PRI, PAN, and PRD are political parties currently active in Mexico.

Again, I will give you the tablet so that you can take decisions about some worker profiles. Before you do so, I would like to tell you about the context in which you should take such decisions.
COMSA is a livestock feed firm located in the state of Yucatán. Last year the company had an important surge in its profits. Its actions raised 250% and two new production plants were open.
As incentive, the company has decided to increase the wage of some employees.
Imagine you are the head of human resources and your work involves deciding what wage increase should receive each employee without damaging the company.
In what follows I will give you the tablet. Please, carefully read each of the following two profiles and decide the wage raise each employee should have.
Image: {Andrés / Andrea}.
Post: coordination of logistics and distribution.
Age: 23.
Nacionality: Mexican.
Place of birth: {Bogotá, Colombia / Ciudad de México / Hermosillo, Sonora / Boston, Massachusetts}.
Annual review: Reduced the transportation time of products in {10% / 40%}. This performance is slightly {*below / above*} the performance of previous employees in the same post.
Previous experience: worked in the postal service of the city of San Luis Potosí.
Other: {*collabor*ates *sporadically with the independent blog "Return to the left" / collabor*ates *sporadically with a local cinema blog / collabor*ates *sporadically with a local blog of the newspaper "El financiero"*}. Lives with {*boyfriend Marcelo / girlfriend Marcela*} in the city center of Mérida, Yucatán.
Approximately, how much would you raise? Response options: (A) 0% – 25%, (B) 26% – 50%, (C) 51% – 75%, (D) 76% – 100%.
Follow-up question:
[Programming: if option A is chosen, ask] How much between 0% – 25%? Response options: (a) 0%, (b) 5%, (c) 10%, (d) 15%, (e) 20%, (f) 25%.
[Programming: if option B is chosen, ask] How much between 26% – 50%? Response options: (a) 26%, (b) 30%, (c) 35%, (d) 40%, (e) 45%, (f) 50%.
[Programming: if option C is chosen, ask] How much between 51% – 75%? Response options: (a) 51%, (b) 55%, (c) 60%, (d) 65%, (e) 70%, (f) 75%.
[Programming: if option D is chosen, ask] How much between 76% – 100%? Response options: (a) 76%, (b) 80%, (c) 85%, (d) 90%, (e) 95%, (f) 100%.

Source: own elaboration.

Table 6

Descriptive statistics of the experimental variables that change with each worker hypothetical profile

Variable	Obs.	Mean	SD	Min	Max	Description
dismiss	1119	0.25	0.43	0	1	Dismiss
wage cut	1119	18.93	16.57	0	100	Wage cut
wage rise	1120	22.87	17.44	0	100	Wage rise
wage	2239	101.98	26.95	0	200	Final exp. wage
female	2239	0.44	0.50	0	1	Female
male	2239	0.56	0.50	0	1	Male (c)
heterosexual	2239	0.51	0.50	0	1	Heterosexual (c)
homosexual	2239	0.49	0.50	0	1	Homosexual
symmface	2239	0.49	0.50	0	1	Symmetric face
asymmface	2239	0.51	0.50	0	1	Asymmetric face (c)
whiteskn	2239	0.50	0.50	0	1	White skin
brownskn	2239	0.50	0.50	0	1	Brown skin (c)
bthcdmx	2239	0.21	0.41	0	1	Born: Cdmx (c)
bthmexoth	2239	0.21	0.41	0	1	Born: Mx other
bthcsamerica	2239	0.23	0.42	0	1	Born: C/South America
bthusa	2239	0.26	0.44	0	1	Born: USA
lowprod	2239	0.50	0.50	0	1	Productivity: low (c)
highprod	2239	0.50	0.50	0	1	Productivity: high
needtofire	1119	51.57	33.24	10	90	Need to fire

Note. There are two profiles per experimental vignette and 560 employee participants. Hence the total number of measurement occasions is observations is $560 * 4 = 2,240$. One observation was lost due to dropout during the realisation of the experimental task. Therefore, we end up with 2, 239 measurement occasions for the experimental vignettes. Control categories in all regressions are indicated with a (c) symbol in the description.

Source: own elaboration.

Table 7

Marginal effects from pooled OLS regression models for the probability of dismissal, wage cut in bad times and wage rise in good times (all sample)

OUTCOMES:	**Dismiss**	**Wage cut**	**Wage rise**
Female	-0.04	-1.10	-0.68
	(0.026)	(1.030)	(1.102)
Homosexual	-0.02	-1.27	0.37
	(0.026)	(1.016)	(1.050)
Symmetric face	-0.04*	-1.97*	-0.04
	(0.026)	(1.018)	(1.048)
White skin	0.01	0.82	2.02*
	(0.026)	(1.020)	(1.057)
Mexico other	0.04	0.26	-1.94
	(0.036)	(1.432)	(1.613)
Cental/South America	0.11***	2.59*	-2.63*
	(0.036)	(1.443)	(1.474)
USA	0.04	1.70	-0.66
	(0.035)	(1.479)	(1.502)
Need to fire	0.00		
	(0.000)		
Productivity	-0.17***	-2.23**	9.61***
	(0.026)	(1.018)	(1.052)
N	1055	1055	993
R^2	0.05	0.01	0.08

Note. Robust standard errors in parenthesis. *10% significant; **5% significant; ***1% significant.

Source: own elaboration.

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p. 39

Table 8

Marginal effects from pooled OLS regression models for the probability of dismissal, wage cut in bad times and wage rise in good times (managers)

OUTCOMES:	**Dismiss**	**Wage cut**	**Wage rise**
Female	-0.03	-0.82	-0.53
	(0.037)	(1.658)	(1.393)
Homosexual	0.01	-0.93	0.16
	(0.038)	(1.579)	(1.345)
Symmetric face	0.00	-1.30	-0.15
	(0.037)	(1.617)	(1.319)
White skin	0.07*	-0.19	1.90
	(0.037)	(1.606)	(1.385)
Mexico other	0.02	-0.84	-0.54
	(0.053)	(2.331)	(2.016)
Cental/South America	0.13**	2.85	-1.64
	(0.054)	(2.332)	(1.976)
USA	0.03	1.00	-0.91
	(0.051)	(2.268)	(1.987)
Need to fire	0.00		
	(0.001)		
Productivity	-0.22***	-1.52	9.69***
	(0.037)	(1.630)	(1.354)
N	518	518	487
R^2	0.08	0.01	0.10

Source: own elaboration.

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Table 9

Marginal effects from pooled OLS regression models for the probability of dismissal, wage cut in bad times and wage rise in good times (operatives)

OUTCOMES:	**Dismiss**	**Wage cut**	**Wage rise**
Female	-0.05	-1.50	-0.80
	(0.036)	(1.300)	(1.701)
Homosexual	-0.04	-1.76	0.58
	(0.036)	(1.295)	(1.642)
Symmetric face	-0.09**	-2.60**	0.11
	(0.036)	(1.304)	(1.594)
White skin	-0.04	1.60	2.28
	(0.036)	(1.298)	(1.588)
Mexico other	0.06	1.55	-2.80
	(0.050)	(1.746)	(2.487)
Cental/South America	0.11**	2.63	-3.37
	(0.049)	(1.798)	(2.135)
USA	0.05	2.46	-0.41
	(0.048)	(1.942)	(2.191)
Need to fire	0.00		
	(0.001)		
Productivity	-0.12***	-3.01**	9.22***
	(0.036)	(1.279)	(1.586)
N	537	537	506
R^2	0.05	0.03	0.07

Note. Robust standard errors in parenthesis. *10% significant; **5% significant; ***1% significant.

Source: own elaboration.

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Table 10

Hypothesis tests comparing marginal effects in the managers vs opera- tives samples for the probability of dismissal, wage cut in bad times and wage rise in good times. P-values reported.

OUTCOMES:	**Dismiss**		**Wage cut**		**Wage rise**	
	a = b	*a = b = 0*	*a = b*	*a = b = 0*	*a = b*	*a = b = 0*
Female	0.725	0.336	0.746	0.451	0.902	0.828
Homosexual	0.299	0.439	0.683	0.330	0.841	0.931
Symmetric face	0.077*	0.041**	0.528	0.096*	0.901	0.991
White skin	0.043**	0.118	0.384	0.460	0.855	0.135
Mexico other	0.539	0.464	0.409	0.628	0.477	0.506
Central/South America	0.765	0.005***	0.941	0.158	0.548	0.198
USA	0.789	0.463	0.622	0.402	0.865	0.883
Productivity	0.050**	0.000***	0.469	0.039**	0.817	0.000***
Need to fire	0.174	0.370				

Note. Robust standard errors are used to perform inference. *10% significant; **5% significant; ***1% signif- icant. Column $a = b$ represents a test of equality of coefficients in the "a" sample (managers) and "b" sample (operatives), the alternative hypothesis is $a \neq b$. Column $a = b = 0$ represents a join significance tests, the alter- native hypothesis is a $a \neq b \neq 0$ (at least one marginal effect is different from zero).

Source: own elaboration.

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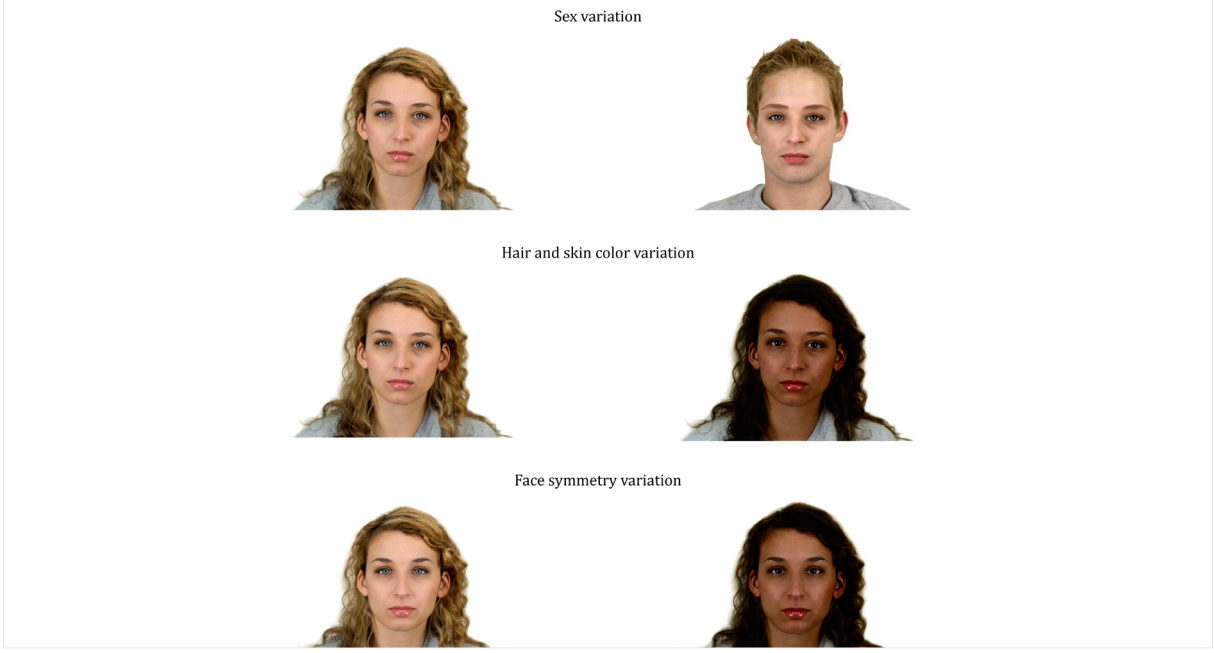
Figure 1

Worker's profile characteristics that vary with the picture.



Source: own elaboration.

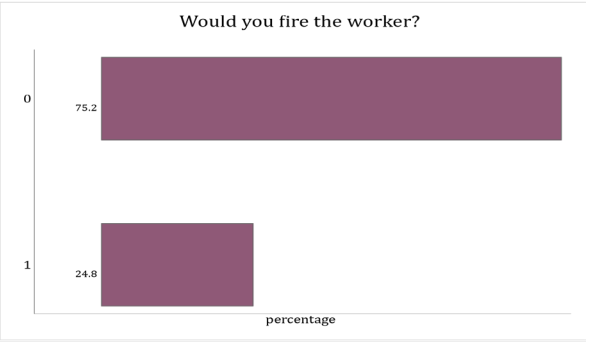
Figure 2

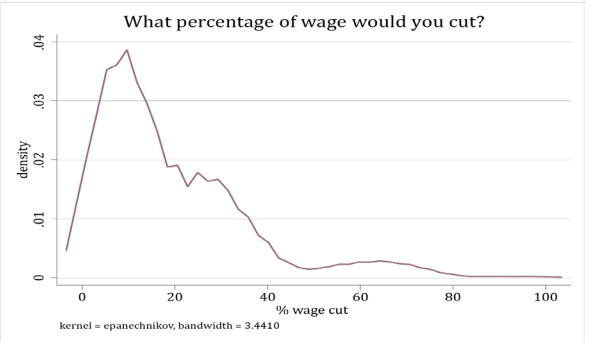
Baseline real person photographs.

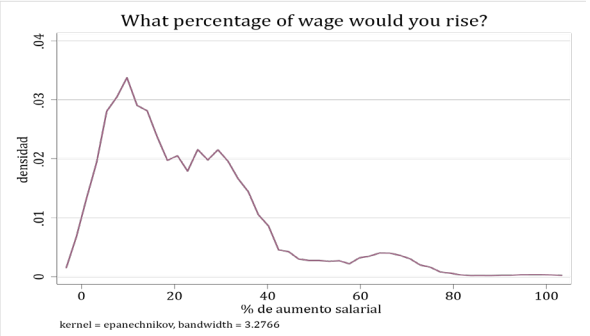
Source: own elaboration.

Figure 3

Distribution of response variables







Source: own elaboration.

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Appendix

In this appendix we include further details on the survey design of the data set used for analysis, as well as a set of robustness checks.

Data appendix

The sample is representative of the set of all medium and large service firms and their employees that were operating during the study time in Mexico City. We explicitly stratified into two groups: (1) medium enterprises; and (2) large enterprises. The sample has a probabilistic stratified two-stage cluster design, where firms are selected in the first stage (PSUs) and employees are selected in the second stage (SSUs). Selection in the first stage was done using systematic sampling to implicitly stratify by geography to ensure the sample was well balanced across Mexico City boroughs (alcaldias).

As sampling frame we used the National Directory of Economic Units (DENUE), which is an administrative list of all firms in Mexico produced by the Mexican National Statistics Institute (INEGI). DENUE clasifies firms in four large categories: (1) agriculture, forestry and fishery; (2) commerce; (3) industry; (4) services. Besides, firms are classified as micro, small, medium, and large, depending on the number of employees. Medium enterprises have between 51 a 100 employees, whereas large enterprises have more than 100 employees. Also, the frame contains information about the county in which the enterprise operates—alcaldias in the case of Mexico City—as well its exact address. For a large proportion of the population telephone and e-mail addresses are available. In 2017/18 the frame contained a total of 6, 148 medium and large service firms located in Mexico City; 53% classified as large sized and 47% classified as medium sized.

To determine the sample size, a binomial test is used to calculate the minimum number of observations that are needed to perform inference for a difference of proportions at a $\alpha = 0.05$ significance level and a maximum margin of error of $E = 0.052$ ignoring stratification and assuming simple random sampling,

$$n = \left[\frac{\left(Z_{\left(1-\frac{\alpha}{2}\right)}\right)^2 p(1-p)}{E^2} \right]$$

where $Z_{\left(1-\frac{\alpha}{2}\right)}$ is the standard normal upper $100\left(1-\frac{\alpha}{2}\right)$ quantile, and $\lceil \cdot \rceil$ denotes the ceiling function. Setting $p = 0.5$ for maximum variability and $\alpha = 0.05$ we obtain that a $n = 355$ of firms is needed to achieve our objectives. Considering budget constraints the target sample of firms was finally set to $n = 350$. At individual level, we planned to interview two employees per firm, leaving the target sample at individual level in 700 observations.

Due to the lack of previous information about the study population, we decided to allocate the sample proportionally across strata and ended up with 165 firms in stratum 1 and 185 in stratum 2. Proportional allocation is popular when no prior information is available for implementing optimal allocation.

Selection of PSUs was performed using systematic sampling with equal probabilities (simple random sampling) in the first stage, and simple random sampling in the second stage. When the selected firm did not allowed random selection of employees for interview, our team ensured that the demographic characteristics of the nominated employees did not follow a systematic pattern to avoid potential bias.

It is well known fact in the literature firms are very reluctant to participate and cooperate with survey/experimental studies. Response rates are typically low. According to Mellahi and Harris (2016), response rates among enterprises are below 50% in Europe and below 45% in the USA. In Latin America, where companies worry about security, Mellahi and Harris (2016) report that response rates are typically below 30%. In such a context, survey studies find it difficult to achieve

target sample sizes and are forced to implement unit substitution strategies when, despite the effort, they are unable to contact and interview all firms that are originally drawn to the sample. To be successful, and not to introduce bias, unit substitution strategy is taken into account as a part of the sample design to ensure that unreachable or uncooperative firms are substituted by randomly chosen units with similar characteristics within the same stratum of the unit that cannot be contacted or is unresponsive. To do it in an orderly way, it is important to anticipate what rate of no contact and what rate of no cooperation the study is likely to face; and to oversample accordingly so that there are enough substitution units that respect the original sample design. Following these procedure we originally selected randomly 3, 701 firms from a universe of 6, 148 firms contained in the DENUE sampling frame. This is clearly well over the n = 350 target sample and allowed us to implement well designed unit substitution when a firm was unreachable or uncooperative.

From the 3, 701 firms originally drawn to the sample, we were able to to establish contact with 1, 246 firms. Reasons for no contact include:

1. The firm had a telephone and/or electronic mail in DENUE but never answered calls or mails. In such case, our team visited the address listed in DENUE and found that the firm was not present at the place—either because the firm did not existed anymore at the time of the visit or because it underwent a change of address and our team was unable to find the current address among neighbors.

2. The firm did not have telephone and/or electronic mail in DENUE. Our team visited the address listed in DENUE and found that the firm was not present at the place and could not find further information from neighbors to locate the new address.

From the 1, 246 contacted firms, a total of 344 agreed to participate in the study; which is equivalent to 98.3% of the 350 sample size that we originally targeted to achieve. From the 344 who accepted to cooperate, 216 were willing to give the two programmed employee interviews (one manager, one operative), 53 only allowed an interview with a management/directive person, and 75 only allowed an interview with an operative person. In total we interviewed 269 employees in management/direction positions and 291 persons in operative positions. From these figures we get a final response rate of 27.6% at firm level among contacted firms and a 81.4% response rate at individual level. The non-contact rate amounts to 34%; which is similar to the 32% one-year firm mortality rate reported by INEGI in the service sector for the country as a whole. Hence, the rate of non-response is broadly justified by the general mortality rate among Mexican firms. Our response rate of 27.6% is also broadly consistent with the typical response rate for surveys to enterprises in Latin America as reported by Mellahi and Harris (2016).

See **tables A1**, **A2** and **A3**.

Correlated random effects models

Table A.1

Marginal effects from correlated random effects models fitted by pooled OLS for the probability of dismissal, wage cut in bad times and wage rise in good times (all sample)

	Dismiss	Wage cut	Wage rise
Female	-0.03	-0.78	-0.71
	-0.026	-1.047	-1.106
Homosexual	-0.02	-1.32	0.41
	-0.026	-1.033	-1.055
Symmetric face	-0.04	-1.98*	-0.16
	-0.026	-1.03	-1.052
White skin	0.01	0.61	2.05*
	-0.026	-1.017	-1.068
Mexico other	0.03	-0.03	-2.01
	-0.037	-1.442	-1.616
Cental/South America	0.10***	2.04	-2.77*
	-0.037	-1.457	-1.475
USA	0.03	1.23	-0.98
	-0.035	-1.494	-1.505
Need to fire	0.00		
	(0.000)		
Productivity	-0.17***	-2.34**	9.48***
	-0.026	-1.033	-1.052
N	1041	1041	979
R^2	0.05	0.03	0.10

Note. Robust standard errors in parenthesis. *10% significant; **5% significant; ***1% significant. Marginal effects from correlated random effects linear models using Mundlak (1978) and Chamberlain (1980) device fitted by pooled OLS are reported. In all cases, we let age, sex, and education of the interviewee enter $E(c_i \mid x_i)$.

Table A.2

Marginal effects from correlated random effects models fitted by pooled OLS for the probability of dismissal, wage cut in bad times and wage rise in good times (managers)

	Dismiss	**Wage cut**	**Wage rise**
Female	-0.02	-0.22	-0.66
	(0.038)	(1.720)	(1.396)
Homosexual	0.02	-1.05	0.09
	(0.038)	(1.614)	(1.347)
Symmetric face	0.00	-1.38	-0.39
	(0.037)	(1.640)	(1.337)
White skin	0.07*	(0.640)	1.89
	(0.038)	(1.597)	(1.396)
Mexico other	0.02	-1.14	-0.45
	(0.053)	(2.358)	(2.029)
Cental/South America	0.12**	2.35	-1.97
	(0.054)	(2.317)	(1.982)
USA	0.03	1.00	-1.26
	(0.051)	(2.288)	(2.029)
Need to fire	0.00		
	(0.001)		
Productivity	-0.23***	-1.92	9.46***
	(0.038)	(1.653)	(1.358)
N	510	510	479
R^2	0.10	0.04	0.12

Note. Robust standard errors in parenthesis. *10% significant; **5% significant; ***1% significant. Marginal effects from correlated random effects linear models using Mundlak (1978) and Chamberlain (1980) device fitted by pooled OLS are reported. In all cases, we let age, sex, and education of the interviewee enter $E(c_i \mid x_i)$.

Table A.3

Marginal effects from correlated random effects models fitted by pooled OLS for the probability of dismissal, wage cut in bad times and wage rise in good times (operatives)

	Dismiss	**Wage cut**	**Wage rise**
Female	-0.04	-1.44	-0.72
	(0.037)	(1.327)	(1.707)
Homosexual	-0.05	-1.76	0.71
	(0.036)	(1.310)	(1.653)
Symmetric face	-0.09**	-2.56*	0.01
	(0.036)	(1.333)	(1.605)
White skin	-0.04	1.66	2.34
	(0.036)	(1.315)	(1.617)
Mexico other	0.05	1.43	-3.04
	(0.052)	(1.760)	(2.501)
Cental/South America	0.10*	2.22	-3.75*
	(0.051)	(1.854)	(2.164)
USA	0.04	1.93	-0.96
	(0.049)	(2.010)	(2.195)
Need to fire	0.00		
	(0.001)		
Productivity	-0.12***	-2.98**	9.34***
	(0.036)	(1.321)	(1.594)
N	531	531	500
R^2	0.05	0.04	0.09

Note. Robust standard errors in parenthesis. *10% significant; **5% significant; ***1% significant. Marginal effects from correlated random effects linear models using Mundlak (1978) and Chamberlain (1980) device fitted by pooled OLS are reported. In all cases, we let age, sex, and education of the interviewee enter $E(c_i \mid x_i)$.

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