Journal of Current Research and Review
Volume 13, Number 9; September-2022;
ISSN: 2836-5615 | Impact Factor: 6.19
https://zapjournals.com/Journals/index.php/jcrr/index
Published By: Zendo Academic Publishing

# BREAKING BOUNDARIES: EXAMINING THE INTERSECTION OF GENDER DISCORDANT NAMES AND SOCIOECONOMIC ATTAINMENT

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**Article Info**

**Keywords:** gender discordant names, educational attainment, labor market earnings, gender measurement, discrimination, gender nonconformity, gender stereotypes, signaling, Brazil.

**Abstract**

This paper explores the effects of gender discordant names, which are names that are given to individuals of a different gender, on educational attainment and labor market earnings. Using a large administrative dataset from Brazil, a country known for prevalent discrimination against women in employment and prejudice against gender nonconforming individuals, we investigate the consequences of having a name that sends an ambiguous or conflicting signal about a person's gender. Our measure of discordance is based on the percentage of men and women with each first name, ranging from names that send consistent gender signals to names that send ambiguous signals. The results show that both men and women with gender discordant names tend to have lower levels of educational attainment. Additionally, having a gender discordant name is negatively associated with earnings, although the effect diminishes when controlling for education. Specifically, only individuals with the most discordant names continue to experience significantly lower earnings. We further examine a secondary measure of discordance based on the perceived femininity/masculinity of names, obtained from a survey of Brazilians. The analysis reveals that men with less masculine names and women with less feminine names also tend to have lower education and earnings. These findings highlight the disadvantages faced by individuals with gender discordant names, which persist in the long term. The research contributes to the literature on names, signaling, gender stereotypes, and gender measurement. It is particularly relevant in the context of increasing interest in the consequences of gender nonconformity and the recognition of nonbinary genders. By identifying a connection between economic outcomes and subtle variations in perceived gender within a general population sample of adults, our analysis offers a unique perspective in this emerging field of study.

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## Introduction

Social science research often uses people's names as proxies for their demographic characteristics. Scholars have relied on differences in the distribution of names to study disparities in everything from birth outcomes (e.g. Lauderdale 2006) and life expectancy (e.g. Cook et al., 2016; Elo et al., 2004) to trends in authorship of scientific research (e.g. Krapf et al., 2016). In audit studies, the race and gender associations with first names are frequently used to measure discrimination (Bertrand and Mullainathan 2004; Pager 2003; Rivera and Tilcsik 2016), and names have been shown to carry age, religion, and social class connotations as well (Gaddis 2019; Johfre 2020; Martiniello and Verhaeghe 2021). In most studies, names are used for analytical leverage because they are believed to send clear signals about – or have strong associations with – the demographic characteristic of interest. In this paper, we examine names that do the opposite: when the observed association with a particular demographic group sends an ambiguous or conflicting signal about the person's demographic group membership. We focus on the consequences of having a gender discordant name – one that is also given to people of a different gender – on educational attainment and labor market earnings. To do so, we use a large administrative dataset from Brazil, a country where discrimination against women in employment (Ben Yahmed 2018; Muniz and Veneroso 2019) and prejudice against gender nonconforming persons (Costa et al., 2013, 2015) are prevalent. Our primary measure of discordance is based on the percentage of men and women with each first name. Names range from those that send consistent gender signals (when a person's gender matches the gender of more than 99% of people with the same name) to those that send ambiguous or conflicting gender signals (when a person's gender matches the gender of less than 50% of people with the same name).

We find that both men and women with gender discordant names completed significantly fewer years of schooling. A gender discordant name is also negatively and significantly associated with earnings, though the estimates decrease in models that include controls for education, such that only people with the most discordant names continue to have significantly lower earnings. Our secondary measure of discordance, which we constructed from a survey of Brazilians, is based on the perceived femininity/masculinity of each first name. We find that men with less masculine names and women with less feminine names have significantly lower education and earnings. Even when the analysis is restricted to persons with gender-exclusive names, the perceived femininity of male names and the perceived masculinity of female names are both negatively associated with educational attainment.

All in all, the evidence suggests that persons with gender discordant names are disadvantaged, and this disadvantage persists in the long term. These findings contribute not only to the literature on names, and the literature on signaling and gender stereotypes, but also to research on gender measurement. Interest in the consequences of gender nonconformity is rising across the social sciences and public health, in tandem with the acknowledgement of nonbinary genders. Our analysis is unique, even among this emerging literature, by identifying a connection between unequal economic outcomes and subtle gradations in perceived gender, in a general population sample of adults.

## 1. Related literature

### **1.1.** Gender signaling and stereotypes

The literature on gender inequality in educational and labor outcomes is vast and the favored theoretical perspectives vary across disciplines (Acker 1990; Blau and Kahn 2017; Koch, D'Mello, and Sackett 2015; Misra and Murray-Close 2014). One that has enjoyed increasing attention recently, particularly in management and organizational behavior circles, is signaling theory (Connelly et al., 2011; Spence, 1978) and its gendered counterpart, role incongruity theory (Eagly and Karau 2002). The basic idea is that people can improve their chances in the labor market by sending positive signals of their abilities, from the quality of their education to their potential for leadership. However, the same signal can be interpreted differently when given by different types of people, based on its congruence with social norms or stereotypes (Heilman 2012). A classic example of this asymmetry is the stereotype that women are communal and men are agentic, which leads to the gendered expectation that men will be better leaders than women.

Much of the research in this area focuses on signals that are relatively changeable and dynamic (endogenous to the individual), such as ways of speaking or presenting oneself on a resume (e.g., Yang et al., 2020). However, other signals are relatively static and fixed (exogenous to the individual). This distinction between the types of signals that people can and cannot control when communicating with others is echoed by symbolic interactionist approaches in sociology. As

Goffman (1959, 1963) noted, there are signs that people

"give," or purposefully express, and there are signs that people – often unintentionally – "give off." Physical appearance, voice, language, and name (among other characteristics) are all signals that are perceived to convey information not only about a person's gender identity but also other genderrelated traits. These gender signals may often complement and reinforce gender norms and expectations. However, they may be incongruent with norms and expectations, making them "gender discordant" signals.

Some experimental research suggests the consequences of sending a discordant signal are negative – particularly when doing so is perceived as breaking from social norms or is otherwise seen as dishonest or deceptive. Masculinity has been described as especially "precarious," in this respect, with men often being penalized to a greater extent than women for exhibiting gender nonconformity (Schrock and Schwalbe 2009; Mize and Manago 2018). Women who are associated with masculinity also may reap advantages, whereas men who are associated with femininity may be at a disadvantage, because masculinity is typically more valued than femininity and men generally have higher status in society. However, other work suggests the consequences of gender discordance depend on whether the imputed characteristics are favorable or unfavorable. For example, studies that adopt an experimental design to investigate the attitudes of participants toward masculinized/feminized faces find that "feminine" faces are considered more attractive (Perrett et al., 1998; Rhodes et al., 2000), which conveys an advantage for discordant men but a disadvantage for discordant women. Yet, "masculine" faces are considered more competent (Sczesny et al., 2006; Oh et al., 2019), a disadvantage for discordant men but an advantage for discordant women.

In the context of politics, discordant male candidates are given higher ratings when "women's" political issues are salient and lower ratings when "men's" issues are salient, while the opposite occurs for discordant female candidates (Lammers et al., 2009). Ma and Correll (2018) also uncover a systematic advantage of discordance. They find that targets with lower gender prototypicality are more likely to avoid the negative stereotypes associated with their gender relative to targets with higher prototypicality. Thus, previous research on gender signaling provides mixed expectations for the effect of perceived gender discordance on educational and labor market outcomes: it could be equally disadvantageous for men and women, it could be more disadvantageous for men than women, or the direction and magnitude of the effect could depend on the specific outcomes or context in question.

**1.2.** Names as signals

Pilcher (2017) explicitly theorizes that names display and construct sex and gender. Names are "doing words" which are involved in the continuous regulation of gender conduct across the life course. In her view, names help to maintain the gender hierarchy in which masculinities are elevated above femininities. Names are both "tools of compliance with the doing of sex and gender as binaries" and, potentially, "tools of resistance … disrupting the normative gender order" (pp818819). Pilcher uses the term "contradictory embodiment" to describe the situation when the combination of body, sex, gender, and name does not conform to norms and expectations. Indeed, one way "a person's femininity or masculinity may be disrupted" is by a gender discordant name.

Although technically changeable, names given at birth are effectively exogenous to the individual. A person's name signals gender by carrying a set of associations – gendered meanings and stereotypes – that influence attitudes and behaviors toward that person. The gendered associations stem from the uneven distribution of given names across a population but can also come from the relationship between naming patterns and family background, the changes in identity and behavior induced by names in their bearers, and the phonological characteristics of names themselves. In what follows, we review the quantitative social science literature on names, with attention to work on gender discordant names.

One strand of research uses demographic data on births to investigate naming patterns (Lieberson and Bell 1992; Lieberson et al., 2000; Sue and Telles 2007; Barry and Harper 2014; Bush et al., 2018). Lieberson and Bell (1992) examine data on births in the State of New York from 1973 to 1985. They contend that naming is a social process, and the patterns of names reflect the influence of social norms, the imagery associated with names, and expectations that parents have for their children, among other social forces. Their results emphasize how naming patterns differ by race and by class. For example, they find that less educated mothers are more likely to give their daughters "traditional" or "conventional" names than more educated mothers. More educated mothers are more likely to give their daughters names that connote goodness, strength, activity, sincerity, and intelligence. Generally, mother's education is less correlated with naming patterns for boys, but less educated mothers are more likely to give their sons names that connote strength. Thus, the available evidence suggests that relative to parents with higher socioeconomic status, parents with lower socioeconomic status may favor names that reflect traditional gender norms.

Other studies using demographic data highlight trends for gender discordant names (Lieberson et al., 2000; Barry and Harper 2014). Lieberson et al. (2000) perform a close analysis of 45 names which are relatively popular for both boys and girls. Among other insights, they report that such names tend to be less anchored to one gender by history or phonology. Additionally, both Lieberson et al. (2000) and Barry and Harper (2014) report that girls are more likely to be given names that boys also have, and that some names go through a life cycle in which the name is first used mostly for boys, gains popularity among girls, and then loses popularity among boys at a tipping point.

Another strand of research investigates the characteristics associated with names. There is evidence that physical features are predictive of names, which may imply names shape appearance. Zwebner et al. (2017) conducted a series of experiments demonstrating that people's faces convey information that is correlated with the names they have. Computer and human participants were able to correctly match names to faces, above and beyond chance. Furthermore, more feminine characteristics are attributed to men with androgynous names, and more masculine characteristics are attributed to women with androgynous names (Mehrabian 2001). Experimental evidence confirms that the phonological properties of names – or how they sound when spoken – convey information about gender (Cassidy et al., 1999; Slepian and Galinsky 2016) and personality traits (Sidhu et al., 2019) to perceivers. Nevertheless, studies typically do not find a systematic relationship between names and self-reported personality traits (Ellington et al., 1980; Rickel and Anderson 1981; Sidhu et al., 2019).

The most robust insight from this literature is that more common names are more likely to be associated with positive characteristics like competence and attractiveness (Harari and McDavid 1973; Garwood et al., 1980;

Mehrabian 1992; Karlin and Bell 1995; Cotton et al., 2008). With a series of experiments, Macrae et al. (2002) report that it took less time to categorize familiar names as male/female, and that familiar male names were considered more masculine and familiar female names were considered more feminine, relative to unfamiliar names.

Only a handful of studies investigate the outcomes associated with names. Garwood (1976) reports that primary school students with more desirable names, based on ratings by teachers, had higher scores on a national achievement test than students with less desirable names. On one hand, the research suggests that some men may suffer from having a feminine name. Figlio (2007) finds that boys with majority female names tend to misbehave disproportionately in middle school. On the other hand, the research suggests that some women may benefit from having a masculine name. Coffey and McLaughlin (2009) find that women with more masculine names are more likely to become judges, while Urbatsch (2018) finds that female political candidates with more masculine names received a higher vote share. Both of these studies measure name masculinity/femininity by using the percentage of men and women with the name, and both interpret their findings using a theory of gender signaling.

### 1.3. Consequences of gender nonconformity

Gender nonconformity occurs when individuals do not conform to social norms that regulate what behaviors and identities are appropriate for men and women (Toomey et al., 2010; Martin-Storey and August 2016; Sandfort et al., 2021). Childhood gender nonconformity is measured with one or more questions, often asked retrospectively, about gender-typed behaviors and feelings, e.g., favorite toys and activities (Egan and Perry 2001; Roberts et al., 2013; Sandfort et al., 2021). Nonconformity in adolescence or adulthood is usually measured with a question about how masculine and how feminine an individual perceives themselves to be or how they are perceived by others (Toomey et al., 2010; Hart et al., 2019; Sandfort et al., 2021). Our measure of gender discordant names does not reflect gender nonconformity, per se, though having a gender discordant name could produce similar indirect effects to the extent that names influence a person's behavior and to the extent they are interpreted as signals of gender nonconformity by others. Given this, we briefly review what is known about the consequences of gender nonconformity on various life outcomes.

Gender nonconforming children and adolescents experience different social environments than gender conforming children and adolescents. Nonconformity is thought to raise the likelihood of social exclusion (Bos and Sandfort 2015; Zosuls et al., 2016; Braun and Davidson 2017; Kleiser and Mayeux 2021) and victimization (Martin-Storey and August 2016; Zosuls et al., 2016; Navarro et al., 2016; Smith and Juvonen 2017). Among children and young adults, nonconformity is associated with lower self-esteem and other measures of adjustment (Egan and Perry 2001; Yunger et al., 2004; Toomey et al., 2010; Smith and Juvonen 2017). Among adults and young adults, it is associated with higher anxiety (Skidmore et al., 2006; Sandfort et al., 2007; Lippa 2008), depression (Logie et al., 2012; Roberts et al., 2013; Li et al., 2016; Martin-Storey and August 2016), and suicidality (Ploderl and Fartacek, 2009).

Few studies explore the consequences of nonconformity beyond social exclusion and mental health. Weber et al. (2019) examine use of alcohol and illegal drugs, Sandfort et al. (2015) examine HIV infection, and Hart et al. (2019) examine both physical and mental health. Hart et al. (2019) find that people who reported being perceived as gender nonconforming by others also had worse self-reported health, particularly when they did not identify as gender nonconforming themselves. Thus, although the experimental research reviewed above points to potentially positive and possibly asymmetric relationships with gender discordant signaling, observational research finds uniformly negative associations with gender nonconformity. Our hybrid approach – using an implicit measure of gender discordance with real-world data on socioeconomic outcomes – extends the literature on these important questions.

## 2. Methods

### **2.1.** Estimation sample

We make use of RAIS, an administrative dataset that includes the universe of Brazilians employed in the formal sector (Minist´erio do Trabalho e Emprego, 2012–2015). Annually, employers provide information on their employees to the Ministry of Labor, which utilizes the information to study the labor market and determine certain labor benefits. RAIS includes formal workers in the private and public sectors as well as self-employed persons who have registered a company. According to the Ministry of Labor, RAIS covers 97% of all formal workers in the country.

Altogether, the estimation sample contains 2,678,643 men and 1,739,760 women. The 2015 estimation sample was constructed in four steps:

1. We made a comprehensive list of persons who had consistent gender for all entries and had more than one employer across the years 2012, 2014, and 2015.
2. We selected a 20% random sample of persons, due to the size of RAIS and limits on computing power.
3. We compiled all entries associated with these selected persons in 2015 and collapsed the information so that there was one observation per person.
4. We limited the sample to the most popular 2500 personal names, retaining about 86% of persons.

Limiting the sample to common names is intended to exclude rare and unique names for which population-level measures of gender discordance are less statistically meaningful. Limiting the sample to persons with consistent gender across multiple employers is intended to minimize the prevalence of measurement error in gender. Information on gender is considerably more reliable when multiple employers provide corroborating perspectives on a person's gender.

Without this sample refinement, measurement error could be problematic. The online Supplementary Material demonstrates that measurement error is present in the "wide" sample, which includes persons with consistent gender regardless of number of employers, but is minimal in our "refined sample," which includes persons with consistent gender across multiple employers. The Supplementary Material also demonstrates that even if some measurement error were present in the refined sample, it could not explain the pattern of results we obtain.

Note that the refined sample, our estimation sample, is 43% of the size of the wide sample. Appendix Table 1 compares the characteristics of persons in the two samples. The refined sample is similar to the wide sample with respect to gender, race/color, birth cohort, education, and earnings. However, as expected, persons in the refined sample have many fewer months of tenure with their employer than persons in the wide sample.

### 2.2. Dependent variables

RAIS 2015 is used to construct the dependent variables. "Years of education" is the number of years of education completed, based on the highest level of schooling reported by a person's employer. "College completion" is a binary indicator that equals one if a person's employer reported that he or she had completed college and equals zero otherwise. "Log of annual earnings" is the natural logarithm of all earnings reported in 2015. Earnings are top-coded at the 99th percentile to limit the influence of extremely high values.

### 2.3. Independent variables derived from RAIS

Our primary measure of gender discordance is based on the percentage of persons with a name who do not share the same gender.

| Names given to men | | | | Names given to women | | | |
|---|---|---|---|---|---|---|---|
| [A] | [B] | [C] | [D] Most discordant | [A] Least discordant | [B] | [C] | [D] Most discordant |
| | | | ALCIONE | ADRIANA | | | CLEIDIMAR |

**Table 1**

Examples of names by level of gender discordance. Least discordant

ANDERSON ADAIR ARIEL CONCEICAO ALCIONE ANTONIO ALTAIR ATILA CLAIRALINE FRANCINE ELIS DARCI BRUNO CHRISTIAN CLAUDENIR GENECIANA GEANE IRACI DIONE CARLOS CRISTIAN CLEOMAR IVANIR BRUNA GENI IRANI DIRLEI FABIO DONIZETE DARCI JOCELI CAMILA IONE IRIS ELI FRANCISCO EDIMAR DEVANIR LEONI CRISTIANE JAINE IVANI FRANCIS JOAO EDMAR DIONE LUCIMAR FERNANDA JANE IVANIR GILVANE JOSE GEOVANE ELI LUZIMAR JESSICA NOELI LUCIMAR JACI LEANDRO GEOVANI ELISMAR MARIA JULIANA ODETE NADIR JOSE LUIZ GIOVANE ELOI NADIR LUCIANA STEFANI NELCI JURACI MARCELO ITAMAR FRANCIMAR NELCI MARCIA STEFANY ROSIMAR LUCINEI MARCOS JOSIMAR FRANCIS ROSIMAR MARIA TAINA SILVANE MURIEL PAULO LINDOMAR JUCIMAR ROSINEI PATRICIA TAYNA SIRLEI RENI RAFAEL RENE JURACI SIRLEI RENATA THAINA SIRLEY VALDECI RODRIGO YURI VALDECI VALDETE VANESSA THAYNA VALDETE VANDERLI

NOTE. The most common 15 names in each category are listed. The RAIS categories are defined according to the percentage of persons with a name who do not share the same gender: [A] less than 1% (least discordant), [B] at least 1% and less than 5%, [C] at least 5% and less than 50%, and [D] at least 50% (most discordant).

Most persons have a name which is virtually gender exclusive and matches their binary gender as recorded in RAIS, but some persons have a name which is given to both genders or is primarily given to the other gender. Our measure reflects the extent to which the population gender distribution associated with a person's name is incongruent with their gender. It was constructed as follows.

1. We made a comprehensive list of persons who had consistent gender for all entries and had more than one employer across the years 2012, 2014, and 2015.
2. For every first (or given) name, we calculated the percentage of men and percentage of women with the name.
3. We merged these name statistics with the estimation sample.
4. We created a set of binary indicators defined according to the percentage of persons with the name who are a different gender: [A] less than 1%, [B] at least 1% and less than 5%, [C] at least 5% and less than 50%, and [D] at least 50%. Category A names are the least discordant, and category D names are the most discordant.

Table 1 lists the most common 15 names in each category. For men, examples of names in B are Edimar and Rene, while examples of names in C are Ariel and Juraci. For women, examples of names in B are Conceiçao and Geane, while examples of names in C are Elis ˜ and Sirlei. Note that names which belong to A, B, or C for one gender will belong to D for the other gender, and names which belong to D for one gender will belong to A, B, or C for the other gender. Table 2 displays the distribution of names in the estimation sample. About 97.6% of persons have category A names, while 2.4% have names that belong to the other categories.

The covariates included in regression models were also constructed from RAIS. "Race/color" is measured with a set of binary variables for branca, parda, preta, amarela, indígena, and not identified. "Popularity of name" entails a set of binary variables corresponding to deciles of the total number of persons with a name, calculated separately for men and women. "Birth cohort" is a set of binary variables corresponding to deciles of birth year. "State fixed effects" cover the 26 states and 1 federal district. "Tenure with employer" is the total number of months that a person had worked with his or her main employer. This covariate is only included in regressions of earnings. Table 3 provides summary statistics for the dependent and independent variables derived from RAIS.

Appendix Table 2 illustrates how the measures of gender discordance vary with the covariates. The level of discordance is rather constant, with the exception of popularity of name. Discordant names are clearly less popular for both men and women. The vast majority of discordant names fall into the three lowest deciles of popularity. Since popularity may wield an independent effect on outcomes, it is vital to control for it in the regression models.

**2.4. Independent variables derived from MTurk**

Our secondary measure of gender discordance is based on social perceptions about how masculine or how feminine a name is. Most names are considered very masculine or very feminine. However, some names are considered somewhat masculine, somewhat feminine, or both masculine and feminine. Our measure reflects the extent to which the gender associations with a person's name are incongruent with their gender.

To construct our social perception measure, we conducted a survey of Brazilian adults (age 18+) using Mechanical Turk (MTurk), an international online labor market operated by Amazon. On the platform, requesters post short tasks for workers to complete for a small payment. In 2020, we posted a survey that was available to MTurk workers who had registered their country as Brazil. Participants were asked to evaluate 100 names with respect to how masculine or how feminine they were. Specifically, they rated each

**Table 2**

Distribution of gender discordant names.

| | Males | | | Females | |
|---|---|---|---|---|---|
| | Number | Percentage | | Number | Percentage |
| RAIS (% different gender with name) | | | | | |
| [A] less than 1% | 2,613,153 | 97.56 | | 1,697,465 | 97.57 |
| [B] at least 1% and less than 5% | 41,084 | 1.53 | | 21,275 | 1.22 |
| [C] at least 5% and less than 50% | 17,805 | 0.66 | | 15,346 | 0.88 |
| [D] at least 50% | 6601 | 0.25 | | 5674 | 0.33 |
| MTurk (FemininityMasculinity Index) | | | | | |
| [A] FMI <1.5 | 691,756 | 90.82 | | 522,647 | 94.32 |
| [B] 1.5 ≤ FMI 2.5 | 12,480<br>3242 | 1.64<br>0.43 | 8312 7.12<br>2834 | 20,306 | 3.66<br>1.50<br>0.51 |

NOTE. The RAIS categories are defined according to the percentage of persons with a name who do not share the same gender: [A] less than 1% (least discordant), [B] at least 1% and less than 5%, [C] at least 5% and less than 50%, and [D] at least 50% (most discordant). The MTurk categories are defined according to the perceived masculinity/femininity of a name: for men (women), names in [A] are closest to very masculine (feminine), names in [B] are closest to somewhat masculine (feminine), names in [C] are closest to both masculine and feminine, and names in [D] are closest to somewhat or very feminine (masculine).

**Table 3**
Summary statistics.

| | Men | | | | Women | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Min | Max | Mean | SD | Min | Max |
| Years of education | 11.203 | 2.905 | 0 | 20 | 12.441 | 2.628 | 0 | 20 |
| College completion | 0.109 | 0.311 | 0 | 1 | 0.235 | 0.424 | 0 | 1 |
| Log of annual earnings | 9.478 | 0.964 | 5.466 | 11.918 | 9.424 | 0.989 | 5.466 | 11.918 |
| Race/color Branca | 0.446 | 0.497 | 0 | 1 | 0.479 | 0.500 | 0 | 1 |
| Parda | 0.342 | 0.474 | 0 | 1 | 0.265 | 0.442 | 0 | 1 |
| Preta | 0.056 | 0.230 | 0 | 1 | 0.041 | 0.197 | 0 | 1 |
| Amarela | 0.006 | 0.079 | 0 | 1 | 0.006 | 0.079 | 0 | 1 |
| Indígena | 0.002 | 0.043 | 0 | 1 | 0.001 | 0.038 | 0 | 1 |
| Not identified | 0.148 | 0.355 | 0 | 1 | 0.207 | 0.405 | 0 | 1 |
| Popularity of name Decile 1 (least common) | 0.100 | 0.300 | 0 | 1 | 0.100 | 0.300 | 0 | 1 |
| Decile 2 | 0.100 | 0.300 | 0 | 1 | 0.100 | 0.300 | 0 | 1 |
| Decile 3 | 0.100 | 0.300 | 0 | 1 | 0.100 | 0.300 | 0 | 1 |
| Decile 4 | 0.102 | 0.302 | 0 | 1 | 0.100 | 0.300 | 0 | 1 |
| Decile 5 | 0.100 | 0.300 | 0 | 1 | 0.100 | 0.300 | 0 | 1 |
| Decile 6 | 0.099 | 0.299 | 0 | 1 | 0.104 | 0.305 | 0 | 1 |
| Decile 7 | 0.100 | 0.300 | 0 | 1 | 0.097 | 0.296 | 0 | 1 |
| Decile 8 | 0.103 | 0.305 | 0 | 1 | 0.107 | 0.309 | 0 | 1 |
| Decile 9 | 0.114 | 0.317 | 0 | 1 | 0.124 | 0.330 | 0 | 1 |
| Decile 10 (most common) | 0.082 | 0.274 | 0 | 1 | 0.067 | 0.251 | 0 | 1 |
| Birth cohort (deciles) Before 1967 | 0.117 | 0.321 | 0 | 1 | 0.097 | 0.296 | 0 | 1 |
| 1967–1972 | 0.096 | 0.294 | 0 | 1 | 0.094 | 0.291 | 0 | 1 |
| 1973–1977 | 0.113 | 0.316 | 0 | 1 | 0.113 | 0.316 | 0 | 1 |
| 1978–1980 | 0.090 | 0.286 | 0 | 1 | 0.091 | 0.288 | 0 | 1 |
| 1981–1983 | 0.109 | 0.311 | 0 | 1 | 0.112 | 0.315 | 0 | 1 |
| 1984–1986 | 0.116 | 0.320 | 0 | 1 | 0.119 | 0.323 | 0 | 1 |
| 1987–1988 | 0.082 | 0.274 | 0 | 1 | 0.085 | 0.279 | 0 | 1 |
| 1989–1991 | 0.120 | 0.325 | 0 | 1 | 0.123 | 0.329 | 0 | 1 |
| 1992–1993 | 0.075 | 0.264 | 0 | 1 | 0.076 | 0.266 | 0 | 1 |
| After 1993 | 0.084 | 0.277 | 0 | 1 | 0.091 | 0.287 | 0 | 1 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Tenure with employer (months) | 22.326 | 40.061 | 0 | 596 | 29.001 | 51.790 | 0 | 598 |

NOTE. The sample size of men is 2,678,643, and the sample size of women is 1,739,760. The set of controls also includes state fixed effects, which are not shown here due to space constraints. name as very masculine, somewhat masculine, both masculine and feminine, somewhat feminine, or very feminine. The 100 names were presented in a random order and drawn randomly from a list of 797 names. The list of 797 names was composed of a 25% random sample of names in category A for one gender (and D for the other) plus a 100% sample of names in B and C for one gender (and D for the other).

In total, 319 participants (201 self-identified men and 118 self-identified women) completed the survey, yielding about 40 ratings

per name. Then, participant ratings were averaged by name. To create the variable "femininity," responses were coded so that larger values indicated more feminine (i.e., very masculine equals 1, somewhat masculine equals 2, both masculine and feminine equals 3, somewhat feminine equals 4, and very feminine equals 5). To create the variable "masculinity," responses were coded so that larger values indicated more masculine (i.e., very feminine equals 1, somewhat feminine equals 2, both masculine and feminine equals 3, somewhat masculine equals 4, and very masculine equals 5).

Then, "femininity" was merged with men in the RAIS estimation sample, while "masculinity" was merged with women in the RAIS estimation sample. This combined variable is the FemininityMasculinity Index (FMI). We created a set of binary indicators defined according to the values of the FMI: [A] FMI $<1.5$, [B] $1.5 \leq$ FMI $<2.5$, [C] $2.5 \leq$ FMI $<3.5$, and [D] $3.5 \leq$ FMI. For men, names in A are closest to very masculine, names in B are closest to somewhat masculine, names in C are closest to both masculine and feminine, and names in D are closest to somewhat or very feminine. For women, names in A are closest to very feminine, names in B are closest to somewhat feminine, names in C are closest to both masculine and feminine, and names in D are closest to somewhat or very masculine. Table 2 displays the distribution of names in the estimation sample. About 90.8% of men and 94.3% of women have names that belong to category A, while 9.2% of men and 5.7% of women have names that belong to the other categories.

Appendix Table 3 shows the relationship between the MTurk and RAIS measures of discordance in the estimation sample. As the table indicates, perceptions of femininity/masculinity are highly correlated with our RAIS measure of gender discordant names. The overlap is greatest at the two ends. For men and women, respectively, 98.5% and 97.2% of MTurk category A names are also RAIS category A names. For men and women, respectively, 81.7% and 80.2% of MTurk category D names are also RAIS category D names.

**2.5. Statistical models**

Multivariate linear regressions are employed to investigate the association between having a gender discordant name and education and labor market outcomes. Logistic models yield similar results as linear models, which are used for ease of interpretation and consistency across dependent variables. In the basic model, which uses one observation per individual, each of the outcomes is regressed on measures of gender discordance, controls for popularity of name, and demographic covariates. That is, the following model is implemented for individual *i* with name *j*:

$Yi = \lambda GDj + \alpha Pj + \beta Xi + \varepsilon ij$, where *Y* is the outcome, *GD* is a set of measures of gender discordance, *P* is a set of controls for popularity of name, and *X* is a set of individual-level covariates.

The main analysis makes use of binary measures of discordance derived from RAIS. We prefer binary measures because they are easier to understand and interpret, allow for nonlinearity, and maintain a parallelism between RAIS and MTurk analyses. Years of education is included as a control in some models to estimate the impact of name discordance on labor outcomes, above and beyond any indirect impacts mediated by education. Models are also run without controls, which is potentially insightful if the inclusion of covariates induces post-treatment bias. Robust standard errors are clustered on personal name, as all persons with the same name share the same values for name statistics.

Two major extensions of the basic model are carried out. One extension is to use models with family fixed effects. Family background, besides having an indirect effect through name signals, may also have a direct effect on outcomes. For this reason, statistical models should control for family background when possible. RAIS does not explicitly identify family relationships, but it is possible to identify "probable siblings" using information contained in the dataset. To do so, the full dataset of individuals who appear in multiple years with consistent gender is restricted to pairs of individuals who are the same gender, have an age gap of 10 years or less, and share a family name which is otherwise absent in their state of employment. By no means does this sample include all sets of siblings. Nevertheless, having a subset of probable siblings allows the inclusion of family fixed effects that control for family-specific factors common to both siblings.

Another extension is to use measures of discordance derived from MTurk. In this exercise, regressions include the set of four binary variables describing levels of the Femininity-Masculinity Index. Note that the sample size decreases somewhat as the MTurk survey was only able to gather information on 797 of the 2500 names. In a related exercise, we restrict the sample to persons with the least discordant names in RAIS (names given to less than 1% of the other gender). The purpose of this exercise is to see if perceptions of femininity/masculinity are still correlated with outcomes even when they are not correlated with percent different gender. Since almost all names which fall into RAIS category A also fall into MTurk category A, it no longer makes sense to include the set of four binary variables in regressions. Instead, we include the Femininity-Masculinity Index as a continuous variable.

### 2.6. Limitations

It is important to recognize the limitations of our research. One is that the statistical relationships that we estimate are not necessarily causal. It is possible that parental characteristics are correlated with both naming practices and child outcomes, but it is not clear whether our estimates are biased upward or downward. Another limitation relates to our dataset. Although the RAIS administrative data is comprehensive, it only allows the examination of persons working in the formal sector. Moreover, potential measurement error in gender led us to restrict the sample to persons with consistent gender across multiple employers. Our findings are also specific to Brazil, so analyses of other social-cultural settings may yield different results. Nevertheless, we believe the case of Brazil is broadly informative. A democracy with a large and diverse population, Brazil provides some rights to sexual minorities and other vulnerable groups. Thus, it is neither a best nor a worst case scenario for gender conformity and inequality.

## 3. Results

### **3.1.** Findings using RAIS measures of discordance

Table 4 displays the results for education. As the table shows, gender discordance is negatively associated with both measures of education. Estimates are much bigger for high discordance (C and D) than for low discordance (B). Estimates are bigger for women than for men. Men with names in category B have about 0.15 fewer years of education, while men with names in categories C and D have 0.47 and 0.38 fewer years of education, respectively.

Likewise, men with names in category B are about 1.6 percentage points less likely to have completed college, while men with names in categories C and D are 3.6 and 3.9 percentage points less likely to have completed college. Women with names in category B have about 0.19 fewer years of education, while women with names in categories C and D have 0.67 and 0.60 fewer years of education, respectively. Likewise, women with names in category B are about 2.6 percentage points less likely to have completed college, while women with names in categories C and D are 8.0 and 7.2 percentage points less likely to have completed college.

Table 5 displays the results for earnings. The estimates demonstrate that gender discordance is negatively associated with earnings as well. Estimates are again much bigger for high discordance (C and D) than for low discordance (B). According to models without controls for education (second column), men with names in categories B, C, and D have about 2%, 6%, and 14% lower earnings, respectively. Women with names in categories B, C, and D have about 5%, 11%, and 10% lower earnings, respectively. Models that include years of education (third and seventh columns) test the extent to which differences in education account for these effects. The magnitudes of coefficients decrease considerably for all groups of persons with discordant names, except for men with the most discordant names. Men with names in category D have 12% less earnings, even holding education constant. Lastly, models that include occupational fixed effects (fourth and eighth columns) test the extent to which differences in occupation account for these conditional effects. Note that the set of fixed effects entails 193 “three-digit” occupational categories in RAIS. Estimated coefficients are only significant for category D. Men and women with names in category D have 9% and 2% lower earnings, respectively. This indicates that some differences in earnings are due to differential sorting across occupations rather than differences in earnings within occupation.

Table 6 displays the results for fixed effects regressions using “probable siblings,” defined as pairs of individuals who are the same gender, have an age gap of 10 years or less, and share a family name which is otherwise absent in their state. The results are qualitatively similar to the previous ones. However, the estimates are smaller in magnitude, and the coefficients for men and women with names in category D are not statistically significant, likely due to low sample sizes. The strongest results are for persons with names in category C. Men with names in category C have about 0.51 fewer years of education and 6% lower earnings, while women with names in category C have about 0.40 fewer years of education and 14% lower earnings. The main take-away from the table is that family- specific factors are unlikely to explain the overall pattern of results in the paper. Even when they share the same surname, people with more gender discordant given names tend to have somewhat lower outcomes than people with less gender discordant given names.

It is also illuminating to examine the estimated coefficients for race/color and popularity of name (see Appendix Table 5). For popularity of name, the same pattern emerges for both men and women. Persons with names of above-average popularity tend to have better socioeconomic outcomes than persons with names of below-average popularity, except for those with the most common names who have the lowest outcomes of all. The estimates for racial disparities help to contextualize our findings on gender discordance. In our view, the best yardstick is the coefficient on pardo, which represents the difference in outcomes between persons identified as “brown” and persons identified as “white,” the two largest racial groups in Brazil. Relative to differences with respect to race, differences with respect to gender discordance tend to be larger for education than employment. Education gaps between persons with names in category C or D and persons with names in category A are roughly three-quarters of the size of education gaps between pardos and brancos. For most employment outcomes, differences with respect to gender discordance are roughly one-quarter of the size of differences with respect to race. Notably, though, the earnings gap between men with names in category D and men with names in category A is twice as large as the earnings gap between pardo men and branco men.

### 3.2. Findings using MTurk measures of discordance

Complementing the main analysis, we use alternative measures of name discordance constructed from the survey that we conducted on MTurk. Table 7 displays the results based on all 797 names included in the survey. Recall that the FMI, which summarizes the ratings for each name, is sorted into four categories from A to D. For men, names in A are closest to very masculine, names in B are

**Table 4**

Multivariate regressions of education on gender discordance and covariates.

| | Men | | | | Women | | | |
|---|---|---|---|---|---|---|---|---|
| | Years of education | | College completion | | Years of education | | College completion | |
| Gender discordance (% different gender) | | | | | | | | |
| [A] less than 1% | (ref.) | (ref.) | (ref.) | (ref.) | (ref.) | (ref.) | (ref.) | (ref.) |
| [B] at least 1% and less than 5% | − 0.300* (0.126) | − 0.154 (0.091) | − 0.016* (0.007) | − 0.033** (0.008) | − 0.187 (0.114) | − 0.406** (0.098) | − 0.026* (0.016) | − 0.055** (0.012) |
| [C] at least 5% and less than 50% | − 0.705** (0.177) | − 0.470** (0.132) | − 0.046** (0.007) | − 0.036** (0.009) | − 0.888** (0.121) | − 0.673** (0.088) | − 0.056** (0.009) | − 0.080** (0.010) |
| [D] at least 50% | − 0.563** (0.113) | − 0.381** (0.073) | − 0.035** (0.006) | − 0.039** (0.005) | − 0.695** (0.117) | − 0.600** (0.095) | − 0.039** (0.012) | − 0.072** (0.012) |
| Controls for popularity and covariates | No | Yes | No | Yes | No | Yes | No | Yes |
| N | 2,678,643 | 2,678,643 | 2,678,643 | 2,678,643 | 1,739,760 | 1,739,760 | 1,739,760 | 1,739,760 |

NOTE. Robust standard errors in parentheses are clustered on personal name. ** and * indicate statistical significance at the 1% and 5% levels, respectively. The set of covariates includes popularity of name, race/color, birth cohort, and state fixed effects. Gender discordance is defined according to the percentage of persons with a name who do not share the same gender: [A] less than 1% (least discordant), [B] at least 1% and less than 5%, [C] at least 5% and less than 50%, and [D] at least 50% (most discordant). The reference (ref.) category is [A], the least discordant.

**Table 5**

Multivariate regressions of labor earnings on gender discordance and covariates.

| | Men | | | | Women | | | |
|---|---|---|---|---|---|---|---|---|
| | Log of annual earnings | | | | Log of annual earnings | | | |
| Gender discordance (% different gender) | | | | | | | | |
| [A] less than 1% | (ref.) | (ref.) | (ref.) | (ref.) | (ref.) | (ref.) | (ref.) | (ref.) |
| [B] at least 1% and less than 5% | − 0.048** | − 0.020 | − 0.006 | − 0.001 | − 0.108* | − 0.049** | − 0.025** | − 0.010 |
| | (0.018) | (0.012) | (0.005) | (0.005) | (0.043) | (0.015) | (0.006) | (0.006) |
| [C] at least 5% and less than 50% | − 0.040* | − 0.063** | − 0.023** | − 0.008 | − 0.032* | − 0.120** | − 0.034** | − 0.008 |
| | (0.019) | (0.019) | (0.009) | (0.006) | (0.014) | (0.014) | (0.006) | (0.005) |
| [D] at least 50% | − 0.094** | − 0.155** | − 0.123** | − 0.093** | − 0.013 | − 0.106** | − 0.025* | − 0.020* |
| | (0.017) | (0.014) | (0.017) | (0.014) | (0.022) | (0.018) | (0.011) | (0.009) |
| Controls for popularity and covariates | No | Yes | Yes | Yes | No | Yes | Yes | Yes |
| Controls for years of education | No | No | Yes | Yes | No | No | Yes | Yes |
| Controls for occupational fixed effects | No | No | No | Yes | No | No | No | Yes |
| N | 2,654,314 | 2,654,314 | 2,654,314 | 2,654,314 | 1,725,247 | 1,725,247 | 1,725,247 | 1,725,247 |

NOTE. Robust standard errors in parentheses are clustered on personal name. ** and * indicate statistical significance at the 1% and 5% levels, respectively. The set of covariates includes popularity of name, race/color, birth cohort, state fixed effects, and tenure with employer. Gender discordance is defined according to the percentage of persons with a name who do not share the same gender: [A] less than 1% (least discordant), [B] at least 1% and less than 5%, [C] at least 5% and less than 50%, and [D] at least 50% (most discordant). The reference (ref.) category is [A], the least discordant.

closest to somewhat masculine, names in C are closest to both masculine and feminine, and names in D are closest to somewhat or very feminine. For women, names in A are closest to very feminine, names in B are closest to somewhat feminine, names in C are closest to both masculine and feminine, and names in D are closest to somewhat or very masculine. To summarize the table, the results using MTurk measures virtually mirror the results using RAIS measures. When men's names are perceived as less masculine, their educational attainment and earnings are also lower, and the same pattern holds when women's names are perceived as less feminine.

Table 8 displays the results based on names included in the MTurk survey but designated as least gender discordant in RAIS. The vast majority of names in RAIS category A also belong to MTurk category A, so the Femininity-Masculinity Index is included directly in regression models in place of the set of binary variables. Even among men and women with (nearly) gender-exclusive names in RAIS, the coefficient on FMI is negative and significant for years of education as well as college completion. Among women, the coefficient is also negative and significant for earnings. Therefore, perceptions of masculinity/femininity, which are presumably related only to the phonological features of names, are correlated with socioeconomic outcomes.

## 4. Discussion

It is useful to interpret these results in light of previous research on gender signaling and stereotypes. Names can be seen as gender signals: they may reflect or shape gender identities (Pilcher 2017) and convey gendered characteristics (Mehrabian 2001; Macrae et al., 2002; Sidhu et al., 2019). Likewise, our results show that gender discordant names given to men are considered less masculine, and gender discordant names given to women are considered less feminine. However, contrary to some previous research on gender incongruity, we find that women are not advantaged by having more masculine or gender discordant names. Instead, in Brazil, both men and women with gender discordant names have worse educational and labor outcomes than their otherwise similar peers with gender concordant names. If anything, Brazilian men experience the greatest earnings penalties associated with gender discordance –

**Table 6**

Fixed effects regressions using probable siblings.

| Men | Years of education | | College completion | | Log of annual earnings | |
|---|---|---|---|---|---|---|
| Gender discordance (% different gender) | | | | | | |
| [A] less than 1% | (ref.) | (ref.) | (ref.) | (ref.) | (ref.) | (ref.) |
| [B] at least 1% and less than 5% | − 0.193* (0.077) | − 0.132 (0.078) | − 0.013 (0.009) | − 0.004 (0.010) | − 0.128** (0.034) | − 0.075* (0.030) |
| [C] at least 5% and less than 50% | − 0.503** (0.122) | − 0.506** (0.122) | − 0.036* (0.015) | − 0.039** (0.015) | − 0.098 (0.054) | − 0.065 (0.047) |
| [D] at least 50% | − 0.325 (0.208) | − 0.375 (0.205) | − 0.018 (0.026) | − 0.029 (0.025) | − 0.011 (0.093) | − 0.058 (0.080) |
| Family fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls for popularity and covariates | No | Yes | No | Yes | No | Yes |
| Controls for years of education | No | No | No | No | No | Yes |
| N | 157,762 | 157,762 | 157,762 | 157,762 | 155,512 | 155,512 |
| Women | | | | | | |

| | Years of education | | College completion | | Log of annual earnings | |
|---|---|---|---|---|---|---|
| Gender discordance (% different gender) [A] less than 1% | (ref.) | (ref.) | (ref.) | (ref.) | (ref.) | (ref.) |
| [B] at least 1% and less than 5% | − 0.155 (0.112) | − 0.075 (0.110) | − 0.003 (0.020) | 0.010 (0.019) | − 0.050 (0.055) | 0.038 (0.047) |
| [C] at least 5% and less than 50% | − 0.374** (0.144) | − 0.399** (0.140) | − 0.020 (0.025) | − 0.049* (0.025) | − 0.025 (0.072) | − 0.150* (0.060) |
| [D] at least 50% | − 0.301 (0.230) | − 0.309 (0.223) | − 0.006 (0.041) | − 0.021 (0.039) | 0.112 (0.115) | 0.065 (0.096) |
| Family fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls for popularity and covariates | No | Yes | No | Yes | No | Yes |
| Controls for years of education | No | No | No | No | No | Yes |
| N | 87,268 | 87,268 | 87,268 | 87,268 | 86,171 | 86,171 |

NOTE. The sample is restricted to pairs of individuals who are the same gender, have an age gap of 10 years or less, and share a family name which is otherwise absent in their state of employment. ** and * indicate statistical significance at the 1% and 5% levels, respectively. The set of covariates includes popularity of name, race/color, birth cohort, state fixed effects, and tenure with employer in earnings models. Gender discordance is defined according to the percentage of persons with a name who do not share the same gender: [A] less than 1% (least discordant), [B] at least 1% and less than 5%, [C] at least 5% and less than 50%, and [D] at least 50% (most discordant). The reference (ref.) category is [A], the least discordant. consistent with theoretical expectations on the “precarity” of higher status positions in general (see Mize and Manago 2018).

Our findings also speak to various issues in the name literature. Unfamiliar names (Macrae et al., 2002) and discordant names (Mehrabian 2001) are associated with intermediate levels of masculinity and femininity, which is exactly what the relationship between RAIS and Mturk measures of discordance suggests. Evidence that boys with majority female names experience negative outcomes in middle school (Figlio 2007) is consistent with our results for men. Notably, our results for women contrast with previous studies that have found women may benefit in some ways from having masculine names (Coffey and McLaughlin 2009; Urbatsch 2018). Popular names are also associated with positive characteristics (e.g., Harari and McDavid 1973; Garwood et al., 1980; Mehrabian 1992), and we find that persons with popular names tend to have higher education and earnings.

The findings provide advances on several fronts related to gender nonconformity, as well. They demonstrate the consequences of perceived nonconformity may extend beyond mental health, which is the focus of much of the literature (e.g., Egan and Perry 2001; Skidmore et al., 2006; MartinStorey and August 2016). Our results also underscore that school is a crucial site, and thus childhood and adolescence are crucial periods, when it comes to gender nonconformity and its sequelae (e.g., Bos and Sandfort 2015; Zosuls et al., 2016; Smith and Juvonen 2017). The associations with education outcomes are relatively large, while the associations with employment outcomes are relatively small, once education is accounted for. Boys and girls with gender discordant names may experience bullying by peers as well as discrimination by teachers, which may give rise to problems with mental health and academic performance. Consistent with this, research suggests that names influence teacher perceptions (Harari and McDavid 1973; Garwood 1976), and names are correlated with the prevalence of behavioral issues among adolescents (Figlio 2007). Moreover, our results suggest that disparities that have emerged during the school years are likely to continue into the labor market. Prejudice by employers against individuals with the most discordance, especially men, may reduce employment opportunities further.

Although nonconformity exists on a continuum, most of the literature has focused on persons who manifest the largest deviations from social norms. Like Roberts et al. (2013) and Li et al. (2016), this paper makes the case that persons with modest to moderate deviations from norms may also experience the negative effects of stigma. Perhaps surprisingly, men and women with modest levels of gender discordance (i.e., those whose name is considered somewhat masculine or feminine or is shared with 1–5% of the other gender) have lower outcomes in some models. This can explain the phenomenon of name "tipping points" (Lieberson et al., 2000), which

Table **7** Multivariate regressions using measures of discordance from MTurk survey.

| Men | Years of education | | College completion | | Log of annual earnings | |
|---|---|---|---|---|---|---|
| < < Femininity-Masculinity Index [A] FMI 1.5 | (ref.) | (ref.) | (ref.) | (ref.) | (ref.) | (ref.) |
| [B] 1.5 ≤ FMI 2.5 | − 0.143 (0.212) | − 0.277** (0.087) | − 0.030** (0.010) | − 0.022** (0.007) | − 0.059** (0.021) | − 0.012 (0.007) |
| [C] 2.5 ≤ FMI <3.5 | − 0.330 (0.225) | − 0.409** (0.100) | − 0.037** (0.010) | − 0.035** (0.008) | − 0.042 (0.027) | − 0.021 (0.011) |
| [D] 3.5 ≤ FMI | − 0.439 (0.260) | − 0.499** (0.160) | − 0.031** (0.011) | − 0.036** (0.008) | − 0.103** (0.034) | − 0.099** (0.022) |
| Controls for popularity and covariates | No | Yes | No | Yes | No | Yes |
| Controls for years of education | No | No | No | No | No | Yes |
| N | 761,710 | 761,710 | 761,710 | 761,710 | 754,203 | 754,203 |

| Women | Years of education | | College completion | | Log of annual earnings | |
|---|---|---|---|---|---|---|
| < < Femininity-Masculinity Index [A] FMI 1.5 | (ref.) | (ref.) | (ref.) | (ref.) | (ref.) | (ref.) |
| [B] 1.5 ≤ FMI 2.5 | − 0.565** (0.175) | − 0.515** (0.096) | − 0.045** (0.012) | − 0.063** (0.012) | − 0.036 (0.020) | − 0.025** (0.009) |

| | | | | | | |
|---|---|---|---|---|---|---|
| [C] 2.5 ≤ FMI <3.5 | − 0.811** (0.174) | − 0.672** (0.107) | − 0.051** (0.013) | − 0.075** (0.013) | − 0.039 (0.023) | − 0.038** (0.010) |
| [D] 3.5 ≤ FMI | − 0.748** (0.190) | − 0.689** (0.119) | − 0.054** (0.014) | − 0.084** (0.015) | − 0.028 (0.026) | − 0.022 (0.018) |
| Controls for popularity and covariates | No | Yes | No | Yes | No | Yes |
| Controls for years of education | No | No | No | No | No | Yes |
| N | 554,099 | 554,099 | 554,099 | 554,099 | 549,118 | 549,118 |

NOTE. Robust standard errors in parentheses are clustered on personal name. ** and * indicate statistical significance at the 1% and 5% levels, respectively. The set of covariates includes popularity of name, race/color, birth cohort, state fixed effects, and tenure with employer in earnings models. The MTurk categories are defined according to the perceived masculinity/femininity of a name: for men (women), names in [A] are closest to very masculine (feminine), names in [B] are closest to somewhat masculine (feminine), names in [C] are closest to both masculine and feminine, and names in [D] are closest to somewhat or very feminine (masculine).

**Table 8** Multivariate regressions using measures of discordance from MTurk survey (only persons with least discordant names in RAIS).

| Men | Years of education | | College completion | | Log of annual earnings | |
|---|---|---|---|---|---|---|
| Femininity-Masculinity Index (FMI) | − 1.099** (0.418) | − 0.490* (0.237) | − 0.081** (0.026) | − 0.045* (0.021) | − 0.099 (0.065) | − 0.031 (0.021) |
| Controls for popularity and covariates | No | Yes | No | Yes | No | Yes |
| Controls for years of education | No | No | No | No | No | Yes |
| N | 697,894 | 697,894 | 697,894 | 697,894 | 691,017 | 691,017 |

| Women | Years of education | | College completion | | Log of annual earnings | |
|---|---|---|---|---|---|---|
| Femininity-Masculinity Index (FMI) | − 1.867** (0.515) | − 1.138** (0.266) | − 0.103** (0.037) | − 0.144** (0.040) | − 0.003 (0.061) | − 0.062* (0.031) |
| Controls for popularity and covariates | No | Yes | No | Yes | No | Yes |
| Controls for years of education | No | No | No | No | No | Yes |
| N | 512,808 | 512,808 | 512,808 | 512,808 | 508,224 | 508,224 |

NOTE. The sample is restricted to persons with the least discordant names in RAIS (<1% different gender). Robust standard errors in parentheses are clustered on personal name. ** and * indicate statistical significance at the 1% and 5% levels, respectively. The set of covariates includes popularity of name, race/color, birth cohort, state fixed effects, and tenure with employer in earnings models. For men, the FMI is a measure of how feminine a name is, and for women, it is a measure of how masculine a name is. suggests that even a small amount of discordance can have significant implications.

An important topic of discussion is whether our coefficients on gender discordance represent causal effects. Taken together, the evidence suggests that estimates are at least partly causal. The most likely alternative hypothesis is that parental characteristics are correlated with both naming practices and child outcomes. To the extent that lower status parents tend to choose gender discordant names for their children, the results in our paper are not causal. Lieberson and Bell (1992) examine this question with a sample of births from New York. Their findings suggest lower status parents are less likely to select gender discordant names for their children, which implies we may be underestimating the magnitude of the effects. However, more evidence is needed, especially in the context of Brazil.

Even if parental status is inversely correlated with name discordance, the alternative hypothesis is unable to explain the entire pattern of results in the paper. Our sample of "probable siblings" suggests that, among people with the same surname, those with more discordant given names have worse socioeconomic outcomes. The influence of family background would mostly operate through educational attainment, yet holding education constant, persons with gender discordant names still have somewhat lower earnings. Additionally, the perceived masculinity/femininity of names remains associated with educational attainment, even among gender- exclusive names. We interpret this to suggest that gender discordant names are disadvantageous in and of themselves, perhaps in addition to and instead of different gender signals the person might attempt to communicate in their interactions with others.

Future research can extend the analysis in various ways. It would be illuminating to study contexts beyond Brazil, measures of gender discordance beyond personal names, and outcomes beyond education and earnings, such as marriage and childbearing (cf. Magliozzi et al., 2016; Naurin et al., 2021). It would also be valuable to investigate the macro and micro drivers of change in gender norms as well as to investigate the extent to which gender norms are responsible for inequality among men and among women. Learning more about the causes and consequences of perceived gender nonconformity is important from both a scholarly and public policy perspective, as society moves to protect and empower individuals who experience social stigma in their daily lives.

**Appendix A. Supplementary data**

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ssresearch.2022.102842.

**Table A.1**

Averages for refined and wide sample

| | Men | | Women | |
|---|---|---|---|---|
| | Refined | Wide | Refined | Wide |
| Race/color: Branca | 0.446 | 0.446 | 0.479 | 0.446 |
| Race/color: Parda | 0.342 | 0.312 | 0.265 | 0.247 |
| Race/color: Preta | 0.056 | 0.051 | 0.041 | 0.037 |
| Race/color: Amarela | 0.006 | 0.007 | 0.006 | 0.007 |
| Race/color: Indígena | 0.002 | 0.002 | 0.001 | 0.002 |

| | | | | |
|---|---|---|---|---|
| Race/color: Not identified | 0.148 | 0.183 | 0.207 | 0.262 |
| Birth cohort: Before 1967 | 0.117 | 0.181 | 0.097 | 0.164 |
| Birth cohort: 1967–1972 | 0.096 | 0.114 | 0.094 | 0.118 |
| Birth cohort: 1973–1977 | 0.113 | 0.117 | 0.113 | 0.122 |
| Birth cohort: 1978–1980 | 0.090 | 0.085 | 0.091 | 0.089 |
| Birth cohort: 1981–1983 | 0.109 | 0.097 | 0.112 | 0.100 |
| Birth cohort: 1984–1986 | 0.116 | 0.096 | 0.119 | 0.098 |
| Birth cohort: 1987–1988 | 0.082 | 0.064 | 0.085 | 0.066 |
| Birth cohort: 1989–1991 | 0.120 | 0.090 | 0.123 | 0.091 |
| Birth cohort: 1992–1993 | 0.075 | 0.057 | 0.076 | 0.055 |
| Birth cohort: After 1993 | 0.084 | 0.099 | 0.091 | 0.096 |
| Years of education | 11.203 | 11.001 | 12.441 | 12.188 |
| College completion | 0.109 | 0.122 | 0.235 | 0.234 |
| Log of annual earnings | 9.478 | 9.621 | 9.424 | 9.502 |
| Tenure with employer (months) | 22.326 | 52.499 | 29.001 | 57.544 |

NOTE. The "refined" sample includes persons with consistent gender across multiple employers (our estimation sample), and the "wide" sample includes persons with consistent gender regardless of number of employers. For the refined sample, the sample sizes are 2,678,643 (men) and 1,739,760 (women). For the wide sample, the sample sizes are 6,041,461 (men) and 4,263,563 (women).

**Table A.2**

Level of gender discordance by covariates

| | Men | | | | Women | | | |
|---|---|---|---|---|---|---|---|---|
| | [A] Least | [B] Most | [C] | [D] | [A] Least | [B] Most | [C] | [D] |
| Race/color | | | | | | | | |
| Branca | 0.975 | 0.015 | 0.007 | 0.002 | 0.977 | 0.012 | 0.009 | 0.003 |
| Parda | 0.977 | 0.015 | 0.006 | 0.002 | 0.976 | 0.013 | 0.008 | 0.003 |
| Preta | 0.976 | 0.015 | 0.007 | 0.002 | 0.975 | 0.013 | 0.008 | 0.003 |
| Amarela | 0.975 | 0.015 | 0.008 | 0.002 | 0.978 | 0.011 | 0.008 | 0.004 |
| Indígena | 0.971 | 0.017 | 0.009 | 0.004 | 0.971 | 0.016 | 0.010 | 0.003 |
| Not identified | 0.974 | 0.016 | 0.007 | 0.003 | 0.973 | 0.012 | 0.010 | 0.004 |
| Popularity of name | | | | | | | | |
| Decile 1 (least common) | 0.890 | 0.055 | 0.044 | 0.011 | 0.889 | 0.059 | 0.037 | 0.015 |
| Decile 2 | 0.916 | 0.065 | 0.014 | 0.006 | 0.914 | 0.044 | 0.035 | 0.007 |
| Decile 3 | 0.954 | 0.033 | 0.009 | 0.004 | 0.960 | 0.020 | 0.016 | 0.004 |
| Decile 4 | 0.999 | 0.000 | 0.000 | 0.001 | 0.998 | 0.000 | 0.000 | 0.002 |

(*continued on next page*)

**Table A.2** (*continued*)

| | Men | Women |
|---|---|---|

| | [A] Least | [B] | [C] | [D] Most | [A] Least | [B] | [C] | [D] Most |
|---|---|---|---|---|---|---|---|---|
| Decile 5 | 0.999 | 0.000 | 0.000 | 0.001 | 1.000 | 0.000 | 0.000 | 0.000 |
| Decile 6 | 0.999 | 0.000 | 0.000 | 0.001 | 1.000 | 0.000 | 0.000 | 0.000 |
| Decile 7 | 1.000 | 0.000 | 0.000 | 0.000 | 1.000 | 0.000 | 0.000 | 0.000 |
| Decile 8 | 1.000 | 0.000 | 0.000 | 0.000 | 0.999 | 0.000 | 0.000 | 0.001 |
| Decile 9 | 1.000 | 0.000 | 0.000 | 0.000 | 0.999 | 0.000 | 0.000 | 0.001 |
| Decile 10 (most common) | 0.999 | 0.000 | 0.000 | 0.001 | 0.999 | 0.000 | 0.000 | 0.001 |
| Birth cohort (deciles) | | | | | | | | |
| Before 1967 | 0.974 | 0.013 | 0.010 | 0.004 | 0.955 | 0.017 | 0.020 | 0.008 |
| 1967–1972 | 0.970 | 0.016 | 0.010 | 0.004 | 0.958 | 0.016 | 0.019 | 0.006 |
| 1973–1977 | 0.970 | 0.018 | 0.008 | 0.004 | 0.969 | 0.013 | 0.014 | 0.005 |
| 1978–1980 | 0.975 | 0.015 | 0.007 | 0.003 | 0.977 | 0.010 | 0.010 | 0.004 |
| 1981–1983 | 0.978 | 0.014 | 0.006 | 0.002 | 0.982 | 0.008 | 0.007 | 0.003 |
| 1984–1986 | 0.977 | 0.015 | 0.006 | 0.002 | 0.985 | 0.008 | 0.005 | 0.002 |
| 1987–1988 | 0.977 | 0.016 | 0.006 | 0.002 | 0.985 | 0.008 | 0.004 | 0.002 |
| 1989–1991 | 0.978 | 0.015 | 0.005 | 0.001 | 0.987 | 0.009 | 0.003 | 0.001 |
| 1992–1993 | 0.979 | 0.016 | 0.004 | 0.001 | 0.985 | 0.011 | 0.002 | 0.001 |
| After 1993 | 0.979 | 0.015 | 0.004 | 0.001 | 0.972 | 0.024 | 0.002 | 0.001 |

NOTE. The sample size of men is 2,678,643, and the sample size of women is 1,739,760. Gender discordance is defined according to the percentage of persons with a name who do not share the same gender: [A] less than 1% (least discordant), [B] at least 1% and less than 5%, [C] at least 5% and less than 50%, and [D] at least 50% (most discordant).

**Table A.3**

Relationship between MTurk and RAIS measures of discordance

| | MTurk (Femininity-Masculinity Index) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Men | | | | Women | | | |
| | [A] [1.0,1.5) | [B] [1.5,2.5) | [C] [2.5,3.5) | [D] [3.5,5.0] | [A] [1.0,1.5) | [B] [1.5,2.5) | [C] [2.5,3.5) | [D] [3.5,5.0] |
| gender with name) | | | | | | | | |
| [A] less than 1% | 98.52 | 30.21 | 97.24 | 22.58 | | | | |
| [B] at least 1% and less than 5% | 1.48 | 54.41 | 10.66 | 2.44 | 39.02 | 7.00 | | |
| [C] at least 5% and less than 50% | 14.80 | 73.59 | 18.32 | 0.32 | 38.16 | 64.75 | 19.76 | |
| [D] at least 50% | 0.58 | 15.75 | 81.68 | 0.24 | 28.25 | 80.24 | | |
| Column sum | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
| MTurk sample size | 691,756 | 54,232 | 12,480 | 3242 | 522,647 | 20,306 | 8312 | 2834 |

NOTE. Numbers are percentages. All columns sum to 100. The RAIS categories are defined according to the percentage of persons with a name who do not share the same gender: [A] less than 1% (least discordant), [B] at least 1% and less than 5%, [C] at least 5% and less than 50%, and [D] at least 50% (most discordant). The MTurk categories are defined according to the perceived masculinity/femininity of a name: for men (women), names in [A] are closest to very masculine (feminine), names in [B] are closest to somewhat masculine (feminine), names in [C] are closest to both masculine and feminine, and names in [D] are closest to somewhat or very feminine (masculine).

**Table A.4**

Multivariate regressions using percent different gender directly

| Men | Years of education | | College completion | | Log of annual earnings | |
|---|---|---|---|---|---|---|
| Percent different gender with name | − 0.0089** (0.0016) | − 0.0055** (0.0010) | − 0.0006** (0.0001) | − 0.0006** (0.0001) | − 0.0014** (0.0002) | − 0.0016** (0.0002) |
| Controls for popularity and covariates | No | Yes | No | Yes | No | Yes |
| Controls for years of education | No | No | No | No | No | Yes |
| N | 2,678,643 | 2,678,643 | 2,678,643 | 2,678,643 | 2,654,314 | 2,654,314 |

| Women | Years of education | | College completion | | Log of annual earnings | |
|---|---|---|---|---|---|---|
| Percent different gender with name | − 0.0134** (0.0015) | − 0.0107** (0.0011) | − 0.0008** (0.0001) | − 0.0013** (0.0001) | − 0.0002 (0.0003) | − 0.0004** (0.0001) |
| Controls for popularity and covariates | No | Yes | No | Yes | No | Yes |
| Controls for years of education | No | No | No | No | No | Yes |
| N | 1,739,760 | 1,739,760 | 1,739,760 | 1,739,760 | 1,725,247 | 1 ,725,247 |

NOTE. Robust standard errors in parentheses are clustered on personal name. ** and * indicate statistical significance at the 1% and 5% levels, respectively. The set of covariates includes popularity of name, race/color, birth cohort, state fixed effects, and tenure with employer in earnings models.

**Table A.5**

Results for race/color and popularity of name

| | Men | | | Women | | |
|---|---|---|---|---|---|---|
| | Years of education | College completion | Log of earnings | Years of education | College completion | Log of earnings |
| Race/color Branca | (ref.) | (ref.) | (ref.) | (ref.) | (ref.) | (ref.) |
| Parda | − 0.643** (0.014) | − 0.063** (0.002) | − 0.059** (0.002) | − 0.613** (0.003) | − 0.095** (0.013) | − 0.094** (0.002) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Preta | − 0.990** | − 0.076** | − 0.079** | − 0.987** | − 0.121** | − 0.089** |
| | (0.019) | (0.003) | (0.003) | (0.019) | (0.004) | (0.004) |
| Amarela | − 0.056 | 0.016** | 0.035** | 0.069* | 0.024** | 0.043** |
| | (0.036) | (0.004) | (0.007) | (0.028) | (0.005) | (0.009) |
| Indígena | − 0.677** | − 0.020** | − 0.087** | − 0.348** | − 0.019* | − 0.042** |
| | (0.052) | (0.005) | (0.012) | (0.052) | (0.008) | (0.016) |
| Not identified | 0.940** | 0.107** | − 0.017** | 1.255** | 0.220** | 0.100** |
| | (0.034) | (0.003) | (0.002) | (0.057) | (0.007) | (0.008) |
| Popularity of name | | | | | | |
| Decile 1 ( least common) | (ref.) | (ref.) | (ref.) | (ref.) | (ref.) | (ref.) |
| Decile 2 | 0.002 | − 0.000 | − 0.004 | 0.017 | 0.002 | 0.001 |
| | (0.048) | (0.004) | (0.004) | (0.049) | (0.007) | (0.005) |
| Decile 3 | − 0.011 | − 0.001 | − 0.006 | − 0.043 | − 0.007 | − 0.002 |
| | (0.074) | (0.006) | (0.005) | (0.059) | (0.008) | (0.005) |
| Decile 4 | 0.098 | 0.005 | − 0.005 | 0.021 | − 0.000 | − 0.004 |
| | (0.073) | (0.007) | (0.005) | (0.071) | (0.009) | (0.006) |
| Decile 5 | 0.256* | 0.021* | 0.002 | 0.153 | 0.018 | 0.010 |
| | (0.104) | (0.010) | (0.007) | (0.085) | (0.013) | (0.009) |
| Decile 6 | 0.124 | 0.011 | − 0.001 | 0.213* | 0.024 | 0.012 |
| | (0.112) | (0.009) | (0.007) | (0.095) | (0.014) | (0.009) |
| Decile 7 | 0.569** | 0.059** | 0.037** | 0.242** | 0.025 | 0.011 |
| | (0.076) | (0.008) | (0.006) | (0.077) | (0.013) | (0.009) |
| Decile 8 | 0.571** | 0.054** | 0.036** | 0.323** | 0.038** | 0.024** |
| | (0.064) | (0.008) | (0.007) | (0.059) | (0.010) | (0.009) |
| Decile 9 | − 0.049 | 0.002 | − 0.009** | 0.294** | 0.037** | 0.026** |
| | (0.141) | (0.009) | (0.003) | (0.062) | (0.010) | (0.008) |
| Decile 10 (most common) | − 0.700** | − 0.040** | − 0.014** | − 0.676** | − 0.075** | − 0.032** |
| | (0.032) | (0.003) | (0.003) | (0.034) | (0.005) | (0.003) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Controls for covariates | Yes | Yes discordance and | Yes | Yes | Yes | Yes |
| Controls for years of education | No | No | Yes | No | No | Yes |
| N | 2,678,643 | 2,678,643 | 2,654,314 | 1,739,760 | 1,739,760 | 1,725,247 |

NOTE. Robust standard errors in parentheses are clustered on personal name. ** and * indicate statistical significance at the 1% and 5% levels, respectively. The set of covariates includes birth cohort, state fixed effects, and tenure with employer in earnings models.

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