Birds of a Feather Earn Together.
Gender and Peer Effects at the Workplace*

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Abstract

We use rich Brazilian administrative data to examine peer effects on wages for an entire local labor market, distinguishing between within-gender and cross-gender peer effects. Both individuals and peers average abilities are unobserved, so we estimate them by taking advantage of the panel structure of the data controlling for workers sorting into occupations and firms. We find that within-gender peer effects are remarkably larger (about double) than cross-gender peer effects in the workplace for both men and women. In addition, differences between within-gender and cross-gender peer effects are attenuated in more egalitarian contexts. These patterns are consistent with economic models of behavior and interactions that incorporate the psychology and sociology of identity.

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1 Introduction

In a series of influential studies, Akerlof and Kranton (2000, 2002, 2005, 2008) (AK from now on) incorporate the psychology and sociology of identity into economic models of behavior that illustrate how identity can affect social interactions and economic outcomes. In their framework, identity, a persons sense of self, is associated with different social categories and how people in these categories should behave. For instance, when considering gender as an aspect of identity, there are two abstract social categories, "man" and "woman", which are in turn associated with different prescribed behaviors. Because deviating from those prescribed behaviors or social norms decreases utility, individuals try to minimize the discrepancies between their actions and choices and those in consonance with their gender's behavioral prescriptions. Therefore, the economics of identity predicts that same-sex peers may have a stronger influence on individuals' behavior than opposite-sex peers.

Numerous multidisciplinary studies have stressed the importance of gender identity and gender norms for individual decisions, social interactions, and a wide variety of socioeconomic outcomes. However, little is known about how gender identity affects social interactions in the workplace. To test this prediction, we estimate the effect of same-gender and cross-gender peers' permanent component of productivity on individual wages using Brazilian matched employer-employee data covering the universe of formal workers in 2003-2018. The identification of peer effects in the workplace presents several challenges that we address as follows.

First, both individuals and peers are unobserved and we measure them by wage fixed effects, which we estimate by taking advantage of the panel structure of the data. Following Arcidiacono, Foster, Goodpaster, and Kinsler (2012), we apply an iterative algorithm to consistently estimate multiple fixed effects in a non-linear model that yields estimates of both same-gender and cross-gender peer effects parameters. Given the complexity of the computational problem and the large size of RAIS, we limit the main analysis to the state of Sao Paulo and we provide robustness checks for other regions.

Additionally, we account for high-ability workers sorting into high-ability peer groups by controlling for worker fixed effects. Occupation-firm fixed effects account for non-random selection into occupations within firms, and we include firm-year and occupation-year fixed effects to account for time-variant firm-specific and occupation-specific confounding factors. Our main identifying assumption is that there are no time-varying peer group-specific wage shocks that are correlated with shocks to peer group ability once firm specific and occupation specific shocks are accounted for. We provide supportive evidence of this assumption by means of Monte Carlo Simulations, which show that the bias potentially induced by time-varying peer group level shocks once firm-year, occupation-year, and worker effects are partialed out, could not be large enough to spuriously generate the results.

Our main finding is that same-gender peer effects are remarkably larger than cross-gender peer effects in the workplace, although the latter are not negligible neither for males nor for females. We label this pattern gender-based peer effects. In particular, the estimated wage elasticities with respect to the average ability of same-gender and cross-gender peers amount to 0.14-0.16 and 0.07-0.08, respectively, and the ability of peers of the same gender influences both male and female workers' wages about twice as much as the ability of cross-gender peers.

We provide two extensions of the main empirical result that are consistent with our model's prediction that gender-driven peer effects are exacerbated (attenuated) in contexts with more (less) traditional gender norms.

First, we allow for heterogeneous effects across high- and low-skilled occupations because many studies have shown that traditional gender norms are more prevalent among low educated individuals, while highly educated individuals tend to hold more egalitarian views on the role of men and women in society.[1] In line with this idea, we find that same-gender peer effects are between 1.6 and 1.9 times larger than cross-gender peer effects on wages among the 50% of occupations with the highest educational content. By contrast, same-gender peer effects are 3.4 times larger than

[1] See Du, Xiao, and Zhao (2021) and references therein.

cross-gender peer effects in the bottom half of the occupations as ranked by their average level of education.

Second, we estimate differential peer effects in more and less egalitarian firms following a two-step procedure. In the first step, we follow Card, Cardoso, and Kline (2015a) to estimate gender wage gaps for each establishment in the sample controlling for worker sorting due to observable and unobservable permanent factors. Using the estimates from the first stage regression to classify firms as more or less egalitarian, we assess gender-based asymmetries in peer effects across more and less egalitarian firms. As expected, in highly egalitarian firms (i.e., those with gender wage gaps in the lowest quartile) the impacts of same-gender and cross-gender peers are very similar for both men and women. Instead, strong gender asymmetries in peer effects are found in those firms where the wage gap against women is larger.

Our study contributes to several strands of the literature. First, our research makes significant contributions to studies that analyze gender asymmetries in diverse social contexts. For instance, there is an empirical literature that documents generally significant within-gender (as compared to cross-gender) role models for females in grades, test scores, educational attainment, educational and occupational choices, working in a job that involves math or science, subject enjoyment, subject confidence (de Gendre, Feld, Salamanca, and Zölitz, 2023; Kofoed et al., 2019; Porter and Serra, 2020), lifetime family income and even longevity (Card, Domnisoru, Sanders, Taylor, and Udalova, 2022). In a recent paper, Patnaik, Pauley, Venator, and Wiswall (2023) have documented gender asymmetries in role model effects for both males and females by estimating how exposure to economics alumni speakers impact students future course-taking, finding evidence of stronger within-gender role model effects. A related strand of the literature has looked into gender asymmetries in peer effects among teenagers, generally finding that same-gender effects are larger than cross-gender peer effects on high-school indicators such as GPA (Hsieh and Lin, 2017) or smoking (Hsieh and Lin, 2017; Nakajima, 2007; Soetevent and Kooreman, 2007; Kooreman, 2007). However, none of these studies have investigated gender asymmetries in peer effects on wages in actual workplaces.

Second, our work also speaks to the literature that investigates overall peer effects on workers' output and productivity through field and experimental lab studies.[2] Previous evidence is mostly based on laboratory experiments,[3] or on real-world data from very specific occupations and firms such as cashiers in a large US supermarket chain (Mas and Moretti, 2009), workers in a leading UK based fruit farm (Bandiera, Barankay, and Rasul, 2005, 2010), call center workers of a multi-national mobile network operator (Lindquist et al., 2015), workers who hand-pick leaves from tea bushes for a large agricultural firm in Malawi (Brune et al., 2020), or professional golfers (Guryan et al., 2009). By contrast, Cornelissen et al. (2017) study peer effects in wages using worker-firm matched data for Germany, while Nix (2015) and Martins and Jin (2010) estimate the returns to co-workers' education using Swedish and Portuguese administrative data, respectively. None of these studies, however, look into gender asymmetries.

Finally, our study also adds to a broad and growing body of literature that recognizes the significant role played by gender social norms in behaviors and outcomes. Social norms are important determinants of health and education outcomes (Rodríguez-Planas and Sanz-de Galdeano, 2019; Rodríguez-Planas, Sanz-de Galdeano, and Terskaya, 2022; Guiso, Monte, Sapienza, and Zingales, 2008; Pope and Sydnor, 2010; Nollenberger, Rodríguez-Planas, and Sevilla, 2016; Anghel, Rodríguez-Planas, and Sanz-de Galdeano, 2020). Additionally, research has shown that gender roles and attitudes towards gender identity vary across countries and impact fertility decisions, family formation, and female labor supply (Antecol, 2000, 2001; Fortin, 2005; Fernández and Fogli, 2006, 2009; Bertrand, Kamenica, and Pan, 2015; Olivetti, Patacchini, and Zenou, 2020). Our study builds on this literature by investigating how gender identity and social norms shape the impact of peers on workplace wages, thereby bridging the gap between this research and the peer effects literature. Moreover, our

[2] See Cornelissen (2016); Herbst and Mas (2015) and the references therein for a recent review of the literature.

[3] See for example Van Veldhuizen, Oosterbeek, and Sonnemans (2018); Rosaz, Slonim, and Villeval (2016); Beugnot, Fortin, Lacroix, and Villeval (2019); Bellemare, Lepage, and Shearer (2010).

findings can shed further light on the sources of gender gaps in the labor market because, in the presence of strong gender asymmetries in peer effects as the ones we uncover, gender imbalances in the workplace may be exacerbated due to social multiplier effects on wages.

The remainder of the paper is organized as follows. Section 2 describes the theoretical framework. Section 3 describes our empirical strategy and discusses our identifying assumptions. Section 4 describes the data, outlines the sample selection criteria and shows descriptive statistics. Section 5 presents our main results, and in Section 8 we conduct several extensions and robustness checks. Section 7 concludes.

2 Theoretical Framework

To guide our empirical estuimation, this section develops a simple model of social interactions in the workplace that incorporates elements of the economics of identity Akerlof and Kranton (2000, 2002, 2005, 2008). In the model, peers' output affects individuals' actions through peer pressure. Given the features of our administrative data, described in Section 4, we assume in the model that individuals may identify themselves with two gender categories, men and women.[4] When gender norms are egalitarian, the productivity of all coworkers affects an individual's wages in a similar fashion, regardless of their gender. In contrast, when gender norms are non egalitarian, the productivity of coworkers from the same social category may have a greater impact.

Production and effort functions. Worker i produces according to the following function:

[4]The data contain binary information on workers' sex as it appears in their ID, but not their gender identity or their sense of self gender-wise. While for most people, the sex in their ID will be a good description of their gender identity, this may not be the case for all individuals. This introduces measurement error in our gender variable, as discussed in Section 4. Throughout the paper, we use the term gender instead of biological or legal sex, as gender identity is the key determinant that drives the underlying mechanisms we are investigating.

$$f_i = a_i + e_i + \epsilon_i \tag{1}$$

, where a_i is individual i's ability, e_i is individual i's effort, and ϵ_i is a random component of productivity independent of ability and effort. Ability is continuous and exogenously given such that $a_i \in [0, A]$ and is distributed with probability density function (PDF) $h(a_i)$. Instead, individual effort is chosen by the individual to maximize utility. We assume that exerting effort is costly, following a quadratic cost function defined by:

$$C(e_i) = ce_i^2 \tag{2}$$

, where $c > 0$ is a scale parameter.

Peer pressure. Workers' utility depends on peer pressure stemming from co-workers, as in Kandel and Lazear (1992), Mas and Moretti (2009), and Cornelissen et al. (2017). If worker i deviates from her coworkers' production, peer pressure reduces her utility. This function can be parameterized to be increasing in the distance between a worker's output and the expected value of coworkers' output as follows:

$$P\Big(f_i, \mathbb{E}(f)\Big) = \delta\Big(\mathbb{E}(f) - f_i\Big)^2 \tag{3}$$

, where $\mathbb{E}(f)$ is the expected value of the production of workers and δ is a scale parameter that denotes how painful peer pressure is.

If social categories matter, individuals may feel different degrees of peer pressure depending on their gender and the gender of their peers. For instance, individuals may feel more social pressure if they deviate from the output of peers of their gender than if they deviate from the output of peers of the opposite gender. In this case, the peer pressure function can be given by:

$$P\Big(f_i, \mathbb{E}(f_{c_i}), \mathbb{E}(f_{\notin c_i})\Big) = (\eta + \eta_s)(\mathbb{E}(f_{c_i}) - f_i)^2 + \eta(\mathbb{E}(f_{\notin c_i}) - f_i)^2 \tag{4}$$

, where $\mathbb{E}(f_{c_i})$ is the expected value of the production of workers who belong to the same social category as i and $\mathbb{E}(f_{\notin c_i})$ is the expected value of production of workers who belong to a different social category than i. There are two social categories, women and men, such that $c_i \in \{W, M\}$. For instance, if i is a woman ($c_i = W$), $\mathbb{E}(f_{c_i}) = \mathbb{E}(f_W)$ and $\mathbb{E}(f_{\notin c_i}) = \mathbb{E}(f_M)$.[5]

The parameter $\eta \geq 0$ in equation 4 represents the pain of peer pressure that is independent of the social category of the worker. Instead, $\eta_s \geq 0$ represents potential asymmetries in the level of peer pressure. We assume that η_s depends on gender norms. If $\eta_s = 0$, gender norms are egalitarian, and all workers experience the same level of peer pressure from men and women peers, irrespective of their gender. However, if $\eta_s > 0$, individuals experience more peer pressure from the same social category peers than from different social category peers. The higher is η_s, the less egalitarian gender norms are.

Optimal level of effort. Workers chose a level of effort that maximizes the difference between their earnings, the costs of providing effort, and the pain associated with peer pressure. The problem can be written as follows:

$$Max_{e_i}\mathbb{E}\Big[b_{c_i}f_i - ce_i^2 - P\Big(f_i, \mathbb{E}(f_{c_i}), \mathbb{E}(f_{\notin c_i})\Big)\Big] \tag{5}$$

, where b_{c_i} is the wage that may also vary by social category. For instance, if there is a gender wage gap, $b_W < b_M$.

The first-order condition of this problem derived in Appendix A implies that

$$e_i = \alpha a_i + \rho_s b_{c_i} + \rho_o b_{\notin c_i} + \theta_s \mathbb{E}(a_{c_i}) + \theta_o \mathbb{E}(a_{\notin c_i}) \tag{6}$$

, where $\alpha = \frac{-(2\eta+\eta_s)}{c+2\eta+\eta_s}$, $\rho_s = \frac{\eta+c}{2c(c+2\eta)}$, $\rho_o = \frac{\eta}{2c(c+2\eta)}$, $\theta_o = \frac{\eta}{c+2\eta}$, and $\theta_s = \frac{(\eta+\eta_s)(c+\eta)+\eta^2}{(c+2\eta)(c+2\eta+\eta_s)}$. Because $\theta_s > 0$ and $\theta_o > 0$, the output of peers enters positively the effort function. Moreover, note that

[5] See Appendix A for derivations of $\mathbb{E}(f_M)$ and $\mathbb{E}(f_W)$.

$$\theta_s - \theta_o = \frac{c\eta_s}{(c+2\eta)(c+2\eta+\eta_s)} \tag{7}$$

, which implies that the effect of the same social category peers on effort is greater than the effect of the opposite social category peers if and only if $\eta_s > 0$. If the social pressure function is symmetric ($\eta_s = 0$), the same and opposite social categories have identical impacts on workers' effort, i.e., $\theta_o = \theta_s$. Note that $\theta_s - \theta_o$ is monotonically increasing in η_s,[6] i.e., the less egalitarian gender norms are, the lager will be the gap in the response of workers to peers of the same gender with respect to their response to peers of the opposite gender. Equation (6) also shows that wages from the worker social category and the opposite social category increase workers' effort, but the effect of same-gender wages is always higher than the effect of opposite-gender wages, which only affect worker's effort through peer pressure.[7]

In this stylized framework, workers' output is observable and firms take wages as given. Hence, individual earnings are defined in a piece rate system that depends on gender (because wage rates for men and women are potentially different) and individual output. Introducing (6) into (1), we obtain an expression for workers' earnings:

$$w_i = b_{c_i} f_i = b_{c_i}[(1+\alpha)a_i + (\rho_s b_{c_i} + \rho_o b_{\notin c_i}) + \theta_s \mathbb{E}(a_{c_i}) + \theta_o \mathbb{E}(a_{\notin c_i}) + \epsilon_i]. \tag{8}$$

Individual earnings are positively affected by workers' ability and wages, but they also depend on the ability of peers of the same and opposite social categories. The objective of our empirical analysis is to estimate θ_o and θ_s, which as discussed above are informative about η_s. Note however that we cannot take equation (6) to the data, because a_i, a_{c_i}, and $a_{\notin c_i}$ are not observable. We instead estimate them using worker fixed effects, as described in Section 3. But as equation (6) highlights, the estimate of worker fixed effects is a combination of individual ability and other determinants of

[6]If $\eta_s > 0$, then $\frac{d(\theta_s - \theta_o)}{d\eta_s} = \frac{c}{(c+\eta_s+2\eta)^2} > 0$.

[7]See that $\rho_s - \rho_o = \frac{c}{2c(c+2\eta)} > 0$. Moreover, note that in the absence of peer pressure ($\eta = 0$), opposite-gender wages do not change the effort of workers ($\rho_o = 0$) according to equation (6).

earnings summarized by $b_{c_i}(1+\alpha)a_i$. For instance, if women have on average lower wages than men, their fixed effect will be on average lower than that of men.

To better understand the impact of approximating ability by workers' fixed effects on the interpretation of the results, let us define the workers' fixed effect as $\tilde{a}_i = b_{c_i}(1+\alpha)a_i$. Averaging across individuals in c_i, we obtain $\mathbb{E}(\tilde{a}_{c_i}) = b_{c_i}(1+\alpha)\mathbb{E}(a_{c_i})$. Similarly, $\mathbb{E}(\tilde{a}_{\notin c_i}) = b_{\notin c_i}(1+\alpha)\mathbb{E}(a_{\notin c_i})$. Thus, we can rewrite (8) in terms of $\tilde{a}_i$ for each $c_i \in \{W, M\}$

$$w_i = \alpha_W + \tilde{a}_i + \tilde{\theta}_s^W \mathbb{E}(\tilde{a}_W) + \tilde{\theta}_o^W \mathbb{E}(\tilde{a}_M) + v_i \quad \forall i \in W \tag{9}$$

$$w_i = \alpha_M + \tilde{a}_i + \tilde{\theta}_s^M \mathbb{E}(\tilde{a}_M) + \tilde{\theta}_o^M \mathbb{E}(\tilde{a}_W) + u_i \quad \forall i \in M \tag{10}$$

, where $\alpha_W = b_W(\rho_s b_W + \rho_o b_M)$, $\alpha_M = b_M(\rho_s b_M + \rho_o b_W)$, $v_i = b_W \epsilon_i$, and $u_i = b_M \epsilon_i$. $\tilde{\theta}_s^W = \tilde{\theta}_s^M = \frac{\theta_s}{1+\alpha}$, $\tilde{\theta}_o^W = \frac{b_W}{b_M}\frac{\theta_o}{1+\alpha}$, $\tilde{\theta}_o^M = \frac{b_M}{b_W}\frac{\theta_o}{1+\alpha}$.

Equations (9) and (10) represent the baseline models in our empirical analysis. First, note that if $b_M = b_W$ (there is no wage gender gap), $\tilde{\theta}_s > \tilde{\theta}_s$ if and only if $\theta_s > \theta_o$, or $\eta_s > 0$. When wages of men and women are different, proposition 1 defines a necessary and sufficient condition for $\eta_s > 0$ in terms of the estimated parameters of the empirical model.

Proposition 1 *In the framework of the described model and assuming that $\theta_s \geq 0$ and $\theta_o \geq 0$, the following holds*

- $\tilde{\theta}_s^W \tilde{\theta}_s^M > \tilde{\theta}_o^W \tilde{\theta}_o^M$ *if and only if* $\theta_s > \theta_o \Longleftrightarrow \eta_s > 0$
- $\tilde{\theta}_s^W \tilde{\theta}_s^M = \tilde{\theta}_o^W \tilde{\theta}_o^M$ *if and only if* $\theta_s = \theta_o \Longleftrightarrow \eta_s = 0$

And we define

$$\tilde{\eta}_s = \sqrt{\tilde{\theta}_s^W \tilde{\theta}_s^M} - \sqrt{\tilde{\theta}_o^W \tilde{\theta}_o^M} = \frac{\eta_s}{c + 2\eta}. \tag{11}$$

, which increases linearly on η_s.

Proof. The proof is straightforward from the observation that $\tilde{\theta}_s^W \tilde{\theta}_s^M = \frac{\theta_s^2}{(1+\alpha)^2}$ and $\tilde{\theta}_o^W \tilde{\theta}_o^M = \frac{\theta_o^2}{(1+\alpha)^2}$. ■

The empirical model described by equations (9) and (10) does not allow recovering η_s, but Proposition 1 shows that $\tilde{\eta}_s > 0$ is a necessary and sufficient condition for $\eta_s > 0$ as long as c and η are greater than zero. Moreover, keeping c and η constant, the higher $\tilde{\eta}$ is, the less egalitarian social norms are.

3 Empirical Strategy

Our goal is to empirically investigate whether same-gender peer effects do significantly differ from opposite-gender peer effects at the workplace. In this section we discuss the empirical model of peer influence with gender asymmetries. In Appendix B, we show a model that abstracts from gender asymmetries, which we use to estimate the average peer effect.

3.1 Baseline Model

Following the standard linear-in-means model of peer influence pioneered by Manski (1993), we estimate the following baseline wage equation:

$$\begin{aligned} Y_{itoj} = a_i + \alpha_1 \bar{a}^f_{\sim i,toj} Female_i + \alpha_2 \bar{a}^f_{\sim i,toj} Male_i + \\ \beta_1 \bar{a}^m_{\sim i,toj} Female_i + \beta_2 \bar{a}^m_{\sim i,toj} Male_i + \mu_{ot} + \rho_{jt} + \delta_{oj} + \varphi X'_{it} + v_{itoj} \end{aligned} \tag{12}$$

, where Y_{itoj} is the wage of individual i at time t in firm j, and occupation o. Worker fixed effects are denoted by a_i, $\bar{a}^f_{\sim i,toj}$ is the average ability of i's female peers, and $\bar{a}^m_{\sim i,toj}$ is the average ability of i's male peers (excluding i from the average in both cases). In what follows, we will refer to a_i as worker i's ability, quality, or the permanent component of worker i's productivity interchangeably. Finally, X'_{it} is a vector of individual time-variant controls that include quadratic forms of age and firm tenure (number of months individual i had been working in the same firm j by period t).

A worker's peer group is defined as all workers who work in the same plant and occupation with a four-digit code at the same time. Equation (12) includes time-specific occupation and establishment fixed effects (μ_{ot} and ρ_{jt}, respectively), as well as occupation-firm fixed effects denoted by δ_{oj}.[8]

The coefficient α_1 (α_2) represents the effect of female co-workers' ability, while β_1 (β_2) represents the effect of male co-workers' ability on the wages of females (males). If same-gender peer effects are stronger than opposite-gender peer effects, then $\alpha_1 > \beta_1$ and $\beta_2 > \alpha_2$.

The estimation of peer effects in the workplace presents several challenges, some of which generally apply to all observational studies on peer effects (Manski, 1993). Additionally, we need to deal with the fact that workers' ability (a_i) is unobserved. We discuss these issues sequentially.

3.1.1 Sorting and Omitted Variables

We condition on a large set of fixed effects to deal with sorting and omitted variables as in (Cornelissen et al., 2017), which in turn extends the worker and fixed effects model initially proposed by (Abowd et al., 1999). We now outline the role played by each set of fixed effects for identification.

Peers are not randomly allocated and workers may sort themselves into peer groups. For instance, high ability workers may select into high ability peer groups. In this case, co-workers average ability ($\bar{a}^{m}_{\sim i,toj}$ and $\bar{a}^{f}_{\sim i,toj}$) and wages (Y_{itoj}) are likely positively correlated even if there was no peer effect since both variables are correlated with worker i's ability. This issue is dealt with controlling for worker fixed effects (a_i).

Additionally, even if we hold workers' ability constant by including worker fixed effects, co-workers' ability is likely related to other wage determinants such as the quality of the occupation-firm they work in. In particular, high ability peers may concentrate in high quality occupation and/or firms. Highly productive occupation-firms are in turn likely to pay higher wages, which may lead to overestimating the

[8]Throughout the text, the term "firm" is used to refer to firm's establishments.

peer effects because it would capture peer effects as well as the impact of omitted occupation-firm characteristics. Hence one must also control for occupation-firm fixed effects (δ_{oj}) to account for nonrandom selection into occupations within firms.

Moreover, occupation-firm characteristics may change over time such that the ability of their workforce changes too. For instance, firms that adopt productivity-enhancing technologies are likely to need higher skilled workers, and to pay higher wages too. To account for time-variant firm-specific and occupation-specific confounding factors we control for time-specific occupation and firm fixed effects (μ_{ot} and ρ_{jt}, respectively).

In order to estimate the peer effects consistently in equation (12), one needs to make the identifying assumption that there are no occupation-firm specific time-variant confounding factors that may affect wages, and that are correlated with co-workers' average ability. Note also that the identification also requires that there is within worker variation in $\bar{a}^{m}_{\sim i,toj}$ and $\bar{a}^{f}_{\sim i,toj}$. This variation is present if: (i) i changes jobs; and (ii) if new peers join or old peers leave his/her workplace.

Furthermore, as it is shown in Arcidiacono et al. (2012), the estimated peer effects are $\sqrt{N}$ consistent and an asymptotically normal estimators if the residuals (ν_{itoj} in (12)) across any two observations are uncorrelated. This assumption rules out serial correlation as well as the presence any wage shocks common to the peer group. However, the results from Monte Carlo simulations provided 6.5 indicate that: i) the bias in the peer effect estimate due to serial correlation of a plausible size is modest; ii) time-varying peer group level shocks may lead to an upward bias, but this bias is not large enough to spuriously generate the level of peer effects that we document.

3.1.2 Estimation of the Model with Unobserved Ability

Estimation of (12) is further complicated because individual ability, a_i, is unobserved and needs to be estimated. Given that equation (12) includes the products of α_1 and α_2 with $\bar{a}^{f}_{\sim i,toj}$, and β_1 and β_2 with $\bar{a}^{m}_{\sim i,toj}$, all of which need to be estimated, the model becomes a non-linear least squares problem. Moreover, given that we control for an extensive set of high dimensional fixed effects (we have 7,663,777 workers, 111,478 firms, and 570 occupations), standard non-linear least squares techniques are not applicable. If $\bar{a}^{f}_{\sim i,toj}$ and $\bar{a}^{m}_{\sim i,toj}$ were instead observed, the model would be linear and could be estimated with standard techniques.

To estimate equation (12) with unobserved a_i, we adapt the iterative algorithm proposed by Arcidiacono et al. (2012) to estimate spillover effects using panel data.[9] We estimate the peer effects by minimizing the following sum of squared residuals:

$$\begin{aligned}\min_{a,\alpha,\beta,\rho,\delta,\mu,\varphi} \textstyle\sum_{i=1}^{N}\sum_{t=1}^{T} \Big(& Y_{itoj} - a_i - \alpha_1 \bar{a}^{f}_{\sim i,toj} Female_i - \alpha_2 \bar{a}^{f}_{\sim i,toj} Male_i - \\ & \beta_1 \bar{a}^{m}_{\sim i,toj} Female_i - \beta_2 \bar{a}^{m}_{\sim i,toj} Male_i - \mu_{ot} - \rho_{jt} - \delta_{oj} - \varphi X'_{it} - v_{itoj} \Big)^2 \end{aligned} \tag{13}$$

The algorithm proceeds as follows:

1. Set an initial guess for the vector of fixed effects (a) a^0.

2. Conditional on a^0, compute $\bar{a}^{f}_{\sim i,toj}$ and $\bar{a}^{m}_{\sim i,toj}$ and estimate $\alpha_1, \alpha_2, \beta_1, \beta_2$, and the rest of the parameters (μ_{ot}, ρ_{jt},δ_{oj},φ) by OLS.

3. Update a^1 according to equations (C.17) and (C.18), the first order conditions for (13) derived in Appendix C.

4. Iterate steps 2 and 3 until convergence of $\alpha_1, \alpha_2, \beta_1$, and β_2 is achieved.

Convergence is achieved if the sum of squared residuals diminishes with every iteration, which requires the right-hand side of equations (C.17) and (C.18) to be a contraction mapping. The following theorem provides sufficient conditions for convergence.

Theorem 2 *Denote N_f as the number of females and N_m as the number of males. Denote $g^f(a) : \mathbb{R}^{N_f} \rightarrow \mathbb{R}^{N_f}$ and $g^m(a) : \mathbb{R}^{N_m} \rightarrow \mathbb{R}^{N_m}$, where the i^{th} element of $g^f(a)$ is given by the right-hand side of* (C.17) $\forall i \in N_f$*, and the i^{th} element of $g^m(a)$ is given by the right-hand side of* (C.18) $\forall i \in N_m$*. $g^f(a)$ and $g^m(a)$ are contraction mappings if $\alpha_k < 0.2$ and $\beta_k < 0.2$ for $k = 1, 2$.*

[9] This is also the algorithm used to estimate peer effects on wages in Germany by Cornelissen et al. (2017).

The proof of this Theorem is provided in Appendix C. Intuitively, Theorem 2 indicates that convergence might be not achieved if peer effects are very large.

4 Data

We use Brazilian data from the Relação Anual de Informações Sociais (RAIS), an administrative employer-employee matched dataset collected annually by the Brazilian Labor Ministry. containing annual information from 2003-2018 on earnings and demographic characteristics of formal sector workers in Brazil as reported by employers. RAIS data are based on a mandatory survey filled in annually by all formally registered firms in Brazil and, according to the Ministry of Labor estimates, RAIS covers 98% to 99% of officially existing firms.

RAIS includes information about workers (gender, age, education), their jobs (type of contract, occupation, average monthly wage earned during the year/employment spell within the establishment, and the amount of hours usually worked per week), as well as some characteristics of the establishment (sector, region, municipality, number of employees). Importantly, RAIS also provides firm, establishment, and worker unique and anonymized identifiers, which, together with the dates of separation and admission, allow us to follow workers and employers over time, and to identify job stayers and movers.

To measure wages we use the average wage of the worker over the year or over the employment spell within the establishment (if the worker changed employment at some point during the year). Wages in RAIS are measured as a multiple of the minimum wage in December of that year —for example, the value 2 means that the individual's average wage during the year was 2 times the minimum wage. To convert the wage variable to real values, we multiply it by the national minimum wage in December of that year deflated with the consumer price index.

4.1 Sample Selection and Peer Group Definition

We use 2003-2018 data for the city of São Paulo instead of using data for Brazil as a whole in order to ease the computational burden implied by the inclusion of firm-year, occupation-year and firm-occupation effects in addition to worker fixed effects. We focus on one large local labor market rather than a random sample of all Brazilian formal workers to capture most worker mobility, which is crucial for our identification strategy. We select full-time[10] private sector workers aged between 15 and 65 with valid information on gender, wages, firm tenure, occupation, and establishment identifiers. In what follows we will refer to establishments as firms or workplaces for simplicity.

We define a worker's peer group as all workers employed at the same time in the same firm and the same four-digit occupation. Specifically, occupations are classified according to the Brazilian Classification of Occupations CBO 2002.[11] Four-digit level occupational definitions are arguably detailed enough to ensure that workers can potentially interact, observe and assess their peers' performance, which may generate knowledge spillovers, social pressure, and/or competitive behaviors that in turn translate into peer effects in wages. Particularly, CBO 2002 includes 620 four-digit occupations. Some examples of four-digit occupations are human resource managers, computer engineers, IT administrators, nutritionists, lawyers, telephone operators, home sellers, etc. Since a narrower occupational classification —up to six-digit codes— is also available, in Section 6.2 we conduct a robustness check in which wee use six-digit codes. For example, within the 4-digit occupation category of "lawyer," a 6-digit code distinguishes between different types of lawyers, including corporate lawyer, civil lawyer, public lawyer, criminal lawyer, specialized lawyer, labor lawyer, and legal consultant. Therefore, if men and women sort into different narrow occupations within their 4-digit occupation, it is likely to be captured by the 6-digit

[10]Employees who work at least 30 hours per week

[11]The classification is available at `http://www.mtecbo.gov.br./cbosite/pages/home.jsf`. Prior to 2003, occupations were classified according to CBO 1994. For that reason we do not include earlier years in our analysis.

occupation code. In total, we can distinguish 2,696 6-digit occupations.

To analyze whether men and women are employed in systematically different 6-digit occupations within the peer groups (defined using 4-digit occupations), we examine gender differences in occupational characteristics within the peer groups. Specifically, we calculate the average wages and the share of women at the 6-digit occupation level. Then, we run a regression of each of these variables on the female dummy and on the vector of peer group fixed effects. We find that women are employed in occupations with wages that are 0.09 percent lower and have a 0.29 percentage point higher share of females than men from the same peer group. These differences are very small, which assures us that there are no systematic differences in the tasks performed by men and women who we classify as peers.

Job spells can end as well as start any month during the year. Hence, in order to ensure that the members of the peer group have indeed been in the same workplace and occupation at some point during the year, we only include workers who were employed in that occupation-firm in November. Additionally, whenever individuals have more than one job, we always keep the observation with the highest paying job. These restrictions yield a sample of 57,945,322 observations.

In order to estimate 12, we need to observe at least one male peer and one female peer for each employee. We therefore drop all peer groups with less than 2 males and 2 females. This further reduces our sample to 27,744,610 observations. Finally, we also restrict our analysis to the biggest connected mobility group because the fixed effects are only identified within firms directly or indirectly (via other firms) connected by worker mobility throughout the sample period, which leaves us with 27,698,010 observations.

4.2 Descriptive Statistics

Table 1 describes the panel structure of our analytic sample, which consists of 27,698,010 worker-year observations on 7,663,777 unique formal employees, 111,478 firms, 570 four-digit occupations, and 918,393 peer groups (occupation-firm-year combinations).

The statistics reported indicate that the degree of worker mobility across firms and occupations is non-trivial, which will allow the identification of worker, firm-occupation, firm-year, and occupation-year fixed effects. In particular, throughout our sample period (2003-2018) workers are observed 3.61 periods on average, and they work on average for 1.6 different firms and in 1.45 different occupations.

Table 1: Panel Structure of the Sample

Number of worker-year observations	27,698,010
Number of workers	7,663,777
Number of firms	111,478
Number of occupations	570
Number of firm-occupation observations	254,722
Number of firm-year observations	506,158
Number of peer groups (firm-occupation-year observations)	918,393
Number of worker-occupation observations	11,110,045
Number of worker-firm observations	12,229,470
Average number of occupations/peer groups per firm-year	1.81
Average number of firms per worker	1.60
Average number of occupations per worker	1.45
Average number of occupations within firm per worker	1.76
Average number of time periods per worker	3.61

Notes: Statistics based on RAIS data for 2003-2018. The overall sample (N=27,698,010) has been constructed applying the criteria outlined in Section 4.1.

Table 2 provides additional descriptive statistics by gender. In our sample, which has 49.2% of female observations, the gender wage gap is considerable, as females earn on average 35.8% lower wages than males. Female employees are also more educated than male employees on average, as the share of employees with only primary (secondary or post-secondary) education is lower (higher) among females than among males. This suggests that there may be selection into employment based on education and gender, but we account for this sort of selection by controlling for worker fixed effects in equation 12.

We use the terms skilled/unskilled occupations to refer to the top/bottom 10% of occupations with a highest/lowest share of employees with post-secondary education. Despite the educational gender gap favoring females in our sample, males are slightly less likely than females to work in the 10% most unskilled occupations. The average and the median peer group size are 30.2 and 10 employees, respectively, with the former being slightly larger for males (31.1) than for females (29.3).

Implementing our identification strategy requires several types of variation in our data. First, we need within peer-group variation in wages, and the evidence presented in the third panel of Table 2 indicates that wage variation across employees in the same peer group (occupation-firm-year) is by no means small. In particular, the average within-peer group standard deviation of log real wage residuals (obtained from a regression of log real wages on year fixed effects and quadratic forms of age and firm tenure) constitutes about 42% and 45% of the overall standard deviations in log real wages for males and females, respectively.

Second, within individual wage variability is also relevant for us because peer effects on wages can only exist if wage rigidities do not fully prevent individual wages from reacting to changes in productivity generated by changes in peers' ability. The bottom panel of Table 2 presents suggestive evidence that this is unlikely to be the case, since the average annual growth rate over our sample period is 6% for both females and males —so wage adjustments to negative idiosyncratic productivity shocks need not necessarily translate into nominal or real wage cuts—, and the percentage of employees receiving a real wage cut larger than 5% is on average 14% among job stayers.

Third, as discussed in Section 3.1.1, identifying the wage effects of peers' ability or quality in equation 12 requires that there is within worker variation in peers' ability, which arises when employees change jobs and hence peer groups, and/or when they do not change jobs but their peer group composition changes because some employees join or leave the group. Tables 3 illustrates the extent of this variation for both males and females. The standard deviation of the annual change in average peers quality is 0.16 (0.15) for male peers (female peers), which amounts to about 32% of the overall variation in both average male peers' quality ($\bar{a}^{m}_{\sim itoj}$ in equation 12) and female peers' quality ($\bar{a}^{f}_{\sim itoj}$).

As expected, within worker variation in peers' ability is about three times higher among movers (0.27 and 0.30 for male and female peers of movers, respectively)

Table 2: Summary Statistics by Gender

	Total	Males	Females
Real Monthly Wage (BRL 2005)	1916.21	2201.70	1621.09
Log of wage	7.10	7.21	6.98
Less than Primary Educ.	0.09	0.10	0.07
Primary Educ.	0.14	0.16	0.12
Secondary Educ.	0.52	0.50	0.55
Post-Secondary Educ.	0.24	0.24	0.25
Unskilled occupation	0.10	0.09	0.11
Skilled occupation	0.10	0.10	0.10
Peer group size			
Mean	30.16	31.07	29.27
Median	10.00	10.00	10.00
Standard Deviation of Wages			
Raw Std. Dev. of log Real Wage	0.85	0.88	0.80
Standard Deviation of log Real Wage Residuals	0.56	0.58	0.53
Average Within Peer-Group Std. Dev. of log Real Wage Residuals	0.37	0.37	0.36
Wage Flexibility and Wage Growth			
Probability of >5% real wage cut (only stayers)	0.14	0.15	0.13
Average annual wage growth	0.06	0.06	0.06
N	27,698,010	14,078,976	13,619,034

Notes: Skilled (unskilled) occupations are defined as the 10% of occupations with the highest (lowest) percentage of post-secondary educated employees. Residuals used to compute the standard deviation of log real wage residuals are obtained from a log-wage regression that controls for time fixed effects, education, and quadratic forms of age and firm tenure.

than among stayers (0.09 and 0.1 for male and female peers of stayers, respectively). However, within worker variation in peers ability among job stayers is not negligible, as it represents about 18% and 22% of the overall variation in average male and female peers' ability, respectively. In Section 6.1 we separately analyse peer effects for movers and stayers.

Table 3 also shows that the correlation between individual workers' quality and their peers' average quality is positive and high (about 0.8) for both male peers and female peers. This suggests that high quality employees sort into high quality peer groups, underlining the importance of controlling for worker's quality (a_i) in equation 12. We also uncover positive correlations between average peers' quality and firm-occupation effects (δ_{oj}), firm-time effects (ρ_{jt}), and occupation-time effects (μ_{ot}).

This is suggestive that high quality peer groups concentrate in highly productive and high-wage occupation-firms, hence it is also important to control for occupation-firm effects, firm-time effects, and occupation-time effects in equation (12).

Table 3: Peer Quality

	(1) Total	(2) Males	(3) Females
Standard deviation worker fixed effects	0.57	0.61	0.51
Standard deviation average male peers' fixed effects	0.49	0.52	0.46
Standard deviation average female peers' fixed effects	0.46	0.49	0.43
Standard deviation change of average male peers' fixed effects between t 1 and t	0.16	0.16	0.16
Standard deviation change of average female peers' fixed effects between t 1 and t	0.15	0.15	0.14
Standard deviation change of average male peers' fixed effects between t 1 and t -Movers	0.27	0.28	0.25
Standard deviation change of average female peers fixed effects between t 1 and t - Movers	0.30	0.30	0.30
Standard deviation change of average male peers' fixed effects between t 1 and t -Stayers	0.09	0.10	0.09
Standard deviation change of average female peers' fixed effects between t 1 and t - Stayers	0.10	0.10	0.10
Correlation worker fixed effects and average male peers' fixed effects	0.80	0.81	0.77
Correlation worker fixed effects and average female peers' fixed effects	0.79	0.78	0.79
Correlation occupation-time effects and average male peers' fixed effects	0.14	0.13	0.15
Correlation occupation-time effects and average female peers' fixed effects	0.14	0.11	0.16
Correlation firm-time effects and average male peers' fixed effects	0.15	0.14	0.15
Correlation firm-time effects and average female peers' fixed effects	0.14	0.12	0.15
Correlation occupation-firm effects and average male peers' fixed effects	0.32	0.30	0.34
Correlation occupation-firm effects and average female peers' fixed effects	0.31	0.27	0.34
N	27,698,010	14,078,976	13,619,034

Notes: Worker fixed effects are estimated using equation (12) and the algorithm described in Section 3.1.2.

5 Results

5.1 Overall Peer Effects

As a benchmark for later comparisons, in this section we estimate the overall effect of peers' quality on individual wages in the full sample and by gender. Table 4 reports the estimated peer effect from equation (B.12) in the full sample (Column 1), as well as for males (Column 2) and females (Column 3).[12] On top of controlling for quadratic forms of age and firm tenure, we always control for each worker's own fixed effects (to account for sorting of high/low quality workers into high/low quality peer groups), occupation-year fixed effects (to account for time-varying wage shocks at the occupation level common to all firms), firm-year fixed effects (to account for time-varying wage shocks at the firm level common to all occupations), and occupation-firm fixed effects (to account for nonrandom selection into occupations within firms that may arise if firms attract better hires to high quality occupations by paying higher wages).

We find that male and female employees' wages are equally affected by their peers' quality: a 10% increase in peers' quality increases the wages of both male and female workers by 2.5% on average. The equality of peer effects for men and women masks relevant asymmetries between same-gender and opposite-gender peers, as we will show in Section 5.2.

The magnitude of our estimated peer effects is in range with the estimated peer effects on focal worker output previously uncovered by laboratory experiments and field studies based on specific settings, which amount on average to 0.12 (SE=0.03) according to the meta-analysis by Herbst and Mas (2015). Interestingly, our estimated peer effects are much larger than the 0.1% wage increase induced by a 10% increase in peers' quality estimated by Cornelissen et al. (2017) using matched employer-

[12] To separately estimate peer effects for male and female employees, we interact $\bar{a}_{\sim itoj}$ in equation (B.12) with the gender dummy. Peers' average ability is unobserved and needs to be estimated, which requires the full sample. Hence, estimation by subsamples is not possible and all the heterogeneity analyses are conducted using interactions between group indicators and peers' average ability with group indicators.

Table 4: Overall Peer Effects on Wages

The effect on...	(1) Pooled Sample	(2) Males	(3) Females
Average peers' ability	0.253	0.253	0.253
	(0.002)	(0.003)	(0.003)
N	27,698,010	14,078,976	13,619,034
Worker FE	yes	yes	yes
Occuation-year FE	yes	yes	yes
Occupation-firm FE	yes	yes	yes
Firm-year FE	yes	yes	yes

Note: The table shows the overall effect of average peer quality on individual log wages in the full sample and by gender. All specifications control for quadratic forms of age and firm tenure. Coefficients can approximately be interpreted as elasticities. Bootstrapped standard errors clustered at the firm level are displayed in parentheses.

employee data for an entire local labor market in Germany. While the source of cross-country differences in peer effects at work is outside the scope of this paper, it is worth stressing that our study focuses on a developing country, where the scope for formal training programs is more limited than in developed countries like Germany. Hence, learning or knowledge spillovers from co-workers and/or improving performance due to peer pressure may be more important vehicles for productivity enhancement and wage growth in developing than in developed countries.

5.2 Gender Asymmetries in Peer Effects on Wages

We now turn to our main question of interest: do same-gender and opposite-gender peers have the same impact on individual wages? To answer this question, we estimate equation (12), which includes all the controls previously considered when estimating overall peer effects, and it additionally allows peer effects to differ among same-gender and opposite-gender peers.

Table 5 displays these results for both male and female employees in Columns 1 and 2, respectively. We find that that the influence of same-gender peers' ability on the wages of focal workers –be they men or women– is much stronger (about double) than that of opposite-gender peers' ability. In particular, a 10% increase in female peers' quality increases female wages by 1.56%, about twice as much as the female wage increase generated if male peers' quality increases by 10%. Similarly, a 10% increase in male peers' ability increases male wages by 1.43%, while the effect on male wages of a 10% increase in female peers' quality is 0.83%. All coefficient estimates of peers' ability as well as the gender asymmetries highlighted are statistically significant at the 1% level.

This is evidence that gender identity norms are relevant for peer effects in the workplace because, in line with Akerlof and Kranton (2000, 2002, 2005, 2008), individuals' wages are more responsive to the quality of their peers if their gender identity is the same. In their papers, Akerlof and Kranton propose a framework in which ones identity enters the utility function and, since norms as to how individuals should behave depend on their social category ("men" and "women" in our context), deviating from such norms decreases utility. As a consequence, individuals try to minimize the discrepancies between their actions and choices and those in consonance with their social category's behavioral prescriptions. If such behavioral prescription are signalized by actions of peers of the same social category, individuals may want to minimize the distance between their actions and that of their peers with the same social category. Moreover, if within-gender interactions are more common than cross-gender interaction, individuals may learn more from same-gender peers than from the opposite-gender peers.

5.3 Are Gender Asymmetries Exacerbated in Contexts with More Traditional Gender Norms?

We now investigate if the gender asymmetries in peer effects at work that we have uncovered are exacerbated/attenuated in less/more egalitarian contexts. This is our expectation, as the framework in Akerlof and Kranton (2000) predicts that the removal or attenuation of gendered behavioral prescriptions would decrease the identity loss of women (men) engaging in behaviors more common among men (women). According to this framework, more gender equal identity norms would induce men to

Table 5: Gender Asymmetries in Peer Effects on Wages

The effect on	(1) Males		(2) Females
Male peers' average ability	0.143		0.074
	(0.002)		(0.001)
Female peers' average ability	0.083		0.156
	(0.002)		(0.002)
$\hat{\hat{\eta}}_s$		0.070	
		(0.001)	
N	14,078,976		13,619,034
Worker FE	yes		yes
Occuation-year FE	yes		yes
Occupation-firm FE	yes		yes
Firm-year FE	yes		yes

Note: The Table reports the estimated effect of average same-gender and opposite-gender peers' average quality on individual log wages (see equation (12)) by gender. $\hat{\hat{\eta}}_s$ is computed according to equation (11). All specifications control for quadratic forms of age and firm tenure. Bootstrapped standard errors clustered at the firm level are displayed in parentheses.

be relatively more influenced by their female peers (with respect to their male peers) and women to be relatively more influenced by their male peers (with respect to their female peers).

5.3.1 Skilled *versus* Unskilled Occupations

Numerous multidisciplinary studies on gender identity have shown that traditional gender norms are more prevalent among low educated individuals, while highly educated individuals tend to hold more egalitarian views on the role of men and women in society (see Du et al. (2021) and references therein). Brazil is no exception to this pattern, as highly educated Brazilian participants to the World Value Survey are less likely to hold traditional gender views than their less educated counterparts.[13]

Therefore, one would expect that the discrepancies between same-gender and opposite-gender peer effects to be larger in unskilled than in skilled occupations, which we define as the bottom/top 50% of occupations with a lowest/highest share of

[13] Using World Value Survey data for Brazil in 2010-2014 we have uncovered negative correlations between having completed college and agreeing with statements reflecting traditional gender norms such as (i) *"It is a problem if women have more income than husband"* and (ii) *"When jobs are scarce, men should have more right to a job than women"* in Brazil.

employees with post-secondary education. The results presented in Table 6 indicate that this is indeed the case: in the top 50% most skilled occupations, same-gender peer effects are 1.6 and 1.9 times larger than opposite-gender peer effects for men and women respectively. By contrast, in unskilled occupations the gap between same-gender and opposite-gender peer effects is much larger. In particular, in the bottom 50 % least skilled occupations, same-gender peer effects are about 3.4 times larger than opposite-gender peer effects for both men and women. In sum, our evidence indicates that gender asymmetries in peer effects at work are much stronger (weaker) in more (less) traditional contexts.

Table 6: Gender Asymmetries in Peer Effects in Skilled versus Unskilled Occupations

The effect of...	(1) Average male peers' ability	(2)	(3) Average female peers' ability	(4)
	Males	Females	Males	Females
Panel A: 50% Skilled				
Elasticity	0.121	0.068	0.076	0.132
	(0.002)	(0.002)	(0.003)	(0.002)
$\hat{\hat{\eta}}_s$			0.057	
			(0.001)	
Panel B: 50% Unskilled				
Elasticity	0.259	0.080	0.075	0.271
	(0.002)	(0.002)	(0.002)	(0.002)
$\hat{\hat{\eta}}_s$			0.193	
			(0.003)	

Note: The table reports the estimated effect of same-gender and opposite-gender peers' average quality on individual log wages (see equation (12)) by gender and for employees in skilled and unskilled occupations. $\hat{\hat{\eta}}_s$ is computed according to equation (11). All specifications control for quadratic forms of age and firm tenure, employee fixed effects, occupation-year fixed effects, firm-year fixed effects, and occupation-firm fixed effects. Skilled (unskilled) occupations are defined as the 50% of occupations with the highest (lowest) percentage of post-secondary educated employees. Bootstrapped standard errors clustered at the firm level are displayed in parentheses.

5.3.2 Firms with Larger *versus* Smaller Gender Wage Gaps

Previous studies suggest that male-female wage differentials are larger in contexts with less egalitarian gender identity norms (Antecol, 2001; Fortin, 2005). In line with this idea, we now use firm-level gender wage gaps (net of education, age and year fixed effects) as a proxy for firm-level gender social norms.

We proceed as follows. Separately for men and women, we regress wages (in logs) on the level of education, a quadratic form of age, and year fixed effects. We obtain the residuals from these regressions, and we compute their mean at the firm-year level for both men and women. We compute the female-male gender gap in these firm-level residuals as the difference between women's mean residuals and men's mean residuals. We next estimate same-gender and cross-gender peer effects for both men and women at the bottom and the top quartiles of the female-male wage gap distribution. Finally, we compare the magnitude of the gender asymmetries in the estimated peer effects across firms in which women are relatively better/worse paid than men.

Table 7 reports the results of this analysis. Panels A and B display peer effects estimates in firms with a female-male wage gap below the $25-th$ percentile and above the $75-th$ percentile, respectively. In firms at the bottom quartile of the female-male wage gap (Panel A), the effect of same-gender peers is 2.5 and 1.4 times larger than the effect of opposite-gender peers for women and men, respectively. In contrast, gender asymmetries in peer effects are smaller in firms at the top quartile of the female-male wage gap distribution (Panel B), as the corresponding ratios reduce to 1 and 1.3 for women and men respectively. Hence, gender asymmetries in peer effects are attenuated in firms in which female employees are relatively better paid with respect to their male counterparts.

6 Robustness Checks

6.1 Movers *versus* Stayers

There are two sources of variation that allow us to identify the effect of peers quality: i) changes in peers quality due to focal workers leaving their jobs (job movers); and ii) changes in peers quality due to the fact that peers of job stayers join or leave the peer group. As illustrated in Table 3, both sources of variation matter but, as expected, the

Table 7: Gender Asymmetries in Peer Effects in Firms with Larger versus Smaller Gender Wage Gaps

The effect of...	(1) Male peers' average ability	(2)	(3) Female peers' average ability	(4)
	Males	Females	Males	Females
Panel A: Bottom Quartile of the Female-Male Wage Gap Distribution				
Elasticity	0.139	0.0639	0.100	0.160
	(0.002)	(0.002)	(0.002)	(0.002)
$\hat{\hat{\eta}}_s$			0.069	
			(0.002)	
Panel B: Top Quartile of the Female-Male Wage Gap Distribution				
Elasticity	0.124	0.115	0.092	0.123
	(0.002)	(0.002)	(0.002)	(0.002)
$\hat{\hat{\eta}}_s$			0.021	
			(0.002)	

Note: The table reports the estimated effect of average same-gender and opposite-gender peers' quality on individual log wages (see equation (12)) by gender and for employees in firm-year cells where the female-male wage gender gap net of education, age, and year fixed effects is below the bottom quartile (Panel A) and above the top quartile (Panel B). $\hat{\hat{\eta}}_s$ is computed according to equation (11). All specifications control for quadratic forms of age and firm tenure, employee fixed effects, occupation-year fixed effects, firm-year fixed effects, and occupation-firm fixed effects. Bootstrapped standard errors clustered at the firm level are displayed in parentheses.

former is more relevant than the latter. To avoid concerns related to the endogeneity of mobility decisions in the presence of match-specific effects, we now replicate our main analysis of gender asymmetries (displayed in Table 5) by separately investigating them for job movers and job stayers, as match-specific effects are accounted for when focusing on stayers. The results of this analysis, reported in Panels A and B of Table 8, are reassuring, as it is still the case that for both movers and stayers peers quality influences focal workers wages, and this influence is much stronger among workers and peers of the same gender. Remarkably, for both movers and stayers we obtain estimates that are similar to the baseline estimates reported in Table 5, indicating that these are not biased because of match-specific effects. Cornelissen et al. (2017) find a similar result (see their Table 7) and, also in line with this evidence, Card et al. (2013) and Card et al. (2015b) find that idiosyncratic job-match effects are not a relevant driver of job mobility.

Table 8: Robustness Checks

The effect of...	(1) Average male peers' ability	(2)	(3) Average female peers' ability	(4)
	Males	Females	Males	Females
Panel A: Stayers Only				
Elasticity	0.144	0.081	0.093	0.158
	(0.002)	(0.002)	(0.002)	(0.002)
$\hat{\hat{\eta}}_s$		0.063		
		(0.002)		
Panel B: Movers Only				
Elasticity	0.129	0.061	0.099	0.170
	(0.002)	(0.002)	(0.003)	(0.002)
$\hat{\hat{\eta}}_s$		0.073		
		(0.002)		
Panel C: Occupation at 6-digit level				
Elasticity	0.150	0.090	0.104	0.167
	(0.001)	(0.001)	(0.001)	(0.001)
$\hat{\hat{\eta}}_s$		0.061		
		(0.001)		
Panel E: Placebo Firm				
t-statistic	0.230	0.302	-0.426	-0.435
Panel D: Placebo Occupation				
t-statistic	-0.641	-0.497	-0.520	-0.188

Note: The Table reports the estimated effect of average same-gender and opposite-gender peers' quality on the individual log wage by gender estimated with equation (12). Placebo occupation is a specification where peer group is defined as workers from the same firm but randomly chosen occupation. Placebo firm is a specification where peer group is defined as workers from the same occupation but randomly chosen firm. Stayers are workers who did not change the occupation-firm. Movers are workers who change occupation-firm. $\hat{\hat{\eta}}_s$ is computed according to equation (11). All specifications control for quadratic forms of age and firm tenure and the full set of fixed effects. Bootstrapped standard errors clustered at the firm level are displayed in parentheses.

6.2 Narrowing the Peer Group Definition

Any peer effects study must thoroughly assess the suitability of the peer group definition used. In our context, the question of interest is: do workers in a given occupation defined at the four-digit level within a firm actually interact, and have the chance to learn from their peers, observe, and judge their productivity, and potentially react to it? If the peer group definition used is too narrow (wide) such that relevant (irrelevant) peers are excluded from (included in) the group, our estimates are likely to be attenuated Perhaps more importantly, if our peer group definition is too wide it may be the case that the gender asymmetries we have so far uncovered simply mask the fact that men and women tend to perform different tasks within the same four-digit occupation in the same firm.

In the bottom panel of Table 8 we replicate our benchmark analysis from Table 5 using a narrower peer group definition: co-workers in the same firm and the same occupation defined at the six-digit (rather than four-digit) level. A six-digit level occupational classification is based on a occupation profile such that occupational groups are classified by tasks performed. After restricting the analysis to peer groups (defined as six-digit level occupations) with at least 2 male and 2 female workers, the estimation sample, which contains 2,133 six-digit occupations, reduces to 25,809,290 observations.

The results, reported in Panel C of Table 8, indicate that peer effects are generally larger when a narrower definition of the peer group is used. The estimated effects of same-gender peers are 1.4 and 1.9 times larger than the effects of opposite-gender peers for men and women, respectively. Hence, the gender asymmetries in peer effects obtained with our benchmark specification are not driven by gender differences in the tasks performed within the same four digit occupation group.

6.3 Placebo Tests

We now perform two placebo tests to rule out the concern that our results are driven by chance. First, we estimate the effects of the quality of workers in other randomly chosen firm in the same four-digit occupation. Note that the effect of peers from other firms need not be zero. Knowledge spillovers may occur between employees from different firms, especially if they are geographically and economically close (Moretti, 2004). However, peer effects are expected to be stronger between peers within the firm than between employees in the same occupation working in different and randomly chosen firms. In line with this expectation, the ability of employees in the same four-digit occupation working in other firms has no influence on focal workers wages. Panel D of Table 8 shows that the estimated placebo peer effects are never never statistically significant and these effects never exceed 0.001 in magnitude.

Second, we estimate the effects of the quality of workers in other randomly chosen four-digit occupation in the same firm. Consistent with our main results being genuine, we find (Panel E, Table 8) no evidence of peer effects across occupations within the same firm.

6.4 Peer Effects in Another Brazilian Local Labor Market: Florianopolis

Table E.1 replicates our main analysis conducted for São Paulo (presented in Table 5) using data from Florianopolis, the capital of the state of Santa Catalina, in the south of Brazil. São Paulo is the industrial hub in Brazil. Florianopolis is much smaller and is characterized by a dynamic service sector. It also has one of the most educated populations in Brazil. Among workers employed in the formal sector in São Paulo, 29% have a college degree, compared to 45% in Florianopolis. The results, reported in Appendix Table E.1 are broadly consistent with those obtained for São Paulo. We find significantly smaller peer effects on wages, possibly due to the more fragmented nature of production (YO ESTA FRASE NO LA ENTIENDO) in the service industries. As expected considering the higher share of college educated workers in Florianopolis, gender asymmetries are attenuated. However, it is still the case that same-gender peer effects are about 1.7 times larger than opposite-gender peer effects for men and women.

6.5 Monte Carlo Simulations

To achieve a $\sqrt{N}$ consistent and asymptotically normal estimator of peer effects for fixed T, it is necessary to assume that the residuals between any two observations are uncorrelated, as outlined in Theorem 1 in Arcidiacono et al. (2012). The presence of random shocks that affect workers in the same peer group would violate this assumption. Similarly, serial correlation in the individual error term would also violate this assumption.

To assess the extent of the bias associated with (i) peer group-specific shocks, and (ii) serial correlation in the individual error term, we conduct Monte-Carlo simulations. Additional details about the simulation can be found in Appendix D.

The results of these simulations are reported in Table E.2 in Appendix E. Biases are computed as the difference between the estimated effects and the coefficients assumed in the data generating process. The results suggest that a peer group-specific shock is associated with an upward bias of 0.003-0.008 when the variance of the peer-group shock as a share of the total error variance is assumed to be approximately equal to 3%. This bias is of a similar magnitude regardless of the assumed value of the true coefficients. When assuming that the peer-group specific shock as a share of the total error variance is 6%, the bias ranges between 0.009 and 0.016. However, this bias is small in comparison to the estimated peer effects we obtain, indicating that it is unlikely that our estimates are influenced by peer group-specific shocks that are not accounted for by firm and occupation time-variant fixed effects. Finally, the results presented in Table E.2 in Appendix E also suggest that serial correlation of a plausible magnitude is unlikely to significantly bias our estimates.

7 Conclusion

We present new evidence of strong gender asymmetries of peer effects at the workplace. Using longitudinal matched employer-employee Brazilian data, we find that the impact of same-gender peers' ability on focal workers' wages is about twice as large as the impact of their opposite-gender peers' ability for both female and male workers. This evidence supports the idea that gender identity norms also affect peer effects at the work place, as individual wages are more likely to be influenced by the ability of those peers whose gender identity they share. In line with this notion, we also find that, in contexts with arguably less traditional gender identity norms —such us in high skilled occupations or in firms with lower female-male wage gaps—, the estimated asymmetries between same-gender versus opposite-gender peer effects are attenuated.

Our results contribute to our understanding of the determinants of labor market gender inequalities and their persistence, as the strength of our estimated same-gender peer effects suggests that gender imbalances in the workplace may be exacerbated due to social multiplier effects on wages.

As argued by Arduini et al. (2020a,b), when peer effects are heterogeneous (the effects of all peers are not equal) and both within and between groups interactions are at work, it is crucial that policy makers account for peer effects heterogeneity when designing and evaluating policy interventions. For example, assuming a positive effect of an intervention, if it better targets one group than the other, one would expect an increase in outcome inequality between the two groups when within-group peer effects are high and between-group peer effects are low.

Let us consider, for example, the implication of our results for on-the-job training assignment. There is evidence that women are less likely to participate in on-the-job training than men (Altonji and Blank, 1999). Changes in worker productivity due to on-the-job training have been shown to affect the productivity of non-trained coworkers (Lindquist et al., 2015; De Grip and Sauermann, 2012). If there were no gender asymmetries in peer effects, this would imply that untrained women would benefit from their male co-workers' on-the-job training as much as untrained men. However, our results show that Brazilian women (men) are much more affected by the productivity of their female (male) co-workers' productivity than by that of their male (female) co-workers. Hence, the increase in the productivity of trained men will affect the productivity of untrained men more than the productivity of untrained women, potentially reinforcing the gender wage gap. In contrast, when men and women participate in on-the-job training equally, untrained male and female co-workers equally benefit from social-multiplier effects. Therefore, gender unequal assignment to on-the-job training could increase the gender wage gap not only directly but also indirectly.

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Appendix A Theoretical Model Derivations

Individual's production is given by

$$f_i = a_i + e_i + \epsilon_i \tag{A.1}$$

, where a_i is individual's ability, e_i is individual's effort, and ϵ_i is a random component of productivity independent of individual's ability and effort. We assume that individual's ability is continuous random variable such that $a_i \in [0, A]$ and it is distributed with probability density function (PDF) $h(a_i)$.

We assume that exerting effort is costly and that the cost function is quadratic and defined by the following equation:

$$C(e_i) = ce_i^2 \tag{A.2}$$

, where $c > 0$ is a scale parameter.

Peer pressure function is given by

$$P\Big(f_i, \mathbb{E}(f_{c_i}), \mathbb{E}(f_{\notin c_i})\Big) = (\eta + \eta_s)(\mathbb{E}(f_{c_i}) - f_i)^2 + \eta(\mathbb{E}(f_{\notin c_i}) - f_i)^2 \tag{A.3}$$

where $\mathbb{E}(f_{c_i})$ is the expected value of the production of workers who belong to the same social category as i and $\mathbb{E}(f_{\notin c_i})$ is the expected value of production of workers who belong to a different social category than i. We assume that there are two social categories, women and men, so that $c_i \in \{W, M\}$.

For instance, if i is a woman ($c_i = W$),

$$\mathbb{E}(f_{c_i}) = \mathbb{E}(f_W) = \mathbb{E}(a_W + e_W + \epsilon_W) = \mathbb{E}(a_W) + \mathbb{E}(e_W)$$

$$\mathbb{E}(f_{\notin c_i}) = \mathbb{E}(f_M) = \mathbb{E}(a_M + e_M + \epsilon_M) = \mathbb{E}(a_M) + \mathbb{E}(e_M)$$

The opposite holds when i is a man ($c_i = M$), $\mathbb{E}(f_{c_i}) = \mathbb{E}(f_M)$ and $\mathbb{E}(f_{\notin c_i}) = \mathbb{E}(f_M)$.

Individuals chose a level of effort that maximizes the difference between their wage, the costs, and the peer pressure. The problem can be written as following

$$Max_{e_i}\mathbb{E}\Big[b_{c_i}f_i - ce_i^2 - P\Big(f_i, \mathbb{E}(f_{c_i}), \mathbb{E}(f_{\notin c_i})\Big)\Big] \tag{A.4}$$

, where b_{c_i} is a wage rate that may also vary by social category. For instance, if there is a wage gender gap, $b_W < b_M$.

First order condition of this problem is

$$b_{c_i} - 2ce_i + 2(\eta + \eta_s)(\mathbb{E}(f_{c_i}) - f_i) + 2\eta(\mathbb{E}(f_{\notin c_i} - f_i) = 0 \tag{A.5}$$

Substituting $\mathbb{E}(f_{c_i}) = \mathbb{E}(a_{c_i}) + \mathbb{E}(e_{c_i})$ and $\mathbb{E}(f_{\notin c_i}) = \mathbb{E}(a_{\notin c_i}) + \mathbb{E}(e_{\notin c_i})$, we obtain:

$$e_i = \frac{\frac{b_{c_i}}{2} + (\eta + \eta_s)(\mathbb{E}(a_{c_i}) + \mathbb{E}(e_{c_i})) - (2\eta + \eta_s)a_i + \eta(\mathbb{E}(a_{\notin c_i}) + \mathbb{E}(e_{\notin c_i}))}{c + 2\eta + \eta_s} \tag{A.6}$$

Integrating e_i across individuals of social category c_i, we obtain

$$\mathbb{E}(e_{c_i}) = \frac{\frac{b_{c_i}}{2} + \eta(\mathbb{E}(e_{\notin c_i}) - \mathbb{E}(a_{c_i})) + \eta(\mathbb{E}e_{\notin c_i})}{c + \eta} \tag{A.7}$$

Similarly:

$$\mathbb{E}(e_{\notin c_i}) = \frac{\frac{b_{\notin c_i}}{2} + \eta(\mathbb{E}(a_{c_i}) - \mathbb{E}(a_{\notin c_i})) + \eta\mathbb{E}(e_{c_i})}{c + \eta} \tag{A.8}$$

Substituting (A.8) into (A.7), we obtain

$$\mathbb{E}(e_{c_i}) = \frac{(c+\eta)b_{c_i}}{2c(c+2\eta)} + \frac{\eta b_{\notin c_i}}{2c(c+2\eta)} + \frac{c\eta(\mathbb{E}(a_{c_i}) - \mathbb{E}(a_{\notin c_i}))}{c(c+2\eta)} \tag{A.9}$$

$$\mathbb{E}(e_{\notin c_i}) = \frac{(c+\eta)b_{\notin c_i}}{2c(c+2\eta)} + \frac{\eta b_{c_i}}{2c(c+2\eta)} + \frac{c\eta(\mathbb{E}(a_{\notin c_i}) - \mathbb{E}(a_{c_i}))}{c(c+2\eta)} \tag{A.10}$$

Substituting (A.9) and (A.10) into (A.6), effort function can be written as

$$e_i = \alpha a_i + \rho_s b_{c_i} + \rho_o b_{\notin c_i} + \theta_s \mathbb{E}(a_{c_i}) + \theta_o \mathbb{E}(a_{\notin c_i}) \quad \text{(A.11)}$$

, where $\alpha = \frac{-(2\eta+\eta_s)}{c+2\eta+\eta_s}$, $\theta_o = \frac{\eta}{c+2\eta}$, $\theta_s = \frac{(\eta+\eta_s)(c+\eta)+\eta^2}{(c+2\eta)(c+2\eta+\eta_s)}$, $\rho_s = \frac{\eta+c}{2c(c+2\eta)}$, $\rho_o = \frac{\eta}{2c(c+2\eta)}$.

Appendix B Empirical model without gender asymmetries

We estimate the following wage equation without gender asymmetries:

$$Y_{itoj} = a_i + \gamma \bar{a}_{\sim itoj} + \mu_{ot} + \rho_{jt} + \delta_{oj} + \varphi X'_{it} + v_{itoj} \quad \text{(B.12)}$$

, where Y_{itoj} is the wage of individual i at time t in firm j, and occupation o. Worker fixed effects are denoted by a_i, and $\bar{a}_{\sim itoj}$ is the average of worker fixed effects in worker i's peer group (computed excluding worker i). In what follows, we will refer to a_i as worker i's ability, quality, or the permanent component of worker i's productivity interchangeably. Analogously, $\bar{a}_{\sim itoj}$ denotes the average ability or quality of worker i's peers. Finally, X'_{it} is a vector of individual time-variant controls that include quadratic forms of age and firm tenure (number of months individual i had been working in the same firm j by period t). The parameter of interest is γ, which measures the effect of peer ability on wages. Equation (B.12) also includes time-specific occupation and firm fixed effects (μ_{ot} and ρ_{jt}, respectively), as well as occupation-firm fixed effects denoted by δ_{oj}.

To estimate equation (B.12) with unobserved a_i and $\bar{a}_{\sim itoj}$, we apply the iterative algorithm proposed by Arcidiacono et al. (2012) to estimate spillover effects using panel data. This iterative algorithm estimates γ by minimizing the following sum of squared residuals:

$$\min_{a,\gamma,\rho,\delta,\mu} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(Y_{itoj} - a_i - \gamma \bar{a}_{\sim i,toj} - \mu_{ot} - \rho_{jt} - \delta_{oj} - \varphi X'_{itoj} \right)^2 \quad \text{(B.13)}$$

Solving the first order condition of (B.13) for a_i yields:

$$a_i = \frac{1}{T + \sum_t \frac{\gamma^2}{P_{tn}}} \sum_t \left[\tilde{Y}_{itoj} - \frac{\gamma}{P_{tn}} \sum_{j \in \mathbb{P}_{tn \sim i}} a_j + \sum_{j \in \mathbb{P}_{tn \sim i}} \frac{\gamma}{P_{tn}} \left(\tilde{Y}_{itoj} - a_j - \frac{\gamma}{P_{tn}} \sum_{k \in \mathbb{P}_{tm} i \sim j} a_k \right) \right] \tag{B.14}$$

, where $\tilde{Y}_{itoj} = Y_{itoj} - \mu_{ot} - \rho_{jt} - \delta_{oj} - \varphi X'_{itoj}$, $\mathbb{P}_{tn}$ is the set of individuals in peer group n at time t, and $P_{tn} + 1$ denotes the number of individuals in peer group n at time t.

The algorithm proceeds as follows:

1. Set an initial guess for the vector of fixed effects (a) a^0.
2. Conditional on a^0, compute $\bar{a}^0_{\sim itoj}$ and estimate γ^0 and the rest of the parameters (μ_{ot}, ρ_{jt},δ_{oj},φ) by OLS.
3. Update a^1 according to equation (B.14).
4. Iterate steps 2 and 3 until convergence of γ is achieved.

Convergence is achieved if the sum of squared residuals diminishes with every iteration, which requires the right-hand side of (B.14) to be a contraction mapping. As it is shown in Theorem 2 of Arcidiacono et al. (2012), it is a contraction mapping if $\gamma \leq 0.4$, that is, if the peer effect is not too large.

Appendix C Proof of Theorem 2

Let us start with specifying the first-order condition for a_i for females and males separately. $\mathbf{M}_{nt}$ and $\mathbf{F}_{nt}$ denote the sets of male and female peer group n in period t members respectively. M_{tn} and F_{tn} denote the number of male and female peer group n in period t members respectively.

FOC for females :

$$\sum_{t=1}^{T}\left(Y_{itp}-a_i-\frac{\alpha_1}{F_{tn}-1}\sum_{f\in\mathbf{F}_{nt\sim i}}a_f-\frac{\beta_1}{M_{tn}}\sum_{m\in\mathbf{M}_{nt}}a_m\right)+$$
$$\sum_{t=1}^{T}\sum_{f\in\mathbf{F}_{nt\sim i}}\frac{\alpha_1}{F_{tn}-1}\left(Y_{ftn}-a_f-\frac{\alpha_1}{F_{tn}-1}(\sum_{l\in\mathbf{F}_{nt\sim i\sim f}}a_l+ai)-\frac{\beta_1}{M_{tn}}\sum_{m\in\mathbf{M}_{nt}}a_m\right)+ \tag{C.15}$$
$$\sum_{t=1}^{T}\sum_{m\in\mathbf{M}_{nt}}\frac{\alpha_2}{F_{tn}}\left(Y_{mtn}-a_m-\frac{\alpha_2}{F_{tn}}(\sum_{k\in\mathbf{F}_{nt\sim i}}a_k+ai)-\frac{\beta_2}{M_{tn}-1}\sum_{j\in\mathbf{M}_{nt}\sim m}a_j\right)=0$$

FOC for males :

$$\sum_{t=1}^{T}\left(Y_{itp}-a_i-\frac{\alpha_2}{F_{tn}}\sum_{f\in\mathbf{F}_{nt}}a_f-\frac{\beta_2}{M_{tn}}\sum_{m\in\mathbf{M}_{nt\sim i}}a_m\right)+$$
$$\sum_{t=1}^{T}\sum_{f\in\mathbf{F}_{nt}}\frac{\beta_1}{M_{tn}}\left(Y_{ftn}-a_f-\frac{\alpha_1}{F_{tn}-1}\sum_{l\in\mathbf{F}_{nt\sim f}}a_l-\frac{\beta_1}{M_{tn}}(\sum_{m\in\mathbf{M}_{nt\sim i}}a_m+a_i)\right)+ \tag{C.16}$$
$$\sum_{t=1}^{T}\sum_{m\in\mathbf{M}_{nt\sim i}}\frac{\beta_2}{M_{tn}-1}\left(Y_{mtn}-a_m-\frac{\alpha_2}{F_{tn}}\sum_{k\in\mathbf{F}_{nt}}a_k-\frac{\beta_2}{M_{tn}-1}(\sum_{j\in\mathbf{M}_{nt}\sim m\sim i}a_j+a_i)\right)=0$$

Solving for a_i and collecting terms we have

For females

$$a_i=\sum_{t=1}^{T}\left[\left(Y_{itp}-\frac{\alpha_1}{F_{tn}-1}\sum_{f\in\mathbf{F}_{nt\sim i}}a_f-\frac{\beta_1}{M_{tn}}\sum_{m\in\mathbf{M}_{nt}}a_m\right)+\right.$$
$$\sum_{f\in\mathbf{F}_{nt\sim i}}\frac{\alpha_1}{F_{tn}-1}\left(Y_{ftn}-a_f-\frac{\alpha_1}{F_{tn}-1}\sum_{l\in\mathbf{F}_{nt\sim i\sim f}}a_l-\frac{\beta_1}{M_{tn}}\sum_{m\in\mathbf{M}_{nt}}a_m\right)+ \tag{C.17}$$
$$\left.\sum_{m\in\mathbf{M}_{nt}}\frac{\alpha_2}{F_{tn}}\left(Y_{mtn}-a_m-\frac{\alpha_2}{F_{tn}}\sum_{k\in\mathbf{F}_{nt\sim i}}a_k-\frac{\beta_2}{M_{tn}-1}\sum_{j\in\mathbf{M}_{nt}\sim m}a_j\right)\right]/Den_{fn}$$

where $Den_{fn}=\sum_{t=1}^{T}\left(1+\frac{\alpha_1^2}{F_{nt}-1}+\frac{M_{nt}\alpha_2^2}{F_{nt}^2}\right)$

For males

$$
\begin{aligned}
a_i = \sum_{t=1}^{T} \Bigg[\left(Y_{itp} - \frac{\alpha_2}{F_{tn}} \sum_{f \in \mathbf{F}_{nt}} a_f - \frac{\beta_2}{M_{tn}} \sum_{m \in \mathbf{M}_{nt \sim i}} a_m \right) + \\
\sum_{f \in \mathbf{F}_{nt}} \frac{\beta_1}{M_{tn}} \left(Y_{ftn} - a_f - \frac{\alpha_1}{F_{tn}-1} \sum_{l \in \mathbf{F}_{nt \sim f}} a_l - \frac{\beta_1}{M_{tn}} \sum_{m \in \mathbf{M}_{nt \sim i}} a_m \right) + \\
\sum_{t=1}^{T} \sum_{m \in \mathbf{M}_{nt \sim i}} \frac{\beta_2}{M_{tn}-1} \left(Y_{mtn} - a_m - \frac{\alpha_2}{F_{tn}} \sum_{k \in \mathbf{F}_{nt}} a_k - \frac{\beta_2}{M_{tn}-1} \sum_{j \in \mathbf{M}_{nt} \sim m \sim i} a_j \right) \Bigg] / Den_{mn}
\end{aligned}
\tag{C.18}
$$

where $Den_{mn} = \sum_{t=1}^{T} \left(1 + \frac{\beta_1^2 F_{nt}}{M_{nt}^2} + \frac{\beta_2^2}{M_{nt}^2}\right)$

The iterative method starts at making a first guess about vector a, using this first guess we then generate OLS estimates of the parameters of the model. Then these estimates are plugged into the RHS of the FOC and a_i are updates accordingly. Following Arcidiacono et al. (2012), let us call the first guess a and the next guess a'. We next show that the mapping function $f : a \to a'$ provided by equations (C.17) and (C.18) is a contraction mapping. That is, $d(f(a), f(a')) < \beta d(a, a')$ for some $\beta < 1$, where d is a valid distance function. We use an Euclidian distance function for d to show the conditions under which f is a contraction mapping for some $\beta < 1$. Let us define $\tilde{a} = a - a'$. Summing up (C.17) and (C.18) into one vector, we can write the condition as follows

$$
\begin{aligned}
\Bigg[\sum_{i=1}^{N_f} \left(- \sum_{t=1}^{T} (\gamma_{1nt} \sum_{f \in \mathbf{F}_{nt \sim i}} \tilde{a}_f + \delta_{nt} \sum_{m \in \mathbf{M}_{nt}} \tilde{a}_m) / Den_{fn} \right)^2 + \\
\sum_{i=1}^{N_m} \left(- \sum_{t=1}^{T} (\delta_{nt} \sum_{f \in \mathbf{F}_{nt}} \tilde{a}_f + \gamma_{2nt} \sum_{m \in \mathbf{M}_{nt\,\sin i}} \tilde{a}_m) / Den_{mn} \right)^2 \Bigg]^{1/2} < \\
\beta \left(\sum_{i=1}^{N_f} \tilde{a}_i^{\,2} + \sum_{j=1}^{N_m} \tilde{a}_j^{\,2} \right)^{1/2}
\end{aligned}
\tag{C.19}
$$

where N_f refers to the total female population and N_m to the total male population and

$\gamma_{1nt} = \frac{2\alpha_1}{F_{nt}-1} + \frac{\alpha_1^2(F_{nt}-2)}{(F_{nt}-1)^2} + \frac{\alpha_2^2 M_{nt}}{F_{nt}^2};$
$\gamma_{2nt} = \frac{2\beta_2}{M_{nt}-1} + \frac{\beta_2^2(M_{nt}-2)}{(M_{nt}-1)^2} + \frac{\beta_1^2 F_{nt}}{M_{nt}^2};$
$\delta_{nt} = \frac{\beta_1}{M_{nt}(1+\alpha_1} + \frac{\alpha_2}{F_{nt}}(1+\beta_2).$

Next we simplify this inequality using Cauchy-Schwarz Inequality (CSI). Note that this transformation increases the LHS making it less likely that the inequality is satisfied.

$$\left[\sum_{i=1}^{N_f}\sum_{t=1}^{T} T\left(\gamma_{1nt}\sum_{f\in\mathbf{F}_{nt\sim i}}\tilde{a}_f + \delta_{nt}\sum_{m\in\mathbf{M}_{nt}}\tilde{a}_m\right)^2 / Den_{fn}^2 + \sum_{i=1}^{N_m}\sum_{t=1}^{T} T\left(\delta_{nt}\sum_{f\in\mathbf{F}_{nt}}\tilde{a}_f + \gamma_{2nt}\sum_{m\in\mathbf{M}_{nt\,\sin i}}\tilde{a}_m\right)^2 / Den_{mn}^2\right]^{1/2} < \beta\left(\sum_{i=1}^{N_f}\tilde{a}_i^2 + \sum_{j=1}^{N_m}\tilde{a}_j^2\right)^{1/2} \tag{C.20}$$

Applying CSI again yields

$$\left[\sum_{i=1}^{N_f}\sum_{t=1}^{T} T\left(\frac{\gamma_{1nt}^2+\delta_{nt}^2}{Den_{fn}^2}\right)\left((\sum_{f\in\mathbf{F}_{nt\sim i}}\tilde{a}_f)^2 + (\sum_{m\in\mathbf{M}_{nt}}\tilde{a}_m)^2\right) + \sum_{i=1}^{N_m}\sum_{t=1}^{T} T\left(\frac{\gamma_{2nt}^2+\delta_{nt}^2}{Den_{mn}^2}\right)\left((\sum_{f\in\mathbf{F}_{nt}}\tilde{a}_f)^2 + (\sum_{m\in\mathbf{M}_{nt\sim i}}\tilde{a}_m)^2\right)\right]^{1/2} < \beta\left(\sum_{i=1}^{N_f}\tilde{a}_i^2 + \sum_{j=1}^{N_m}\tilde{a}_j^2\right)^{1/2} \tag{C.21}$$

Expanding the square of the sum of $\tilde{a}_i$'s and applying CSI

$$\left[\sum_{i=1}^{N_f}\sum_{t=1}^{T} T\left(\frac{\gamma_{1nt}^2+\delta_{nt}^2}{Den_{fn}^2}\right)\left((F_{nt}-1)\sum_{f\in\mathbf{F}_{nt\sim i}}\tilde{a}_f^2 + M_{nt}\sum_{m\in\mathbf{M}_{nt}}\tilde{a}_m^2\right) + \sum_{i=1}^{N_m}\sum_{t=1}^{T} T\left(\frac{\gamma_{2nt}^2+\delta_{nt}^2}{Den_{mn}^2}\right)\left(F_{nt}\sum_{f\in\mathbf{F}_{nt}}\tilde{a}_f^2 + (M_{nt}-1)\sum_{m\in\mathbf{M}_{nt\sim i}}\tilde{a}_m^2\right)\right]^{1/2} < \beta\left(\sum_{i=1}^{N_f}\tilde{a}_i^2 + \sum_{j=1}^{N_m}\tilde{a}_j^2\right)^{1/2} \tag{C.22}$$

Since the terms γ_{2nt}, γ_{2nt}, δ_{nt}, Den_{fn}, Den_{mn}, F_{nt} and M_{nt} reflect differences in peer group sizes experienced by individual i over time, all the terms on the left hand side will have different multipliers. To address this issue, we substitute all the terms in the numerator (γ_{2nt}, γ_{2nt}, δ_{nt}, F_{nt} and M_{nt}) by it maximum values (denoted by γ_1, γ_2, δ, M and F) and all the terms in denominator (Den_{mn}, Den_{fn}) by its minimum values (denoted by Den_m, Den_f). Note that this transformation is valid since it will strictly increase the LHS making it less likely that the inequality is satisfied.

This transformation leaves us with

$$\left[\sum_{i=1}^{N_f} T^2 \left(\frac{\gamma_1^2+\delta^2}{Den_f^2}(F-1)^2 + \frac{\gamma_2^2+\delta^2}{Den_m^2}FM\right)\tilde{a}_i^2 + \sum_{i=1}^{N_m} T^2 \left(\frac{\gamma_2^2+\delta^2}{Den_m^2}(M-1)^2 + \frac{\gamma_1^2+\delta^2}{Den_f^2}FM\right)\tilde{a}_i^2\right]^{1/2} < \beta \left(\sum_{i=1}^{N_f} \tilde{a}_i{}^2 + \sum_{j=1}^{N_m} \tilde{a}_j{}^2\right)^{1/2} \tag{C.23}$$

Finally, replacing F and M by its maximum value denoted by G and replacing (G-1) by G we arrive to the common multiplier

$$T\left[\left(\frac{\gamma_1^2+\delta^2}{Den_f^2}G^2 + \frac{\gamma_2^2+\delta^2}{Den_m^2}G^2\right)\right]^{1/2} \left(\sum_{i=1}^{N_f} \tilde{a}_i{}^2 + \sum_{j=1}^{N_m} \tilde{a}_j{}^2\right)^{1/2} < \beta \left(\sum_{i=1}^{N_f} \tilde{a}_i{}^2 + \sum_{j=1}^{N_m} \tilde{a}_j{}^2\right)^{1/2} \tag{C.24}$$

Now we need to show for which values of parameters

$T\left[\left(\frac{\gamma_1^2+\delta^2}{Den_f^2}G^2 + \frac{\gamma_2^2+\delta^2}{Den_m^2}G^2\right)\right]^{1/2} < 1$

Next it can be shown that $\frac{T}{Den_{fn}}$ and $\frac{T}{Den_{mn}}$ are always lower or equal that 1. Therefore we need to show that $(G\gamma_1)^2 + 2(G\delta)^2 + (G\gamma_2)^2 < 1$. Substituting G in equations for γ_1, γ_2 and δ we obtain the following inequality:

$$\begin{gathered}\left(2\alpha_1 + \alpha_1^2(G-2)G/(G-1)^2 + \alpha_2^2\right)^2 + \\ \left(2\beta_2 + \beta_2^2(G-2)G/(G-1)^2 + \beta_1^2\right)^2 + \\ 2\left(\beta_1(1+\alpha_1) + \alpha_2(1+\beta_2)\right)^2 < 1\end{gathered} \tag{C.25}$$

Now we replace $(G-2)G/(G-1)^2$ by $G/(G-1)$ which increases the LHS making it less likely to hold. Since the maximum value of $G/(G-1)$ for $G \geq 2$ is 2, we can replace $(G-2)G/(G-1)^2$ by 2. We end up with the following condition for the parameters

$$\left(2\alpha_1 + 2\alpha_1^2 + \alpha_2^2\right)^2 + \left(2\beta_2 + 2\beta_2^2 + \beta_1^2\right)^2 + 2\left(\beta_1(1+\alpha_1) + \alpha_2(1+\beta_2)\right)^2 < 1 \tag{C.26}$$

It can be shown that the inequality will be satisfied when all the coefficients are below 0.2.[14]

Appendix D Monte Carlo Simulations

In order to assess the magnitude of the bias associated with (i) peer group specific shocks, and (ii) serial correlation in the individual error term, we conduct Monte-Carlo simulations. We simulate the dependent variable as follows:

- Predict log wages in our estimation sample using the coefficients of the control variables and the fixed effects obtained when estimating our baseline model. We consider several scenarios regarding the magnitude of peer effects:
    1. Peer effects are equal to zero.
    2. Same-gender and opposite gender peer effects are both equal to 0.05.
    3. The effect of same-gender peers is equal to 0.1 and the effect of opposite-gender peers is equal to 0.05.
    4. Same-gender and opposite gender peer effects are similar to our baseline estimates: the effect of same-gender peers is equal to 0.15 and the effect of opposite-gender peers is equal to 0.07.
- Simulate peer-group specific shocks as normally distributed errors composed of an idiosyncratic component and a peer-group specific component. We consider the following scenarios:
    1. No peer-group specific component.
    2. The variance of the peer-group shock as a share of the total error variance is equal to 0.0267, which is the R^2 of the regression of the residuals from our main specification on peer group fixed effects.

[14] This can be shown assuming that $\alpha_1 = \alpha_2 = \beta_1 = \beta_2 = x$ and solving the inequality for x.

3. The variance of the peer-group shock as a share of the total variance is 0.06, which is the value considered in Cornelissen et al. (2017).

- Simulations of serially correlated errors. We add a normally distributed error term with variance equal to the estimated error variance from the baseline model. We also assume first-order serial correlation in the error term with an autocorrelation coefficient equal to 0.34, which is the value obtained when regressing the residuals from our baseline model on its lagged value.
- For each type of error we run 5 simulations. Therefore, we have a total of 80 simulated dependent variables (4 peer effect coefficients $\times$ 4 errors $\times$ 5 simulations).
- We then estimate our main specification for each simulated dependent variable and compute average peer effect coefficients over 5 simulations.

Appendix E Tables and Figures

Table E.1: Gender Asymmetries in Peer Effects on Wages in Florianopolis

The effect on	(1) Males		(2) Females
Male peers' average ability	0.059		0.032
	(0.010)		(0.011)
Female peers' average ability	0.042		0.071
	(0.011)		(0.009)
$\hat{\hat{\eta}}_s$		0.028	
		(0.007)	
N	230,252		245,229
Worker FE	yes		yes
Occuation-year FE	yes		yes
Occupation-firm FE	yes		yes
Firm-year FE	yes		yes

Note: The Table reports the estimated effect of same-gender and opposite-gender peers' average quality on individual log wages (see equation (12)) by gender. $\hat{\hat{\eta}}_s$ is computed according to equation (11). All specifications control for quadratic forms of age and firm tenure. Bootstrapped standard errors clustered at the firm level are displayed in parentheses.

Table E.2: Monte-Carlo Simulations

	Females on females	Males on female	Females on males	Males on males
	Panel A			
True effect	0.000	0.000	0.000	0.000
i.i.d	0.000	0.000	0.000	0.000
Peer group shock (3%)	0.005	0.006	0.007	0.005
Peer group shock (6%)	0.011	0.012	0.014	0.010
Serial correlation ($\rho = 0.34$)	0.001	0.000	0.000	0.000
	Panel B			
True effect	0.050	0.050	0.050	0.050
i.i.d.	0.048	0.049	0.049	0.048
Peer group shock (3%)	0.055	0.056	0.057	0.054
Peer group shock (6%)	0.061	0.063	0.065	0.060
Serial correlation ($\rho = 0.34$)	0.049	0.048	0.049	0.049
	Panel C			
True effect	0.100	0.050	0.050	0.100
i.i.d.	0.097	0.049	0.049	0.097
Peer group shock (3%)	0.105	0.056	0.057	0.104
Peer group shock (6%)	0.111	0.064	0.066	0.109
Serial correlation ($\rho = 0.34$)	0.098	0.049	0.049	0.097
	Panel D			
True effect	0.150	0.070	0.070	0.150
i.i.d.	0.145	0.069	0.068	0.146
Peer group shock (3%)	0.154	0.077	0.078	0.153
Peer group shock (6%)	0.161	0.084	0.086	0.159
Serial correlation ($\rho = 0.34$)	0.146	0.069	0.069	0.146

Note: The Table reports the results of Monte-Carlo similations. The data generation process (DGP) is described in section D. Row "True Coefficient" reports the peer effects coefficients by the DGP. Row "i.i.d." reports simulation results when the errors are assumed to be *iid* normally distributed and the variance of the errors is equal to the variance of the residuals from our main specification given by equation (12). Rows "Peer group shock (3%)" and "Peer group shock (6%)" simulation results when peer group specific shocks constitute 3% and 6% of the total error variance, respectively. Row "Serial correlation ($\rho = 0.34$)" reports simulation results when the errors are generated as first-order serially correlated with an autocorrelation coefficient equal to 0.34. Each coefficient is computed as the average coefficient obtained in 5 simulations.