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The Intersection of Organizational Inequalities

How Gender, Migrant Status, and Class Inequality Relate to Each Other in French workplaces

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Introduction

Social stratification scholars have long centered their analyses around social class, gender and race/ethnicity. Yet, too often, these forms of inequality are addressed separately. Intersectional approaches have called attention to the way inequalities overlap and interact (Browne and Misra 2003; Cho, Crenshaw, and McCall 2013; McCall 2001). In most quantitative studies, intersectionality is implemented through the introduction of interaction terms between different individual variables such as gender, race, migration status and occupation. The interaction-terms approach nonetheless tends to overlook the workplace heterogeneity in the making of inequality (Baron and Bielby 1980; Tomaskovic-Devey and Avent-Holt 2019). As Acker (2006) famously argued, organizations are unique "inequality regimes". The flourishing relational inequality literature builds on Acker's influential insight to document how firms vary substantially in the way they produce categorical inequalities such as migrant status/ethnic/racial/gender wage gaps (Stainback, Ratliff, and Roscigno 2011; Stainback, Tomaskovic-Devey, and Skaggs 2010; Tomaskovic-Devey, Hällsten, and Avent-Holt 2015; Williams and O'Reilly III 1998).

While relational inequality research made it clear that workplaces may be more or less equal across different dimensions, it did not systematically investigate the relations between these organizational-level inequalities. More precisely, this literature provides little insights on whether we should expect inequalities along various dimensions to *reinforce* each other or whether there are *tradeoffs* between them. This article aims at bridging this gap by investigating *how different types of inequalities relate to one another in workplace organizations.*

Our approach stands not only to clarify a central sociological concept (*inequality regimes*) but also to open space for its empirical investigation. We do so using French administration data from 1996 to 2016. This data allows us to scrutinize the correlations between three dimensions of wage inequality measured at the workplace level: class, gender and nativity. We also study how each of these categorical inequality relates to a fourth measure of within-workplace inequality we call intra-categorical. Intra-categorical inequality refers to inequality within the three-level cross-categorization class×gender×nativity. From a methodological point of view, we show how exploring patterns of correlation between different inequality measures within organizations is challenging because of the numerous biases related to the overlapping of categories. Moreover, we discuss and implement solutions to circumvent these problems.

Finally, and beyond the multidimensional description of within-workplace inequality, this research also seeks to document how different mechanisms involved in the (re)production of inequality combine in shaping local inequality regimes. Indeed, the four measures of wage gap we use pertain to different dimensions of inequality (Brubaker 2015; Tilly 1998). Three of them are categorical (class, gender and nativity). We also use a gradient-type measure of inequality within categorical distinctions, or in other words an indicator of inequality beyond categorical distinctions, that we call intra-categorical inequality. Moreover, beyond the categorical/continuous distinction, these four indicators also vary in the degree to which they are embedded in specific labor market mechanisms. Gender and nativity are largely exogenous to the workplace. They are mostly (re)produced in spheres and interactions outside the labor market (e.g. in families, neighborhoods, state legislation and administrative processes, etc.). Conversely, class-based inequality (that we measure through wage gap across broad occupational distinctions) and intra-categorical inequality (that we measure within class×gender×nativity cross-categorization) are largely endogenous to the labor market. Employees are channeled into occupational positions through a complex process of division of labor based, at least partly, on human capital and other productivity-related characteristics (Treiman 2013). This organizational hierarchy translates into a wage hierarchy (Hedström 1991), yet in variable ways across workplaces depending on market mechanisms and human resources procedures and policies. Similarly, workplaces may produce disparate levels of inequality within cross-categorical distinctions depending on "local inequality cultures" (i.e preferences and beliefs in regard the pros or cons of an unequal wage distribution) (Milgrom and Roberts 1988) or on firm-specific returns of individuals characteristics others than class, gender or nativity (soft skills, creativity, organization, autonomy, charisma, etc.). Estimating the correlations between our four measures of wage inequalities at the workplace level consequently enables us to delineate the articulation, within organizations, of (largely) exogenous inequalities (gender and nativity), with (largely) endogenous inequalities (class and intra-categorical inequality). Moreover, documenting the existence of *reinforced inequality regimes or inequality trade-off regimes* within organizations helps us progress in understanding the role of categorical inequality in shaping unequal outcomes in goal-oriented contexts such as workplaces. A positive correlation between categorical inequalities suggests similar underlying processes at play in their importing to the workplace: salient categorical distinctions are readily available to produce inequality within organizations. Conversely, the absence of correlation, or possibly a negative one, suggests the existence of specific mechanisms in the workplace-making of categorical inequality.

After a brief review of the relevant literature, our empirical analysis proceeds in three steps. First, we examine wage gaps by different "intersecting" social positions using interactions effects at the individual level. Second, we shift the lens to the organizational level by analyzing correlations between inequalities within workplaces. This section includes a discussion on related methodological issues. Third, we ask how industry, urban environment, and various workplace characteristics affect these patterns. We find evidence for both reinforcing and inequality trade-off regimes. More specifically, gender and nativity wage gaps are negatively correlated pointing to a trade-off between these categorical inequalities. At the same time, the gender gap is higher in more intra-categorically unequal workplaces, the nativity gap is higher in more intra-categorically equal workplaces. In the conclusion, we discuss mechanisms underlying our findings and their implications for future research.

Bridging Multidimensional Forms of Inequality within Organizations

The class/gender/race trio serves as a basis for thinking about inequality in most contemporary societies. Intersectional scholars have called for studying these forms of inequality together (Cho et al. 2013; McCall 2001, 2005). This perspective is geared towards understanding the constructed (and contested) nature of these categories. It also more broadly calls attention to the overlapping nature of inequality types and the need to simultaneously consider their impact on subjective micro-experiences. Despite epistemological differences, quantitative scholars have contributed to this research agenda. For example, Mandel and Semyonov (2016), and Restifo and Mykyta (2019) decomposed their samples by racial and gendered pairings or interacted these together to estimate wages or wage gaps. Cotter, Hermsen and Vanneman (1999) compared the likelihood that black, Hispanic, and Asian women would approach the different earnings thresholds of white male earnings – their baseline estimate. Studying the overlap of inequalities with interactions in a regression, Greenman and Xie (2008) invalidate the "double jeopardy" hypothesis for minority females. In contrast, they show that the racial/ethnic wage penalty is smaller for women than men.

Research in this vein illuminates how categories combine in shaping individual outcomes, but an equally important element in this discussion is *where* inequality is generated. Research increasingly recognizes organizations as the main locus for inequality. Following classic insights from Acker (2006) and Baron and Bielby (1980), relational inequality scholars argue that workplaces are sites where individual skills, agency, and boundary-making processes interfere with organizational dynamics like discrimination, wage-setting, promotions, demotions, control over profits and managerial power. They have observed, for example, a high degree of organizational heterogeneity by categorical distinctions like race, migration status, gender, and class in a number of different countries (Avent-Holt and Tomaskovic-Devey 2012; Melzer et al. 2018; Tomaskovic-Devey et al. 2020). Most of this work has investigated the distribution of wage inequality across workplaces or focused on particular types of categorical distinctions such as nativity, race, gender, etc. This research has not yet considered how these different types of inequality relate to each other within the workplace.

Addressing this question is important not only because less attention has been paid to how different forms of inequality connect but also because this allows us to see the mechanisms of inequality in a new light. Empirical research drawing on relational inequality theory has been agnostic to whether inequalities cluster together. More fundamentally, both the organizational and intersectional approaches to inequality are not clear about whether we should expect workplaces to be consistently equal (or unequal) on different dimensions of inequality. This research gap is our point of departure in this article.

Two Types of Inequality Regimes

When studying correlations between different dimensions of inequality within workplaces one may differentiate between two ideal-typical situations. First, *a reinforced inequality regime* in which two forms of inequality are positively related to each other. Second, a *trade-off inequality regime* in which two forms of inequality are negatively associated with each other.

Beginning with a reinforced inequality regime, studies show that organizations range from being relatively authoritarian to relatively egalitarian (Roscigno, Hodson, and Lopez 2009). These environments may condition different patterns of inequality. On the more unequal side, for example, Castilla (2008) found similar mechanisms for sex-based discrimination as for race-based discrimination. High inequality environments tend to go hand in hand with multiple forms of disadvantage by race, nativity and gender. For example, nativity gaps were higher in Swedish firms with higher levels of inequality (Tomaskovic-Devey, Hällsten, et al. 2015). The motherhood penalty was larger in these workplaces as well. From a more egalitarian perspective, Kalev (2009) found that when job segregation became more porous through team-based organization, minorities and women were both able to advance in the firm. Tomaskovic-Devey and Avent-Holt summarize this reinforcing dynamic, noting that "when social distinctions of class and citizenship reinforce each other, they exaggerate categorical distinctions, which in turn legitimates exploitation" (2019, p. 121). The reinforcing inequality regime may also be interpreted in a cultural vein: high overall inequality in workplaces fosters the legitimation and acceptance of different forms of inequality within them.

Conversely, inequality types can move in opposite directions pointing to an "inequality trade off" regime. Classic stratification theory, for example, argues that labor markets are often "split" by categorical attributes such as citizenship, ethnoracial status and gender (Bonacich 1972; Doeringer and Piore 1971). This dynamic creates antagonistic work relations, which tends to shift the distribution of resources in favor of the most powerful categories and at the detriment of the most vulnerable ones. Some research indeed documents how groups can mobilize within the workplace to preserve advantages for themselves at the expense of other groups (DiTomaso 2013). For instance, U.S conservative trade unions (e.g. the American Federation of Labor) created lower class-based inequality through collective bargaining while preserving high levels of racial inequality by excluding non-white workers (Arnesen 1998).

Inequality in France

Our study focuses on France. In France, wage inequalities by class, gender, and nativity are well established in empirical research. French labor markets are marked by low union density and increasing labor market flexibility (Amable 2017). Unlike many other countries, wage inequality is relatively stable (Charnoz, Coudin, and Gaini 2011). This is important because France is comparatively less extreme by wage inequality and our results may be more conservative.

France also has a pronounced gender wage gap though one that is slowly declining (Chamkhi and Toutlemonde 2015; Meurs and Pora 2019). In addition to occupational segregation, sorting into firms is a key explanation to the French gender gap (Coudin, Maillard, and Tô 2018). Finally, France has a long history of immigration. The migrant labor force is quite diverse in terms of origin as well as skill (Beauchemin, Hamel, and Simon 2015; Ichou and Goujon 2017). Moreover, there is substantial discrimination for many minority groups – particularly those with North and Sub-Saharan African origin (Quillian et al. 2019; Safi and Simon 2013).

These forms of inequalities in France share connections with each other. The migrant wage gap, for example, is likely connected to the class gap insofar as the migrant labor force is quite bifurcated by skill. Moreover, many lower skilled migrants are increasingly reliant on short-term contracts and other "outsider" employment schemes that put wage and employment pressure on natives. There are also many complex interactions between migration and gender in the French labor market (Safi 2020). For example, female migrants lower the overall female wage share for those in the same skill set (Edo and Toubal 2017). More broadly, the political histories of each type of inequality are highly distinct and could lead to different labor market outcomes. Most importantly, gender equality policies are widely recognized by employers and quite institutionalized. By contrast, similar policies for migrants or even public discussion on migrant workplace rights are relatively scarce and silenced by durable institutional colorblindness (Simon 2008).

Data

We use administrative data from the *Déclarations Annuelles des Données Sociales* (DADS) [1] – a database administered by France's national statistics agency (INSEE). DADS covers all private sector establishments as well as local civil services and public hospitals. [2]Any establishment employing workers is legally mandated to file it each year. DADS contains an exhaustive series with detailed wage and occupation information for all private sector workers in all French regions from 1994 to 2016. We use the log of gross hourly wages in the analyses below. Because the yearly number of hours worked is less reliable for years 1994 and 1995, we begin our analysis in 1996. Our sample includes all prime age (25-55) French employees in the private sector and semi-public sector (i.e. hospital and local civil services) who earn at least half a yearly minimum wage. We thus consider between 13.4 million (in 1996) and 16.3 million (in 2016) employees (Table A1). Finally, because we wish to compute wage gaps at the establishment-level across different categorical positions, it is important for our sample to be consistent across our estimates. We therefore limit the analyses to those establishments with more than 50 employees and those with at least two members of every social category relevant to this study. That is, establishments with at least two female managers/professionals (and workers), two male managers/professionals (and workers), two migrant managers/professionals (and workers), two non-migrant managers/professionals (and workers), two female migrants (and non-migrants), and two male migrants (and non-migrants). In the Appendix, we compare the sample before and after making these changes (Table A1). Despite the sample sizes dropping significantly to accommodate multiple wage gaps, our sample remains representative of the overall French labor market.

We use the DADS data to measure our three categorical inequalities. For class distinction, we follow classic approaches which make distinctions by workplace authority and ownership (Wright 1997) as well as social prestige conferred through education and related forms of closure (Weeden 2002; Weeden and Grusky 2012). We therefore use *aggregated* occupational groups to distinguish between those with workplace authority (managers) and social prestige (professionals) and everyone else (workers). Therefore, while occupational categories are embedded in the class positions, the class positions remain empirically and theoretically distinct from an approach in terms of occupational classification (Zhou and Wodtke 2019). The upper-class position we use corresponds to the standard French class designation known as the *cadres* – an institutionalized category of both managers and professionals (senior managers, commercial executives, administrators, and professional positions such

1. Access to the DADS data was obtained through the CASD dedicated to researchers authorized by the French Comité du Secret Statistique.
2. State civil servants are included only after 2009. For reasons of time consistency, we did not use them for this analysis.

as scientists, lawyers, journalists) (Boltanski 1982).[3] As for gender, we use a binary variable declared in DADS. Finally, we capture the nativity dimension by identifying migrant workers based on the foreign-born criterion[4] (i.e. born outside of France).[5] Unfortunately, information about migrants' country of origin is not consistently available in the data.[6] Nonetheless, we do have information after 2005 whether respondents are EU or non-EU citizens. In the appendix, we use this information to recompute our main results as a robustness check (Figure A1). In addition to these three categorical inequalities, we also measure *intra-categorical inequality* using class×gender×nativity cross-category wage inequality within workplaces.

3. Additionally, condensing social classes makes sense given our data structure because most workplaces contain only a few occupations. More detailed classifications ("micro-classes") would be hard to implement in most workplaces whereas nearly all workplaces are accounted for with the "big class" approach.
4. Information on place of birth is incomplete between 2002 and 2004. In 2011, the information was entirely missing. Similarly, place of birth (in France/abroad) is collected with numerous errors between 2005 and 2008. However, each DADS year-file y contains information both on the current year t and the preceding year *t-1*. Therefore, we take advantage of this structure to build a pseudo-panel dataset merged on common information (establishment ID, gender, number of hours, duration of the job, dates of start and end of the job, municipality of work and residence, wage and age) between year t of year-file *y-1* and year *t-1* of year-file *y*. We can successfully perform a single match with 98% of employees. The pseudo-panel allows us to complete information on place of birth enabling us to make the best use of these variables in our analyses.
5. French official statistical services add a nationality of birth information in most surveys in order to exclude French emigrant's children born abroad and French citizens repatriated from former French colonies (mainly but not always from Algeria) from the immigrant population stock. These categories of population nonetheless represent a limited share of the foreign born population (about 13%) (Beauchemin et al. 2015, p.20). DADS data do not include nationality of birth information which prevent us from distinguishing between "international migrants" and these complex categories of "French national migrants" (Beauchemin and Safi 2020).
6. Historically, Europe has been the main source of migration to France. Nonetheless, the geographical origins of immigrants have been diversifying during the last decades. The share of immigrants from Europe has consequently been decreasing (from 66% in 1975 to 36% in 2014). This decrease is mainly due to the drop in the number of immigrants from Spain, Portugal and Italy. Since 1999, the origins of European immigrants have also been diversifying, with a growing proportion of immigrants born in Eastern Europe. In 2014, 44% of immigrants were born in the African continent. People born in North Africa represent 30% of all immigrants, a stable proportion since the 1980s. Immigration from sub-Saharan Africa is more recent and mainly concerns countries formerly under French administration. Finally, 15% of immigrants come from Asia. Migration from Asian countries other than Cambodia, Laos and VietNam has increased in recent years (Insee 2018).

Methods

We adopt a three-step approach to investigate our research questions. First, we describe the intersection of class, gender and nativity inequalities at the individual level. Second, we approach inequality regimes at the organizational level studying the relation between our different within-workplace measures of inequality (categorical and intra-categorical). Third, we analyze the organizational determinants of the inequality regimes that we document in the second step.

Step 1: Intersection of categorical inequalities at the individual level

In the first step, we estimate the effect of our three categories of inequality – class, gender and nativity – as well as their interactions at the individual level using a standard wage model with workplace fixed effects (*j*) (equation 1). We capture gender, nativity and class advantages with male, native, and manager-professional dummies respectively. We control for age (as well as its squared term), number of hours worked (simple and squared), part-time status, and number of days worked (simple and squared). Unfortunately, due to its administrative nature, the data does not include information on the level of education for workers. However, we control for detailed occupation (2-digit codes), which is important in its own right but also captures substantial differences in education. We also introduce interaction terms between occupation and age, and age squared.

$$\begin{aligned} log(earnings_{ij}) = & X_{ij} \cdot b + b_g \cdot gender_{ij} + b_n \cdot nativity_{ij} + \\ & b_g \cdot gender_{ij} \times class_{ij} + b_{nc} \cdot native_{ij} \times class_{ij} + \\ & b_{gn} \cdot gender_{ij} \times nativity_{ij} + \\ & b_{gnc} \cdot gender_{ij} \times native_{ij} \times class_{ij} + j + w_{ij} \end{aligned} \quad (1)$$

Using this equation, we first aim at estimating individual-level categorical inequality through class, gender and nativity main effects within workplaces. While this is straightforward for the gender (b_g) and nativity gaps (b_n), we cannot estimate the class main effect directly since, as shown in equation (1), we control for 2-digit occupational codes and these occupational codes are nested in our class measure of inequality. We therefore estimate a manager main effect within a post-estimation step by computing a weighted difference between all the occupational estimates that comprise a manager/professional effect and those comprising a worker effect (equation 2):

Manager effect:

$$b_c = \frac{\sum_k \left[p_{mgr_k}\left(b_{mgr_k} + b_{mgr_k \times age}\overline{age} + b_{mgr_k \times age^2}\overline{age^2}\right)\right]}{\sum_k p_{mgr_k}} - \frac{\sum_k \left[p_{wkr_k}\left(b_{wkr_k} + b_{wkr_k \times age}\overline{age} + b_{wkr_k \times age^2}\overline{age^2}\right)\right]}{\sum_k p_{wkr_k}}$$

where b_{mgr_k} , b_{wkr_k} , p_{mgr_k} and p_{wkr_k} are respectively the estimated parameters and the weight of occupation k within the "managers and professionals" or within the "workers" categories and stands for the average age in the full sample.

Step 2: Intersection of categorical and intra-categorical inequalities at the workplace level

In this second step, we focus on the associations between different types of inequality. We first compute correlations at the workplace level between the three residual wage gaps as explained by class, gender and nativity. To do this, we use equation 1's residual log wage w_{ij} as our dependent variable and perform one regression per establishment *j* with class, gender and nativity dummies as three independent variables (equation 3).

$$w_{ij} = a_j + b_{cj} \cdot class_{ij} + b_{gj} \cdot gender_{ij} + b_{nj} \cdot nativity_{ij} + e_{ij} \quad \text{for each } j \qquad (3)$$

Each fixed effect b_{cj}, b_{gj}, b_{nj} describes the positive/negative deviation of the workplace *j*'s gender, nativity and class gaps to the mean gaps calculated in equation 1. Building on equation 3's estimates, we now compute the following correlations (weighted by the number of workers per establishment):

$$cor(b_{kj}, b_{lj}) \quad \text{with } k \neq l \text{ and } (k,l) \subset (class, gender, nativity) \qquad (4)$$

Additionally, we are also interested in the correlation between each of these categorical wage gaps and the intra-categorical workplace inequality. We measure the latter in each workplace with the standard deviation of errors (generally called root mean square error $RMSE_j$ – with $RMSE_j = \sqrt{\frac{\sum_i e_{ij}{}^2}{N_j}}$ and e_{ij} estimated in equation 3) and calculate its correlation with each categorical wage gap.

Our method of correlating workplace regression parameters seeks to circumvent the fact that gender, nativity and class wage gaps overlap with each other. When workplaces are large (i.e. more than one thousand workers), the correlations estimated with equation 4 are the correct ones. In smaller workplaces, b_{cj}, b_{gj}, and b_{nj} are likely to be estimated with error; biasing the variance, covariance, and correlation of these parameters – a problem similar to the "incidental parameter" or the "limited mobility bias" (Gaure 2014). This issue is discussed at length in Appendix A2.

We detail two solutions to correctly estimate the covariance. The first (hereafter called "*vcov*") consists in subtracting the mean of the corresponding element in the variance-covariance matrix of the parameters (c_{kl}) in each workplace *j's* regression from the covariance of equation 3's estimates (equation 5).

$$cov_{vcov} = cov(b_{kj}, b_{lj}) - \frac{\sum_j c_{klj}}{J} \qquad (5)$$

In the second solution (hereafter called "*halves*"), we randomly assign employees of each workplace to two subsamples: "half 1" or "half 2". We then estimate separate regressions on the two randomized halves and calculate cross-halves covariance:

$$cov_{halves} = cov\left[(b_{k1}, b_{k2}), (b_{l2}, b_{l1})\right] \qquad (6)$$

As demonstrated in appendix A2, these two solutions enable us to estimate covariance correcting for measurement errors and they yield nearly identical results on the present dataset and on simulated data.

While these solutions correct for potential biases in covariance, we also need to correct for the variance (i.e. the denominator) in order to compute robust coefficients of correlation. Indeed, on small units, measurement errors may positively bias the variance leading to underestimating the absolute value of the correlation coefficients. As shown in the appendixes, both methods *vcov* and *halves* efficiently compute variances that eliminate these biases.

$$V_{vcov} = V(b_k) - \frac{\sum_j c_{kkj}}{J} \tag{7}$$

$$V_{halves} = cov\left[(b_{k1}, b_{k2}), (b_{k2}, b_{k1})\right] \tag{8}$$

Finally, we compute correlations between each of the categorical inequality estimates and the intra-categorical inequality by the RMSE. In a similar vein, we use the "*halves*" method (equation 6)[7] to correct for eventual bias in the variance, covariance, and ultimately in the correlations:

$$\begin{aligned} cov_{halves} = cov\left[(b_{k1}, b_{k2}), (RMSE_2, RMSE_1)\right] \\ \text{with } k \in (class, gender, nativity) \end{aligned} \tag{9}$$

Step 3: Determinants of within workplace inequalities

In a third step, we explore the determinants of workplace inequalities. As we have four different outcomes measured simultaneously within workplaces, we implement a generalized structural equation model with class, gender and nativity fixed effects (estimated in equation 3) and the root mean square of errors (RMSE) as dependent variables[8]. The model is based on seemingly unrelated regressions allowing for autocorrelations between the error terms of the four equations.

$$\left| \begin{array}{l} b_{gj} = X_j \cdot c_g + \varepsilon_{gj} \\ b_{nj} = X_j \cdot c_n + \varepsilon_{nj} \\ b_{cj} = X_j \cdot c_c + \varepsilon_{cj} \\ RMSE_j = X_j \cdot c_{RMSE} + \varepsilon_{RMSE_j} \end{array} \right. \tag{10}$$

These models control for the composition of the workforce: the share of males, managers, migrants, younger workers, older workers, and the size of the establishment. We also introduce the fixed effects j estimated in equation 1 for each establishment as an indicator of the average wage in the establishment net of compositional effects. We finally control for the larger environments in which these workplaces are nested like industry and urban characteristics.

The advantage of this strategy is that we can estimate the covariances between the residuals of the four equations (ε_g, ε_n , ε_c , and ε_{RMSE}) and monitor the extent to which they decline with the introduction of our set of independent variables. To address the kind of covariance measurement error discussed above, we apply the halves approach for paired outcomes (see equation 11):[9]

$$\left| \begin{array}{l} b_{g12j} = X_j \cdot c_{g12} + \varepsilon_{g12j} \\ b_{c21j} = X_j \cdot c_{c21} + \varepsilon_{c21j} \\ cov(\varepsilon_{g12j}, \varepsilon_{c21j}) \end{array} \right. \tag{11}$$

Results

The intersection of categorical inequalities at the individual level

We start by briefly discussing intersectional inequality based on the individual-level results from equations 1 and 2. Similar to prior research, these analyses use interaction terms. Figure 1 displays the full interaction of gender, nativity and class effects. It also compares the wages of different groups relative to the most disadvantaged group – female migrant workers – our reference category. Figure 2 plots the main and marginal interactions effects from Equation 1.

7. There's no indicator in a regression of RMSE error measurement. Hence, we cannot use the *vcov* method.
8. For these regressions, each establishment is weighted by the number of workers.

9. b_{g12} is a vector combining b_{g1} calculated on half 1 and b_{g2} on half 2.

Figure 1. Wages effects for full set of interactions for each social position

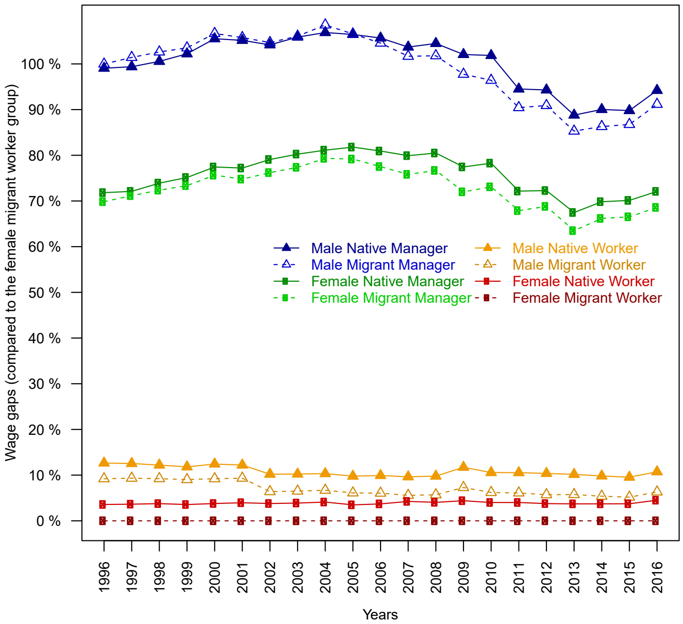
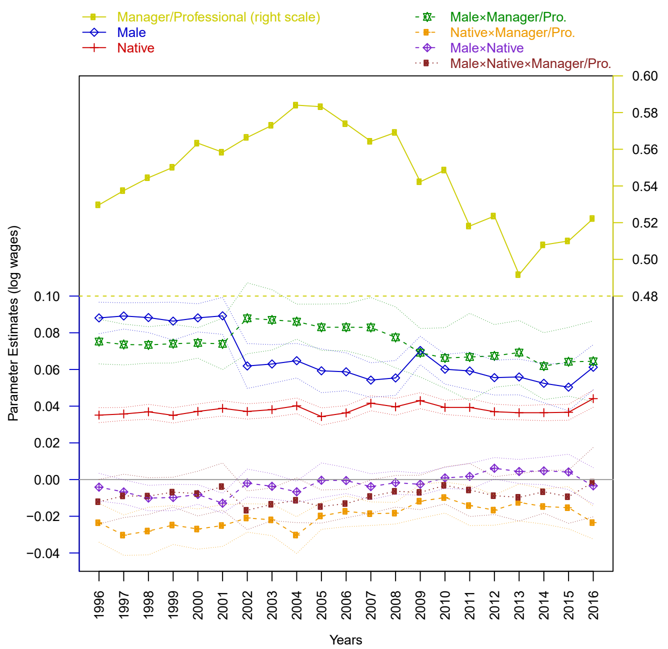


Figure 2. Impact of gender, class and nativity and their interactions on log wages



Note: Gender, class and nativity main effects and their interactions on log earnings are calculated according to equation 1 using a yearly log wage dependent variable controlling for age, number of hours worked, and 2-digit occupation categories and introducing a workplace fixed effect. The 95% confidence intervals are based on cluster-robust standard errors, clustered at the regional level (i.e. French *départements*). Because we control for detailed occupation, class main effects cannot be estimated directly and is post estimated and therefore we could not compute a confidence intervals. Nevertheless, given the size of the effect, we have no doubt that it is highly significant.

Figure 1 shows that the largest wage gap is by class. For example, managers earn on average 75% more than workers during the period – an effect that decreased over time, however. This is followed by gender (with males earning 8.7% more than females) and nativity (with natives earnings 2.6% more than migrants)[10]. There is evidently a cumulative disadvantage effect in line with prior research (Greenman and Xie 2008; Woodhams, Lupton, and Cowling 2015).

Female migrant workers are worse off than female migrant managers (a 73% gap), male migrant workers (a 7% gap) and female native workers (a 4% gap). Both Figures 1 and 2 show that the gender gap is twice as strong among managers (+14%) than among workers (+7%). Conversely the nativity gap exists only among workers (+3.8%) and is null among managers (-0.3% on average).

10. From the first step equation, we can post-estimate the overall gender gap (and similarly overall nativity and class gaps) as the average of the gender gaps measured among respectively migrant workers, native workers, migrant managers and native managers (weighted by the size of these respective four groups).

The Intersection of Inequalities at the Establishment-Level

Do these patterns of intersectional inequality differ at the establishment level? We now answer this question by assessing the relationship between the four forms of inequality defined above. Table 1 displays descriptive statistics of each inequality type and includes values for both the uncorrected and corrected covariances and correlation coefficients (using both *vcov* and *halves* methods).

The second step equation results for class, gender and nativity in Table 1 are close to 0. This is because they are already accounted for in the first step equation. The average standard deviation of errors in the workplace – our intra-categorical inequality indicator – is 0.22. More interestingly, Table 1 shows a considerable variation in the distribution of these inequalities across workplaces, measured with the standard deviation values (note here that the corrected standard deviation values are slightly smaller): 0.07 for gender, 0.05 for nativity, 0.14 for class, and 0.07 for intra-categorical inequality. Overall, the distribution of gender and nativity inequality is less heterogeneous across workplaces than the distribution of class-based inequality. In more concrete terms, 95% of employees work in establishment with gender gaps ranging from -5% to 23%, nativity gaps ranging from -7% to 13%, class gaps from 33% to 134% and intra-categorical inequality from 0.08 to 0.37. Alternatively, if we focus on the extent to which some establishments exhibit reversed wage gaps, we find this to be true for 11% of establishments as far as the "reverse gender gap" is concerned (i.e women on average earn more than men in 11% of establishments net of other covariates accounted for in Equation 1), and for 32% of establishments as for the "reverse nativity gap". Conversely, the class gap is never reversed (managers/professionals consistently earn more than workers in all establishments even after the control for covariates in equation 1). Thus, the class gap varies only in its positive magnitude across establishments, while some of the variation in the gender and nativity gaps is due to "reverse gaps."

Table 1 also highlights the importance of the correction methods. More specifically, while the gender×nativity and class×nativity covariances are essentially the same with or without the correction, the corrected gender×class covariance is half of the size of the uncorrected one. This is due to the strong correlation of the underlying gender and class dummy variables. We also see consistent results across the two correction procedures. For example, the correlation between gender×nativity is -0.227 and -0.248 with *vcov* and *halves* respectively. For class×gender, these respective values are -0.026 and -0.029. For class×nativity the respective values are -0.005 and -0.008.

These values preview our main results. We see, (referring to *vcov*, or method 1) in Table 1, a relatively strong negative correlation coefficient between the gender and nativity inequalities (-0.227). The class×gender gap correlation is close to 0 (-0.026). So too is the class×nativity correlation (-0.005), which is statistically insignificant. Thus, comparing the relationship between the categorical inequalities at the workplace level, these results point to an inequality trade-off between gender and nativity and no correlation between the other wage gap pairs. These results contrast with the individual level interaction effects; at the individual level gender did not seem to imply different payoffs for migrants and natives. Once we move to the establishment level, more gender-equal workplaces tend to be more migrant-unequal.

Next, we move to the associations with intra-categorical wage inequality. That is, we ask if some categorical inequalities are more intense in more intra-categorically unequal workplaces. We find intra-categorical inequality to be strongly and positively correlated with the gender gap (0.309) and negatively, although less intensively, correlated with the nativity gap (-0.114). Intra-categorical inequality is only mildly (but significantly) correlated with the class gap (0.057).

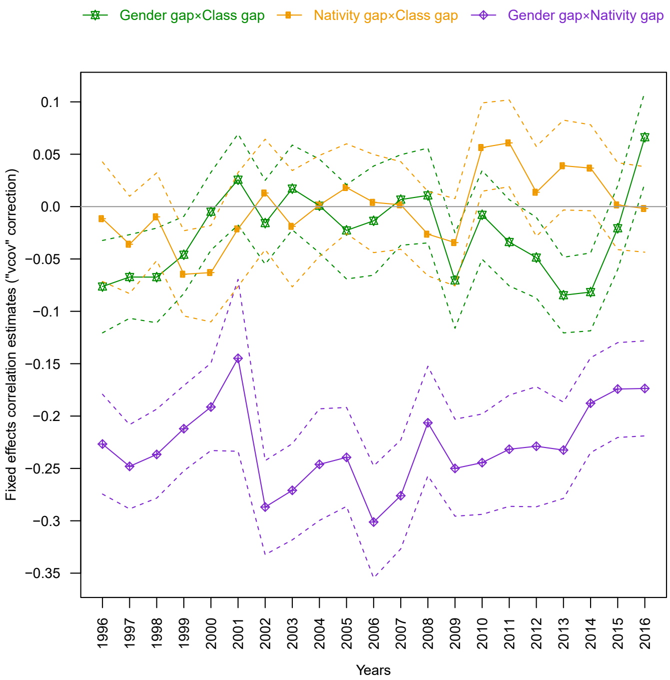
Table 1. Full period uncorrected and corrected covariance and correlation of inequality measures

	Gender	Nativity	Class	Intra-categorical inequality
<u>First step</u> gaps (log wage)	0.083	0.026	0.561	/
(percentage)	8.7%	2.6%	75%	
<u>Second step estimates</u>				
Mean	-0.005	-0.004	0.009	0.224
Std Dev.	0.072	0.065	0.145	0.075
Std Dev. Corrected "*vcov*"	0.065	0.049	0.141	/
Std Dev. Corrected "*halves*"	0.065	0.044	0.139	0.073
<u>Uncorrected Covariance</u>				
Gender		-0.00071	-0.00041	0.00150
Nativity	-0.00071		0.00001	-0.00038
Class	-0.00041	0.00001		0.00060
Intra-categorical inequality	0.00150	-0.00038	0.00060	
<u>Corrected covariance</u>				
Gender	Method 1 vcov ↓	*-0.00070*	*-0.00026*	*0.00146*
Nativity	-0.00072	*Method 2 halves* →	*-0.00005*	*-0.00037*
Class	-0.00023	-0.00003		*0.00057*
Intra-categorical inequality	/	/	/	
<u>Uncorrected Correlation coefficient</u>				
Gender		-0.152 [-0.156 ; -0.148]	-0.039 [-0.044 ; -0.035]	0.281 [0.277 ; 0.285]
Nativity	-0.152 [-0.156 ; -0.148]		0.001 [-0.003 ; 0.006]	-0.078 [-0.082 ; -0.073]
Class	-0.039 [-0.044 ; -0.035]	0.001 [-0.003 ; 0.006]		0.056 [0.051 ; 0.06]
Intra-categorical inequality	0.281 [0.277 ; 0.285]	-0.078 [-0.082 ; -0.073]	0.056 [0.051 ; 0.06]	
<u>Corrected correlation coefficient</u>				
Gender	*Method 2 halves* → Method 1 vcov ↓	*-0.248* *[-0.262 ; -0.236]*	*-0.029* *[-0.038 ; -0.019]*	*0.309* *[0.299 ; 0.32]*
Nativity	-0.227 [-0.239 ; -0.216]		*-0.008* *[-0.019 ; 0.004]*	*-0.114* *[-0.129 ; -0.098]*
Class	-0.026 [-0.035 ; -0.016]	-0.005 [-0.015 ; 0.006]		*0.057* *[0.046 ; 0.067]*
Intra-categorical inequality	/	/	/	

Note: All measures are based on log wages except line 2, which represents gaps in proportion to the wage of the disadvantage group. 95% confidence intervals in square brackets were calculated with bootstrapping (4000 samples).

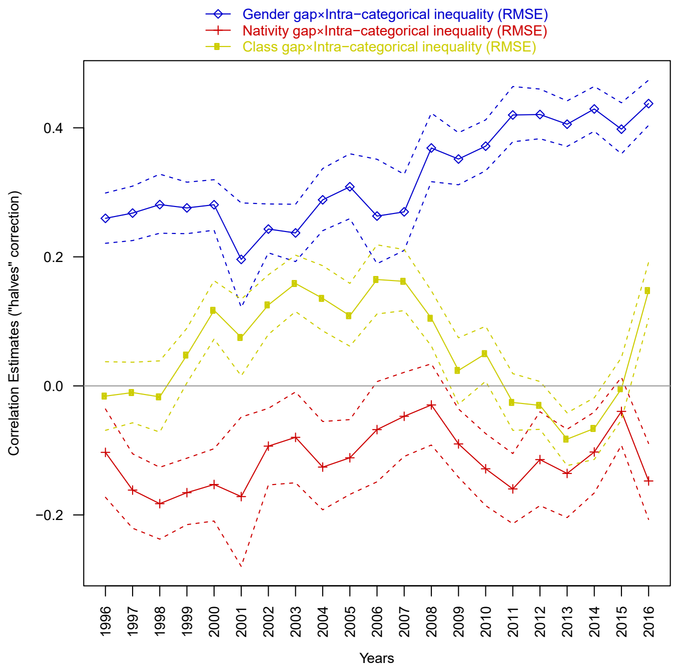
Our inquiry into whether workplaces inequality regimes are reinforcing or compensating shows evidence for both patterns. There are inequality trade-offs within establishments between the gender and nativity gaps. Moreover, we find lower native wage gaps in more egalitarian workplaces overall. We observe patterns of reinforcing inequality between the gender gap and the establishment intra-categorical wage inequality. The gender gap is higher in more intra-categorically unequal workplace environments. Stated slightly differently, we draw two conclusions. First, workplaces are marked by relatively more native or gender equality but not both. One comes at the expense of the other. Second, the level of gender or migrant egalitarianism depends on whether a workplace has high or low wage inequality that is not based on the three categorical distinctions we study in this article.

Figure 3. Yearly correlation of categorical wage gaps



Note: The estimated values are shown in a solid line and the standard errors (estimated with a bootstrap) in dashed lines.

Figure 4. Wages effects for full set of interactions for each social position



Note: The estimated values are shown in a solid line and the standard errors (estimated with a bootstrap) in dashed lines.

In Figure 3, we compare our results over time (relying here on *vcov* method). The overall patterns correspond to the results shown in Table 1, but there is some temporal variation. The gender×nativity gap correlation is strongly negative but with a slightly decreasing magnitude over time. The correlations between the class gap with both the gender and the nativity gap hovers near 0 throughout the series. Figure 4 shows the yearly trend of the association between the intra-categorical establishment wage inequality and each of the (within establishment) categorical inequalities. As in Table 1, we see the gender gap is strongly and positively associated with the intra-categorical inequality, climbing steadily over time to a maximum level of around +0.40 in 2016. Conversely, the negative correlation between the nativity gap and intra-categorical inequality decreased slightly between 1997 and 2008 but then moved below 0 for most of the rest of the series. Again, the nativity gap shows a consistently negative trend, i.e. an "inequality trade off" tendency when paired with both the gender wage gap and the intra-categorical inequality within establishments.

A final issue with regard to our immigration results is worth noting. It is possible that the effect for immigration could vary if we distinguish between migrants along countries of origin. DADS lacks data on national origin, but, beginning in 2005, we have information about EU versus non-EU citizenship. We use this information as a robustness check, re-estimating our correlations on these two subsamples of the migrant population. The results are shown in the Appendix (Figure A1); the overall pattern over time in both cases is the same as the main results described above.

Predictors of Workplace Wage Gaps

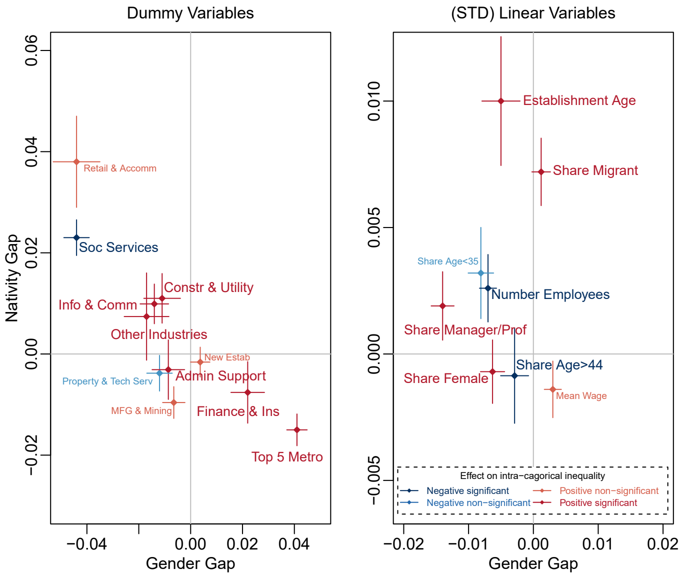
In the last step, we investigate the main factors underlying the correlations observed above. As discussed in the Methods section, we use seemingly unrelated regressions with generalized structural equations. We control for the same set of covariates across models. This includes nine industry dummies, based on the industry groupings in INSEE's *nomenclature d'activités française* (NAF),[11] and with

11. The two digit codes are as follows: Manufacturing & Mining (01-35), Construction & Utilities (36-44), Transportation (45-53), Retail & Accomodation (45-56), Information & Communications (58-63), Finance & Insurance (64-66), Real estate and technical services (68-75), Administrative Support (77-82), Social Services (84-88), and Other (90-99).

transportation as the reference category. To account for urbanization, we also include a dummy for whether the establishment is in the top 5 largest *departments* in France.[12] Additionally, we control for several organizational-level features. We measure establishment age with two variables: 1) a dummy coding the existence of the establishment at the beginning of the panel in 1996, 2) the number of years an establishment is present in the panel. We also control for the log number of employees in an establishment, the mean log wage of the establishment, and the proportion of migrants, women, and managers.[13] Proportions of "younger" workers (25-34) and "older" workers (45-55) are also included as covariates. Finally, we include year fixed effects, but do not report these results for the sake of concision. All of the linear variables are standardized. Our approach is descriptive and does not measure causal effects. Indeed, we use these analyses to account for the contexts in which the patterns we've measured in the former section are the most salient: the negative correlation between gender and nativity, the negative correlation between intra-categorical inequality and nativity, and the positive correlation between gender and intra-categorical inequality.

Full results with the coefficients of the 4 equations are shown in Table 2. We present a visual display of the native×gender×intra-categorical inequalities in Figure 5. The *y* axis reports the coefficients for the nativity gap while the *x* axis reports the coefficients for the gender gap (from Table 2). We separate the coefficients based on dummy variables (left panel) from the standardized linear variables (right panel). Variables on the upper-left hand quadrant are positively associated with the nativity gap and negatively associated with the gender gap while those in the lower right-hand quadrant show the reverse pattern. In addition, we use a color scale to represent sign and significance on a virtual

Figure 5. Parameter estimates for gender, nativity and intra-categorical inequalities



Note: Effect of contextual variables on the gender gap (horizontal scale), the nativity gap (vertical scale) and on intra-categorical inequality (color scale). Estimates drawn from Table 2.

third axis representing intra-categorical inequalities. This data visualization helps us compare coefficients across two of the four equations for the same covariates.

We can observe a diagonal trend moving from the upper-left to the lower-right hand sides in Figure 5. This is particularly pronounced for the dummy variables (the left panel). For example, the retail and accommodation and social services sectors and more generally large workplaces are, relative to the reference category, positively associated with the nativity gap and negatively associated with the gender gap. France does have a relatively lower gender wage gap within the accommodation and retail sector (Coudin et al. 2018) and we may expect social services to be less gender unequal (Allen and Sanders 2002). The relatively high migrant penalty in a sector like social services is in line with prior evidence of immigrant disadvantage in the French public sector (Fougère and Pouget 2003). Moreover, as many civil service positions require European citizenship, migrants tend to be hired in these sectors under conditions that are more precarious and with temporary contracts. This is namely the case in hospitals and local municipal services, which are included in our data (OECD 2008).

12. These are Île-de-France (Paris), Rhône (Lyon), Bouches-du-Rhône (Marseille), Haute Garonne (Toulouse), and Nord (Lille).
13. Another potentially important factor is business performance. Measures of sales and profit are available at the firm-level (albeit, with a degree of missing data). Using it would therefore require us to discard a high number of our establishments. As a robustness check, we nonetheless merged the DADS with another dataset with this information (statistique annuelle d'entreprise) to use these controls. These results do not significantly differ and are available upon request.

Table 2. Generalized Structural Equation Estimates of Workplace Inequalities

	Gender Gap	Nativity Gap	Class Gap	Intra-categorical inequality (RMSE)
Industries: Manufacturing and mining	-0.0065**	-0.0096***	0.073***	0.0035
	(0.0022)	(0.0016)	(0.0071)	(0.0020)
Construction & utilities	-0.011**	0.011***	0.083***	0.0055*
	(0.0036)	(0.0025)	(0.0083)	(0.0026)
Transportation	REF	REF	REF	REF
Retail & accommodation	-0.044***	0.038***	-0.0081	0.011
	(0.0046)	(0.0046)	(0.015)	(0.0075)
Information and communication	-0.014***	0.0099***	-0.0035	0.011***
	(0.0028)	(0.0020)	(0.0076)	(0.0031)
Finance and insurance	0.022***	-0.0076*	0.032**	0.032***
	(0.0033)	(0.0031)	(0.010)	(0.0047)
Property & technical services	-0.012***	-0.0038*	0.021**	-0.0018
	(0.0025)	(0.0018)	(0.0066)	(0.0038)
Administrative support services	-0.0086**	-0.0031	-0.069***	0.023***
	(0.0032)	(0.0030)	(0.0089)	(0.0026)
Social services	-0.044***	0.023***	0.014*	-0.0070***
	(0.0025)	(0.0018)	(0.0073)	(0.0021)
Other industry	-0.017***	0.0074	-0.030*	0.033***
	(0.0044)	(0.0044)	(0.012)	(0.0047)
New establishment (dummy)	0.0037*	-0.0016	0.012*	0.0025
	(0.0019)	(0.0015)	(0.0054)	(0.0020)
Establishment mean log wage*#	0.041***	-0.015***	0.0075	0.052***
	(0.0020)	(0.0016)	(0.0051)	(0.0025)
Establishment age*	0.0030***	-0.0014*	0.0060**	0.00028
	(0.00067)	(0.00057)	(0.0023)	(0.00080)
Top 5 metropolitan areas (dummy)*	-0.0050***	0.010***	-0.040***	0.0088***
	(0.0015)	(0.0013)	(0.0043)	(0.0013)
Number of employees (log)*	-0.0070***	0.0026***	0.00017	-0.0048***
	(0.00067)	(0.00068)	(0.0024)	(0.0010)
Proportion of younger workers*	-0.0081***	0.0032***	-0.0017	-0.0019
	(0.00100)	(0.00092)	(0.0034)	(0.0012)
Proportion of older workers*	-0.0029**	-0.00086	-0.028***	-0.0092***
	(0.0011)	(0.00096)	(0.0035)	(0.0011)
Proportion of managers/professionals*	-0.014***	0.0019**	-0.0072**	0.021***
	(0.00090)	(0.00069)	(0.0025)	(0.0013)
	0.0012	0.0072***	0.021***	0.0085***
Proportion of migrants*	(0.00073)	(0.00068)	(0.0021)	(0.00072)
	-0.0063***	-0.00070	0.024***	0.011***
Proportion of females*	(0.00095)	(0.00064)	(0.0022)	(0.00069)
	-0.055***	0.011**	-0.00013	0.15***
Constant	(0.0044)	(0.0037)	(0.012)	(0.0055)
Year FE	YES	YES	YES	YES

* standardized value

We use the first step establishment fixed effect to measure a mean log wage net of human capital compositional effects.

Additionally, there are important effects for the finance/insurance industry and urbanization. Both variables are positively associated with intra-categorical inequality. The financial/insurance sector and the most urban contexts concentrate material resources and lead to more unequal distribution (Galbraith 2012). These sectors are positively associated with gender gaps as well. The financial sector is known to be highly masculine and gender biased (Roth 2006) including in France (Godechot 2017). Urbanization is also associated with the gender gap and this might be interpreted both as a result of the concentration in these areas of more male dominated decision functions and headquarters and of disparate preferences for commuting across males and females as recent research shows (Le Barbanchon, Rathelot, and Roulet 2020; Wyly 1998). That these two establishment's characteristics are both strongly and positively associated with the intra-categorical inequality and the gender gap therefore helps account for the fact that these two gaps are positively associated with each other. Interestingly, we see opposite trends for the nativity wage gap by these factors. Migrant's wage penalty tend to be smaller in urban areas and within the financial/insurance sector; this also pertains to the dualization of migrant labor between low-skilled workers and high-skilled workers that circulate mainly in global cities and intensively within the financial sector across developed countries (Sassen 2001).

Finally, Table 3 shows the variance and covariances of the residuals for the null and full models of the seemingly unrelated regressions. Adding controls does not change the sign or the significance of the covariance estimates. However, it does generally lead to smaller magnitudes. Compositional characteristics and industry account for between 48% and 80% of the three covariances. De facto, sector practices, such as access to full status in social services, explains a substantial share of the nativity gap and of its negative correlation with gender and intra-categorical inequality. Nevertheless, within the same sector and among workplaces with

Table 3. Estimates of variance and covariance of residuals

Estimates	Null model	Full model
var(intra-categorical ineq)	0.0055***	0.0032***
	(0.00017)	(0.000078)
var(Gender)	0.0050***	0.0038***
	(0.000082)	(0.000070)
var(Nativity)	0.0042***	0.0038***
	(0.000075)	(0.000072)
var(Class)	0.021***	0.019***
	(0.00038)	(0.00036)
cov(intra-categorical ineq×Gender)	0.0015***	0.00079***
	(0.000088)	(0.000045)
cov(intra-categorical ineq×Nativity)	-0.00038***	-0.00016***
	(0.000061)	(0.000042)
cov(intra-categorical ineq×Class)	0.00063***	0.00073***
	(0.00015)	(0.000097)
cov(Gender×Nativity)	-0.00070***	-0.00014***
	(0.000048)	(0.000034)
cov(Nativity×Class)	0.0000098	0.0000083
	(0.000085)	(0.000072)
cov(Gender×Class)	-0.00038**	-0.00022**
	(0.00012)	(0.000079)
Corrected		
cov(Gender×Class)	-0.00024*	-0.000073
	(0.00012)	(0.000079)
Observations	190,878	190,878

the same compositional characteristics, the nativity gap remains negatively correlated with other forms of inequality and gender inequality reinforces intra-categorical inequality.

Discussion and Conclusion

In this article, we combine recent interests in intersectional and organizational mechanisms to ask how different types of inequalities relate to each other within French workplaces. Specifically, we build off Acker's idea of "*inequality regimes*" to explore whether they take the form of a reinforcing inequality regime or an inequality tradeoff regime. We do so with innovative methodological techniques to net out measurement biases that would ordinarily arise from correlating different forms of wage gaps. This is a key contribution of this article.

We find that the gender gap is positively correlated with intra-categorical inequality. Conversely, the nativity gap is negatively correlated with both intra-categorical inequality and the gender gap. Interestingly, the class categorical gap is not significantly associated with other forms of inequality. We also find that several contextual factors, notably industries, contribute to approximately half of the correlation between intra-categorical and gender or nativity inequalities (for the gender-native combination, it is as high as 80%). Additionally, we find that the correlation pattern is only attenuated but does not disappear when controlling for industry and compositional variables.

These findings suggest that organizations articulate differently exogenous salient categorical distinctions such as gender or nativity with endogenous production-related inequalities. Highly unequal workplaces reinforce their intra-categorical inequality with a large gender gap. Less unequal workplaces trade off this internal equity with the reactivation of migrant-native gap. In addition, workplaces trade off between the exogenous categorical distinctions they produce. Specifically, workplaces with low gender gaps tend to have high migrant gap and vice versa. Our findings advance the literature on these differential processes of inequality and their articulation (Brubaker 2015; Mandel and Semyonov 2016; Restifo and Mykyta 2019; Ridgeway 2011).

These results are among the first to describe correlation between different dimensions of inequality within workplaces. They call for supplementary research to confirm these patterns and trends and to explore their underlying mechanisms. Here, we suggest some possible explanations of our findings.

We begin with the finding concerning the positive association between gender and intra-categorical inequality (i.e. a reinforcing regime). First, inequality and competition enhance masculine agentic roles and discourage female workers (Eagly and Karau 2002; Niederle and Vesterlund 2007). Persistent gender roles explain why women are channeled (or self-select themselves) into jobs, functions, hierarchical positions that are less exposed to competition within their workplace. Such positions tend to be less driven by market-related incentives (e.g. bonuses). Consequently, levels of remuneration tend to be lower. The finance industry is one of the most striking illustrations of the coexistence of high gender gap and high wage inequality (Godechot 2017; Roth 2006). Moreover, in a context of a persistent "glass ceiling" at the top, one would find both a high gender gap and overall wage inequality (Baxter and Wright 2000).

By contrast, the trade-off regime that we document between the nativity gap and intra-categorical inequality could be a byproduct of industrial relations and the "dualization" of the labor market. French trade unions had historically tried to include migrants, especially in the 1930 and in the post-WW2 period (Noiriel 1988). However, with the upheaval of a strong version of French colorblindness in the 1980's, even unions on the left side of the political spectrums embraced French universalism and failed to address the specific problems faced by migrant workers (Bataille 1997, 2018; Bruno 2011). In some sectors like public transportations and civil services, unions are furthermore eager to defend insider worker status. In such dualistic contexts, migrant worker's legal vulnerability translates into lower wages. This may explain why larger workplaces and social service sectors, where strong unions are involved in defending insider workers status, combine narrower pay dispersion with larger nativity gaps.

Finally, the negative correlation between the gender and nativity gaps is the most novel result and the most challenging to interpret. Because previous literature generally considers gender and ethnoracial discriminations to share many underlying mechanisms, one could expect gaps along those dimensions to be correlated positively. However, the gender and ethnoracial equality struggles have been increasingly opposed in French society. In the recent public debate, female and migrant rights tend to be depicted in antagonistic ways leading to possible tensions between gender and ethnoracial equality policies. How this opposition translates in the labor market, however, is less understood. Policy differences in tackling discrimination may provide some clues to explaining this tradeoff. Gender discrimination in pay and promotion is well recognized in France. Policies have been implemented since the early 1980s including compulsory gender equality negotiation since 2001 and female quotas on boards of large firms in 2011. By contrast, the recognition of ethnoracial discrimination and corresponding social policy remains much weaker in the "colorblind" French context, despite undisputable empirical evidence of its existence. This may explain, for example, qualitative evidence showing how gender and ethnoracial inequalities are dealt with differently by diversity managers (Bereni 2009; Doytcheva 2010; Doytcheva and Alaoui Hachimi 2010; Safi 2017). These kinds of dynamics could therefore translate into a wage-equality trade-off within the workplace. This result moreover suggests that categorical inequalities are not only imported to the workplace as salient readily available differences; the ways in which they intersect in societies may also shape specific forms of organizational inequality tradeoff between them. To what extent is this negative correlation between gender and migrant status France-specific? Future research investigating these patterns in different countries will be valuable to consolidate this finding and broaden these first elements of interpretation.

Despite these contributions, this study contains several important limitations that warrant discussion. One issue is our measure of nativity. Our variable captures those born outside of France. While this is a widely used measure of immigrant status, we cannot account for important labor-market factors such as age at arrival, fluency in French, abroad accreditation, occupational training, and other aspects that affect immigrant socioeconomic attainment in host countries (Melzer et al. 2018; Tomaskovic-Devey et al. 2015). Perhaps most importantly, it does not capture the racialized dimensions of French immigration from North and Sub-Saharan Africa. While important, our broad-based migration measure likely makes our results more conservative. A second limitation concerns our analyses of the determinants of workplace inequality regimes. Although this exercise helps us delve further into the correlation of the gaps, it is neither an exhaustive nor a causal study of these determinants.

Going forward, we invite researchers to consider specifying inequality regimes and, especially, to study the effects inequality regimes have on the workplace. Different regimes can lead to different organizational environments and interpersonal relations. Future research should consider how overall levels of inequality and the multiple forms in which they relate affect outcomes like this or others (e.g. workplace safety, anti-discrimination policies, collective bargaining capacity). If inequalities move together, for example, it compounds these effects within that space. If there are inequality trade-offs, this can alter the balance of power and claims making strategies available to actors. Addressing these questions can account for the multifaceted character of inequality and its various socio-economic consequences.

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Appendix

Table A1. Description of the sample

	Initial prime age sample						Final sample					
	Workers	Work-places	Males	Na-tives	Mana-gers	Log wages	Workers	Work-places	Males	Na-tives	Mana-gers	Log wages
1996	13,382,593	1,224,448	59%	89%	13%	11.62 (0.57)	3,487,721	7,990	52%	89%	21%	11.86 (0.53)
1997	13,767,723	1,292,112	58%	89%	13%	11.63 (0.57)	3,514,755	8,140	52%	89%	22%	11.88 (0.53)
1998	14,047,096	1,314,708	58%	89%	13%	11.64 (0.57)	3,566,281	8,344	51%	89%	23%	11.89 (0.54)
1999	14,443,934	1,344,340	58%	89%	14%	11.64 (0.57)	3,701,168	8,803	52%	89%	24%	11.9 (0.55)
2000	14,932,800	1,357,696	58%	89%	14%	9.77 (0.58)	3,836,142	9,239	52%	89%	24%	10.03 (0.55)
2001	15,161,580	1,366,335	58%	89%	15%	9.81 (0.57)	3,921,465	9,473	51%	89%	25%	10.06 (0.56)
2002	15,370,174	1,365,657	57%	89%	16%	9.87 (0.58)	4,044,900	9,792	51%	89%	26%	10.12 (0.56)
2003	15,261,320	1,372,886	57%	89%	16%	9.91 (0.57)	4,012,966	9,714	51%	89%	26%	10.14 (0.56)
2004	15,129,715	1,387,688	56%	89%	16%	9.94 (0.56)	3,898,127	9,581	50%	89%	27%	10.18 (0.55)
2005	15,251,007	1,398,425	56%	88%	16%	9.96 (0.56)	3,879,205	9,708	50%	89%	28%	10.21 (0.55)
2006	15,528,411	1,432,299	56%	88%	16%	9.99 (0.56)	3,930,459	9,856	50%	89%	28%	10.23 (0.56)
2007	15,826,029	1,445,613	56%	88%	17%	10.01 (0.56)	3,991,144	9,931	50%	89%	29%	10.25 (0.56)
2008	15,973,637	1,458,731	56%	88%	17%	10.04 (0.56)	4,069,632	10,082	50%	89%	29%	10.27 (0.57)
2009	15,676,126	1,471,207	55%	88%	17%	10.06 (0.55)	3,899,949	9,745	49%	89%	29%	10.29 (0.56)
2010	15,816,056	1,463,731	55%	88%	18%	10.07 (0.56)	3,957,600	9,894	49%	89%	30%	10.3 (0.57)
2011	14,945,106	1,366,884	55%	88%	18%	10.11 (0.56)	3,660,577	9,124	49%	89%	30%	10.34 (0.57)
2012	15,376,397	1,426,690	55%	88%	18%	10.12 (0.56)	3,807,577	9,738	49%	88%	31%	10.35 (0.57)
2013	15,364,034	1,424,821	54%	88%	18%	10.13 (0.56)	3,817,059	9,751	49%	88%	31%	10.37 (0.57)
2014	15,666,632	1,457,806	54%	88%	18%	10.14 (0.56)	3,798,938	9,905	48%	88%	32%	10.37 (0.58)
2015	15,774,948	1,457,228	54%	88%	19%	10.15 (0.56)	3,916,407	10,094	48%	88%	32%	10.38 (0.58)
2016	16,318,580	1,500,671	54%	87%	20%	10.15 (0.57)	4,018,818	10,188	48%	88%	33%	10.38 (0.58)

Appendix A2. Biases in the covariance of the parameters of J regressions

In a first step we estimate a workplace fixed effect regression on yearly log-earnings

$$\begin{aligned} log(earnings_{ij}) = & X_{ij} \cdot b + b_g \cdot gender_{ij} + b_n \cdot nativity_{ij} + \\ & b_g \cdot gender_{ij} \times class_{ij} + b_{nc} \cdot native_{ij} \times class_{ij} + \\ & b_{gn} \cdot gender_{ij} \times nativity_{ij} + b_{gnc} \cdot gender_{ij} \times native_{ij} \times class_{ij} + \\ & j + w_{ij} \end{aligned} \qquad (1)$$

In a second step, we estimate J regressions in each workplaces j on the residual log earnings w_{ij} coming from equation (1)

$$w_{ij} = a_j + b_{cj} \cdot class_{ij} + b_{gj} \cdot gender_{ij} + b_{nj} \cdot nativity_{ij} + e_{ij} \quad \text{for each } j$$

with w_{ij}: residual log wage ; $gender_{ij}$: male dummy; $native_{ij}$: native dummy; $class_{ij}$: upper class dummy; e_{ij}: error; i: individual i; j: workplace j.

Covariance bias

We then estimate:

$$cov(b_k, b_l) = \frac{\sum_j \left(b_{kj} - \overline{b_k}\right)\left(b_{lj} - \overline{b_l}\right)}{J} \qquad \textit{with } k \neq l \textit{ and } (k,l) \subset \textit{(gender, nativity, class)}$$

As w_{ij} is a residual wage already conditional on k and l, we can simplify and consider that the average wage gaps are null ($\overline{b_k} \simeq 0$ and $\overline{b_l} \simeq 0$)

On finite samples b_{kj} and b_{lj} are biased estimators of the true class and gender gaps: β_{kj} and β_{lj}.
We can thus rewrite:

$$\begin{aligned} cov(b_k, b_l) = & \frac{\sum_j (b_{kj} - \beta_{kj} + \beta_{kj})(b_{lj} - \beta_{lj} + \beta_{lj})}{J} \\ = & cov(\beta_k, \beta_l) + \frac{\sum_j (b_{kj} - \beta_{kj})(b_{lj} - \beta_{lj}) + (b_{kj} - \beta_{kj})(b_{lj} - \beta_{lj}) + (b_{kj} - \beta_{kj})\beta_{lj} + \beta_{kj}(b_{lj} - \beta_{lj})}{J} \\ = & cov(\beta_k, \beta_l) + \frac{\sum_j S_j}{J} \end{aligned}$$

Let us examine the expectation of the element S_j for workplace j of this covariance:

$$\begin{aligned} E[S_j] = & E[(b_{kj}-\beta_{kj})(b_{lj}-\beta_{lj})+(b_{lj}-\beta_{lj})\beta_{kj}+(b_{kj}-\beta_{kj})\beta_{lj}] \\ = & E[(b_{kj}-\beta_{kj})(b_{lj}-\beta_{lj})]+E[(b_{lj}-\beta_{lj})\beta_{kj}]+E[(b_{kj}-\beta_{kj})\beta_{lj}] \end{aligned}$$

In the classical OLS regression, the vector of errors in parameter estimations follows the following law:

$$(b_j - \beta_j) \sim \mathcal{N}\left(0, \sigma_j^2 \left(\boldsymbol{X}_j{}'\boldsymbol{X}_j\right)^{-1}\right) \qquad \text{with } \sigma_j^2 \text{ the variance of the residual } e_j.$$

$\sigma_j^2(X_j'X_j)^{-1}$ is the variance-covariance matrix of parameters estimated in the wage regression for workplace j.

As β_{kj} is a constant,

$$E\left[(b_{lj} - \beta_{lj})\,\beta_{kj}\right] = \beta_{kj} E\left[(b_{lj} - \beta_{lj})\right] = 0$$

and similarly

$$E\left[(b_{kj} - \beta_{kj})\,\beta_{lj}\right]$$

Thus

$$\begin{aligned} E\left[S_j\right] =& E\left[\left(b_{jk}-\beta_{kj}\right)\left(b_{lk}-\beta_{lj}\right)\right] \\ =& c_{klj} \end{aligned},$$

where c_{klj} is the k, l element of the matrix $\sigma_j^2(X_j'X_j)^{-1}$.

Hence,

$$cov(b_k, b_l) \rightarrow cov(\beta_k, \beta_j) + \frac{\sum_j c_{klj}}{J}$$

The covariance of fixed effects is therefore a biased estimator of $cov(b_k, b_l)$.

It is worth noting that c_{klj} depends on $X'X$. When there are two independent variables (for instance k=class and l=gender), the inverted covariance will depend approximately on $-a\sigma^2.cor(k,l)$ (with a>0)) . The more the independent variables (gender and class) are tied positively (resp. negatively) the more c_{klj} will be biased negatively (resp. positively). Similarly, the smaller the variance of the residual, the smaller c_{klj} and therefore the bias. With three variables, the structure of the bias can become more complex.

We have thus two strategies for estimating $cov(\beta_k,\beta_l)$

1/ The first one (further called "*vcov*") is to estimate

$$\boxed{cov_{vcov}(\beta_k, \beta_l) \simeq cov(b_k, b_l) - c^*_{kl}}$$

with c_{kl}* the average of the c_{klj} of the variance covariance of parameters

2/ The second (further called "*halves*") is to divide randomly each workplace j in two halves, to estimate separate regressions on the two randomized halves and to calculate cross-halves covariance:

$$cov(b_{k1}, b_{l2}) = cov(\beta_k, \beta_l) + \frac{\sum_j \left(b_{k1j}-\beta_{kj}\right)\left(b_{l2j}-\beta_{lj}\right) + \left(b_{k1j}-\beta_{kj}\right)\beta_{lj} + \beta_{kj}\left(b_{l2j}-\beta_{lj}\right)}{J}$$

$$cov(b_{k1}, b_{l2}) \rightarrow cov(\beta_k, \beta_j) + \frac{\sum_j E\left[\left(b_{k1j}-\beta_{kj}\right)\left(b_{l2j}-\beta_{lj}\right)\right]}{J}$$

Because $(b_{k1j}$-$\beta_{kj})$ and $(b_{l2j}$-$\beta_{lj})$ are parameter errors measured on two independent groups, they follow two independent probability laws. Therefore $E((b_{k1j}\text{-}\beta_{kj})(b_{l2j}\text{-}\beta_{lj}))=0$

$$cov(b_{k1}, b_{l2}) \rightarrow cov(\beta_k, \beta_l)$$

A way of combining the two cross-halves covariance is to calculate the corrected covariance as follows:

$$\boxed{cov_{halves}(\beta_k, \beta_l) \simeq cov\left[(b_{k1}, b_{l2}), (b_{k2}, b_{l1})\right]}$$

Variance bias

For similar reasons as discussed above, the variance of fixed effects is biased:

$$V(b_k) = \frac{\sum_j \left(b_{kj} - \overline{b_k}\right)^2}{J}$$

And with ($\overline{b_k} \simeq 0$), we can rewrite:

$$V(b_k) = \frac{\sum_j (b_{kj} - \beta_{kj} + \beta_{kj})^2}{J}$$
$$= V(\beta_k) + V(b_k - \beta_k) - 2 \cdot cov(b_k - \beta_k, \beta_k)$$

Therefore, the true variance can be expressed as follows:

$$V(\beta_k) = V(b_k) - V(b_k - \beta_k) + 2 \cdot cov(b_k - \beta_k, \beta_k)$$

Given the error in parameter measurement b_k-β_k is unrelated to β_k, then

$cov(b_k - \beta_k, \beta_k) \rightarrow 0$. Hence, $V(\beta_k) \rightarrow V(b_k) - V(b_k - \beta_k)$

As above, averaging the diagonal element of each regressions' variance-covariance of parameter matrix will enable to estimate $V(b_k\text{-}\beta_k)$

Hence:

$$\boxed{V_{vcov}(\beta_k) \approx V(b_k) - \frac{\sum_j c_{kkj}}{J}}$$

As above, we can also calculate the cross covariance of parameters calculated on randomized halves:

$$cov(b_{k1}, b_{k2}) = cov(\beta_k, \beta_k) + \frac{\sum_j (b_{k1j} - \beta_{kj})(b_{k2j} - \beta_{kj}) + (b_{k1j} - \beta_{k2j})\beta_{kj} + \beta_{kj}(b_{k2j} - \beta_{kj})}{J}$$

$$cov(b_{k1}, b_{k2}) \rightarrow V(\beta_k) + \frac{\sum_j E[(b_{k1j} - \beta_{kj})(b_{k2j} - \beta_{kj})]}{J}$$

Because $(b_{k1j}\text{-}\beta_{kj})$ and $(b_{k2j}\text{-}\beta_{kj})$ are parameter errors measured on two independent groups, they follow two independent probability laws. Therefore $E((b_{k1j}\text{-}\beta_{kj})(b_{k2j}\text{-}\beta_{kj}))=0$ and $cov(b_{k1}, b_{k2}) \rightarrow V(\beta_k)$

Hence, our second method

$$\boxed{V_{halves}(\beta_i) \simeq cov\left[(b_{i1}, b_{i2}), (b_{i2}, b_{i1})\right]}$$

We can thus compute the correct correlation coefficient as follows:

$$\boxed{\begin{aligned} Cor_{vcov}(\beta_k, \beta_l) &\approx \frac{cov_{vcov}(\beta_k, \beta_l)}{\sqrt{V_{vcov}(\beta_k)V_{vcov}(\beta_l)}} \\ Cor_{halves}(\beta_k, \beta_l) &\approx \frac{cov_{halves}(\beta_k, \beta_l)}{\sqrt{V_{halves}(\beta_k)V_{halves}(\beta_l)}} \end{aligned}}$$

Covariance of fixed effects and root mean square of errors

We also use the root mean square error $RMSE_j$ (with $RMSE_j = \sqrt{\frac{\sum_i e_{ij}^2}{N_j}}$) as an indicator of workplace *j* intra-categorical inequality and estimate its covariance with categorical inequality. As the *RMSE* measurement error is not estimated in a regression, we cannot use the *vcov* method to correct the covariance and the variance. We therefore use the randomized halves method to produce the same corrected estimates as above.

Hence:

$$cov_{halves}(\beta_k, RMSE) = cov\left[(b_{k1}, b_{k2}), (RMSE_2, RMSE_1)\right]$$
$$\text{with } k \in \text{(Gender, Nativity, Class)}$$

Simulation

To further explore the bias and the quality of our corrections, we rely on simulations. In our baseline simulation, we simulate 20 random datasets consisting of 100,000 workers in 2,000 workplaces (50 workers per workplace on average) where each workplace j has its own k_j (for instance: gender) and l_j (for instance: class) fixed effects. We set the covariance and the correlation between β_k and β_l to -0.4 and the underlying correlation of k and l to 0.1. Our average true correlation between β_k and $RMSE$ is 0.56.
In the following columns, we differ from the baseline simulation by one parameter. In column 2, we double the sample size. In column 3, we double the average number of workers per unit. In column 4 and 5, we change the correlation between β_k and β_l to a stronger absolute value (-0.7) and a null one. In column 6 and 7, we change the correlation of k and l to a weaker one (0.05) and a null one. In column 8, we decrease the correlation between $RMSE$ and β_k.

Simulations show the following results: ☞

- The variance and the covariance of fixed effects are substantially biased.
- The bias in the variance and the covariance of fixed effects is weaker when the unit size is large (column 3).
- The bias in the covariance decreases when the absolute value of the correlation between k and l decreases (column 6). When uncorrelated, the bias is close to 0 (column 7).
- The two methods of correction enable us to correctly estimate the variance, the covariance and the correlation coefficient. They yield very similar results.
- The vcov correction method is relatively more powerful than the randomized halves one (as shown by the smaller standard deviations) which justifies using the former when available.
- The bigger the sample, the better the corrected variances, correlations and covariances (column 2)
- The variance of RMSE and its covariance with β_k does not seem substantially biased. Their correlation coefficient however is biased mainly due to the bias in the variance of fixed effects.

Table A2. Correction of variance, covariance and correlation. A simulation exercise

	Baseline	Larger sample	Larger units	corr(β_k, β_l) stronger	corr(β_k, β_l) =0	corr(k,l) weaker	corr(k,l) =0	corr(RMSE, β_l) weaker
Simulation theoretical parameters								
Number of observations	100,000	200,000	100,000	100,000	100,000	100,000	100,000	100,000
Average number of observations per unit	50	50	100	50	50	50	50	50
Cov(β_k , β_l) and Corr(β_k , β_l)	-0.4	-0.4	-0.4	-0.7	0	-0.4	-0.4	-0.4
Var(β_l) and Var(β_l)	1	1	1	1	1	1	1	1
Corr(k,l)	0.1	0.1	0.1	0.1	0.1	0.05	0	0.1
Var(RMSE)	3.89	3.42	3.85	3.98	3.82	3.9	3.63	6.6
	(0.44)	(0.39)	(0.49)	(0.36)	(0.49)	(0.43)	(0.51)	(0.49)
Cov(RMSE, β_l)	1.11	1.03	1.12	1.12	1.09	1.09	1.06	0.83
	(0.06)	(0.05)	(0.08)	(0.07)	(0.07)	(0.06)	(0.08)	(0.04)
Corr(RMSE, β_l)	0.56	0.56	0.57	0.56	0.56	0.55	0.56	0.32
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
Simulation estimates								
Var(b_k)	3.087	3.096	2.036	3.149	3.081	3.092	3.113	3.095
	(0.088)	(0.04)	(0.118)	(0.157)	(0.115)	(0.095)	(0.098)	(0.121)
Var(b_k) corrected (method: vcov)	0.993	0.999	1.007	1.051	0.983	1.012	1.042	1
	(0.092)	(0.041)	(0.117)	(0.158)	(0.118)	(0.097)	(0.101)	(0.122)
Var(b_k) corrected (method: halves)	0.985	0.999	1.017	1.013	1.016	0.981	1.052	0.962
	(0.139)	(0.068)	(0.099)	(0.184)	(0.161)	(0.112))	(0.156)	(0.156)
Cov(b_k , b_l)	-0.622	-0.605	-0.513	-0.907	-0.227	-0.516	-0.433	-0.631
	(0.082)	(0.05)	(0.068)	(0.071)	(0.071)	(0.077)	(0.067)	(0.11)
Cov(b_k , b_l) corrected (vcov)	-0.407	-0.391	-0.409	-0.692	-0.011	-0.41	-0.432	-0.412
	(0.081)	(0.05)	(0.068)	(0.077)	(0.071)	(0.076)	(0.067)	(0.107)
Cov(b_k , b_l) corrected (halves)	-0.404	-0.396	-0.43	-0.696	-0.011	-0.384	-0.44	-0.419
	(0.098)	(0.075)	(0.078)	(0.101)	(0.101)	(0.107)	(0.088)	(0.147)
Corr(b_k , b_l)	-0.201	-0.196	-0.253	-0.292	-0.074	-0.168	-0.138	-0.202
	(0.026)	(0.015)	(0.03)	(0.021)	(0.023)	(0.025)	(0.02)	(0.033)
Corr(b_k, b_l) corrected (vcov)	-0.408	-0.391	-0.41	-0.694	-0.009	-0.415	-0.411	-0.405
	(0.08)	(0.047)	(0.056)	(0.074)	(0.076)	(0.077)	(0.058)	(0.096)
Corr(b_k, b_l) corrected (halves)	-0.418	0.395	-0.423	-0.721	-0.006	-0.398	-0.415	-0.419
	(0.116)	(0.079)	(0.073)	(0.11)	(0.1)	(0.113)	(0.077)	(0.145)
Var(RMSE)	3.67	3.23	3.74	3.76	3.62	3.69	3.42	6.21
	(0.41)	(0.37)	(0.48)	(0.34)	(0.46)	(0.41)	(0.48)	(0.47)
Var(RMSE) corrected (halves)	3.36	2.93	3.6	3.45	3.31	3.37	3.13	5.86
	(0.42)	(0.36)	(0.47)	(0.34)	(0.46)	(0.41)	(0.47)	(0.47)
Cov(RMSE, b_l)	1.08	0.98	1.09	1.09	1.06	1.04	1.05	0.8
	(0.1)	(0.08)	(0.16)	(0.11)	(0.11)	(0.12)	(0.14)	(0.14)
Cov(RMSE, b_l) corrected (halves)	1.08	0.98	1.09	1.09	1.06	1.02	1.05	0.79
	(0.09)	(0.09)	(0.16)	(0.12)	(0.12)	(0.12)	(0.14)	(0.14)
Corr(RMSE, b_l)	0.32	0.312	0.399	0.323	0.321	0.312	0.323	0.183
	(0.033)	(0.024)	(0.053)	(0.03)	(0.029)	(0.033)	(0.038)	(0.033)
Corr(RMSE, b_l) corrected (halves)	0.6	0.569	0.572	0.608	0.607	0.576	0.579	0.321
	(0.078)	(0.047)	(0.081)	(0.075)	(0.073)	(0.085)	(0.078)	(0.067)

Abstract

In this article, we combine intersectional and organization theoretical insights and ask how different types of inequality are related within French workplaces. Our motivation is to clarify the meaning of workplaces as "inequality regimes" by asking if workplaces reinforce multiple inequalities or if there are tradeoffs between them.
Using French administrative data and novel techniques, we scrutinize correlations between class, gender and nativity wage gaps at the workplace level. We also study how each of these gaps relate to a fourth measure of wage inequality we call intra-categorical inequality (i.e within the three-level cross-categorization class×gender×nativity).
We discuss two sets of findings. First gender and nativity wage gaps are negatively correlated within workplaces. Second, while the gender gap is higher in more unequal workplaces, the nativity gap is higher in more equal workplaces.
Finally, we also ask how industry, urban environment, and various workplace characteristics affect these patterns. Our findings suggest that workplaces are not just sites of producing multidimensional inequality, but sites which specialize in inequality types.

Keywords
Social unequality, intersectionality, worplaces, France, class, gender, migration

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