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Gender Gaps and the Role of Bosses

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Gender Gaps and the Role of Bosses*

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Abstract

This paper investigates the contribution of managers to gender gaps and analyzes whether the over-representation of men in management positions puts women at a disadvantage. Relying on personnel data from one of the largest European manufacturing firms, we separate out the factors explaining gender gaps. Adjusted pay gaps are positive, which means that men earn more than observationally equivalent women. A significant share of pay gaps can be explained by the sorting of men and women to different managers. More importantly, gender gaps in bonus payments causally depend on the manager's gender. Accounting for worker and manager heterogeneity, bonus gaps are larger when the manager is male. This is driven by the fact that performance ratings are more favorable to men if handed out by a male manager. We present suggestive evidence that the relevance of manager gender for pay gaps is driven by discrimination rather than same-gender complementarities in productivity. However, independent of the root cause of these differences in evaluations by manager gender, the findings imply that a lower number of female managers increases gender gaps and thus constitutes a structural disadvantage for women.

Keywords: gender wage gap, performance ratings, managers, manager gender, sorting, personnel data, unconscious discrimination

JEL Codes: J16, J31, J33, J71, M5, D83

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1 Introduction

While the gender wage gap has declined considerably, convergence has slowed down and substantial gender disparities persist. In the US, for example, the unadjusted gender gap has stagnated at around 19% since the turn of the century (BLS, 2019). The adjusted wage gap is even more persistent as, for the past three decades, women have been earning about 9% less than men after adjusting for differences in education, experience, industry and occupation (Blau and Kahn, 2017). Gender pay gaps thus continue to receive significant attention as policy makers discuss gender quotas and many firms and large organizations train managers to be more aware of gender-related biases (Chang et al., 2019). It has been suggested that the adjusted wage gap is driven by differences in productivity, negotiation prowess, temporal flexibility, or (unconscious) discrimination (e.g. Azmat and Ferrer, 2017; Babcock et al., 2003; Goldin, 2014; Sarsons, 2018, respectively). All of these explanations could be closely related to the behavior of bosses. The direct superiors of workers affect productivity, negotiate salaries, shape work environments, and evaluate performance and thereby determine bonus payments (e.g. Lazear et al., 2015; Hoffman and Tadelis, forthcoming; Frederiksen et al., 2019).

In this paper, we use novel personnel data of a large multinational firm in order to shed light on the role of managers for gender gaps. In particular, we ask two novel questions connecting the literature on managers to that on gender gaps. First, do women work for "worse" bosses than men? Similarly to the distribution across occupations, sorting of workers and managers may explain a part of the gender wage gap. In other words, if male workers in the same occupation work for better-paying bosses than their female colleagues, this will drive a wedge between the earnings of equally qualified men and women. Second, are male bosses bad for women? Three main mechanisms come to mind. First, men may undervalue the performance of women due to conscious or unconscious biases. Second, male managers may create work environments that make it harder for women to shine. Third, men might be more productive under male managers due to gender-specific complementarities in productivity.[1] The persistent under-representation of women in powerful positions may therefore be cause and consequence at the same time if—for some reason—female employees are systematically disadvantaged when having male superiors.

[1] The opposite could also be true if women hinder other women, as for example has been documented by Bagues and Esteve-Volart (2010)

In order to separate out the different factors explaining gender disparities and investigate the importance of (male) managers for gender gaps, we bring in unique personnel data provided by one of the largest European manufacturing firms. The panel dataset cover the multinational's entire workforce in the period 2014–2019 and has several key advantages allowing us to address these questions. First, the data contain detailed information on job characteristics, sociodemographics, compensation, and performance evaluations. This allows us to identify the performance-related component of earnings. Second, we are able to trace out the organizational hierarchy and identify every employee's coworkers, superiors, and subordinates. Third, we can condition on time-invariant unobservable characteristics of both employees and their managers.[2]

The paper has two sets of results. The first quantifies to which extent the sorting of male and female workers to different managers can explain gender gaps while also taking into account the contributions of other observables such as sociodemographics and job characteristics. To that end, we implement a Kitagawa-Oaxaca-Blinder-decomposition for base salaries, bonus payouts, contracted bonus targets, and performance ratings (Kitagawa, 1955; Oaxaca, 1973; Blinder, 1973). For male and female workers, we run separate regressions of the outcome of interest on job characteristics, manager indicators, age, tenure, and location controls. The decomposition reveals the following three findings.

First, the raw gender gaps in base salary and bonus payouts are 12.3 log points and 22.2 log points, respectively. Men's contracted bonus targets are on average 2.8% greater than those of women. The raw gender gap in performance ratings is negative as men are two percentage points less likely than women to receive a high performance rating.

Second, 25% of the raw gender gap in base salary and 19% of the gender bonus gap are attributed to the sorting of male and female workers to different managers. The unexplained component of the gender gap is larger for bonuses (16.9%) than for base salaries (8.8%). For performance ratings, we find that a large part of the gender gap cannot be explained. However, while the contribution of standard observables such as age or job characteristics drops substantially, the impact of managers remains sizable. Worker-manager sorting increases the performance gap (in favor of men) by 2.1 log points. This means that if women were assigned to the same jobs and managers, the performance gap would be even more negative.

[2] We will refer to a worker's direct superior as manager. A manager is also a worker from the perspective of his or her manager.

Third, comparing similar employees doing the same job under the same manager, we find significant residual gender gaps in base salaries (1.1%), bonus targets (2.0%), and bonus payouts (3.8%). While all of these gaps favor men, the opposite holds for performance evaluations. Women are 3.5 percentage points (14.2% relative to the mean) *more* likely to receive high a performance rating, which implies above-target bonus payouts. The performance-corrected gap in bonus payouts is thus even larger than the raw gap. We find no evidence that women simply receive better ratings because they would cost the firm less in terms of implied bonus payments. We do not find evidence in favor of the interpretation that residual pay gaps are majorly related to child care obligations.

The second set of results answers the question whether the gender gap is different under male and female managers. Intuitively, we do so by defining within-manager gender gaps and comparing their average sizes between male and female managers in a difference-in-differences framework. As we take into account unobserved worker heterogeneity, identification comes from workers working for managers of different genders over time. As the worker fixed effects fully absorb the absolute level of the gender gaps, we identify by how much the expected gender gap *changes* when the manager is male rather than female.

We find that the over-representation of male managers implies a structural disadvantage for women. In particular, male managers cause the gender gap in bonus payouts to increase by 5.1%. This is driven by a relative increase of the gender gap in performance evaluations of 2.7 percentage points comparing male to female bosses. Hence, while in general men receive lower ratings, this gap closes considerably when the manager is male.

We evaluate which mechanism is likely to drive these findings. While more productive men could work more often for male bosses, this mechanism cannot rationalize our findings as we control for unobserved worker characteristics. Another potential explanation are within-gender complementarities. However, gender gaps do not increase with the share of male coworkers in a team. Assuming that potential within-gender complementarities would also exist among coworkers, we can rule out that the productivity channel drives the results. In contrast, we find suggestive evidence consistent with (unconscious) discrimination, as manager gender tends to matter more for less knowledgeable decision makers. In particular, we split managers into groups who should be more or less informed about the true quality or the needs of their subordinates. While not statistically significant, we find that for all proxies of manager knowledge the effect of manager gender is smaller. The observation that a manager's experience, team size, spatial proximity and the time that a manager has worked with a subordinate all are correlated with a lower effect of manager gender is consistent with discrimination due to biased beliefs of less knowledgeable managers. This mechanism relates to Bohren et al. (2019), who show that decision makers resort to their biased beliefs if little information about workers is available to them.

Related Literature This paper primarily contributes to the vast literature on gender inequality in the labor market summarized among others by Altonji and Blank (1999), or more recently by Bertrand (2011) and Blau and Kahn (2017). One set of papers tries to understand (raw) gender pay gaps. Early papers focused on the role of education and human capital (Altonji and Blank, 1999). As the gender gap in human capital has vanished over time, recent studies have highlighted the role of children as well as differences in occupation and industry. Kleven et al. (2019b) use Danish data to show that the arrival of children creates a substantial long-run gender gap in earnings driven by hours worked, participation, and wage rates (see also Kleven et al., 2019a, for evidence on other countries). Blau and Kahn (2017) document that differences in occupation continue to account for parts of the gender wage gap, and Goldin (2014) finds that work environments rewarding working long hours prevent female wages from fully catching up. Based on an AKM-model (Abowd et al., 1999) in which workers are sorted to firms, Card et al. (2016) find that part of the gender wage gap can be attributed to women working for firms that pay lower premiums. We add to the literature on raw gender wage gaps by showing that the sorting of men and women to different managers in part explains the gender wage gap. To our knowledge, our work is the first to focus on the impact of worker-manager sorting on pay gaps. We bring in a data source—a large manufacturing firm's personnel data—that allows for better control over job characteristics. Research on gender gaps using personnel data dates back to Malkiel and Malkiel (1973) and is vast.[3] However, our data are unique as they identify hierarchical relations between workers and managers while also containing highly detailed information about pay, performance ratings, ranks, and occupations

A second strand of the literature investigates the reasons behind the persistence of the adjusted gender wage gap, in particular with a focus on performance and evaluations. Previous studies come from very specific settings and may there-

[3]For example, Sorensen (1986), Kahn (1992), Ransom and Oaxaca (2005), Barnet-Verzat and Wolff (2008), Dohmen et al. (2008), Ichino and Moretti (2009), Pema and Mehay (2010) or Pekkarinen and Vartiainen (2016) study within-organization gender gaps, mainly based on public sector data.

fore lead to different conclusions. In the context of academia—where performance is relatively easy to measure—Sarsons et al. (forthcoming) show that female researchers get less credit for joint work than male co-authors. Card et al. (2020) conclude that journal editors and referees hand out too few revise-and-resubmit decisions to female-authored papers relative to a citation-maximizing benchmark. Similarly, Hospido and Sanz (2019) find that all-female authored papers are less likely to be accepted for major economics conferences. Outside of academia, female surgeons and financial advisors have been found to be more heavily penalized for bad performances or misconduct (Sarsons, 2018; Egan et al., 2017, respectively). Mengel et al. (2019) show that female university tutors receive systematically lower teaching evaluations. Azmat and Ferrer (2017) find that gender performance differences exist as male lawyers actually outperform their female colleagues and that accounting for this substantially alters the interpretation of the gender wage gap. What distinguishes our work is that we observe wages, bonus payouts and performance evaluations in the context of a large multinational enterprise in the manufacturing sector, i.e. a setting that is highly relevant to many workers in developed economies. In this context, we find that the over-representation of men in top positions does harm women as gender gaps in bonus payments and performance ratings increase substantially under male managers. In addition, our findings challenge the view that productivity differences can account for adjusted gender wage gaps in a wide range of occupations. We further provide suggestive evidence in favor of the biased-beliefs mechanism proposed by Bohren et al. (2019).

We also add to the literature on the effect of male leadership on gender gaps. While the gender composition at the very top of firms does not affect gender gaps (Bertrand et al., 2019; Maida and Weber, 2019), a number of papers show that gender compositions matter when the distance between superior and subordinate is smaller. Kunze and Miller (2017) and Kurtulus and Tomaskovic-Devey (2011) find that a larger share of women at higher ranks increases women's chances of being promoted. However, it is unclear whether individual interactions between workers and managers or firm-wide policies drive these observations. Our paper differs in that we *directly* link workers to their managers at all levels of the firm hierarchy rather than only at the very top. Using cross-sectional survey data, several authors have documented that gender gaps tend to be greater under male superiors (Ragan and Tremblay, 1988; Rothstein, 1997; Abendroth et al., 2017).[4]

[4] Another cross-sectional study by Halldén et al. (2018), based on Swedish survey data, finds that women earn less when their superior is female. However, the data do not allow to make claims about the gender gap.

In the context of schools, Biasi and Sarsons (2020) find that gender pay gaps among teachers increase when principals or superintendents are male. A recent study by Cullen and Perez-Truglia (2019) shows that the gender promotion gap in a Southeast Asian bank widens when the direct superior is male. Relative to their study, we focus on how manager gender impacts within-team gaps in wages and performance evaluations in a wide range of occupations and countries. Our approach also takes into account unobserved manager characteristics, which prove critical to the finding that managers affect gender pay gaps.

Outline The remainder of the paper is structured as follows. Section 2 provides more information about the data and the firm. Section 3 describes our empirical strategy, Section 4 documents the findings, and Section 5 concludes.

2 Data and Setting

The Firm We use the personnel data of a large firm in the manufacturing sector.[5] The firm is among the 250 largest European firms in terms of sales and employment and an industry leader in an R&D-intensive sector. A quarter of the multinational's workforce is located in the firm's home country but it has establishments in over 50 countries. For example, around 20% of the workforce is located in the United States.

While a single firm can hardly be representative of the economy as a whole, its size, international representation, range of occupations, and diversity of skills required ensure that its internal labor market is typical for what a worker would encounter at any large firm. Key variables of our study are earnings and the share of male workers, which we can use to compare the firm to other firms in the same sector. In the US, workers in the same three-digit NAICS industry earned during the sample period around 7.2% less than workers in our data.[6] At the firm, the share of female workers in the US is about 6 percentage points higher than the sectoral average.[7]

By now, administrative data matching employees to firms are widely available. While such kind of data would be preferable to use for a more holistic view, our

[5] We are not allowed to reveal the identity of the firm.

[6] Bureau of Economic Analysis, Wages and Salaries Per Full-Time Equivalent Employee by Industry, https://apps.bea.gov/iTable/iTable.cfm?reqid=13&step=3&isuri=1&nipa_table_list=201&keyword_index=w

[7] Bureau of Labor Statistics, Labor Force Statistics from the Current Population Survey, https://www.bls.gov/cps/cpsaat18.htm

dataset has several unique features. As opposed to administrative data where workers would be linked by working in the same firm and same occupation, we observe precisely who works in the same team and who is each worker's responsible superior. Furthermore, the description of jobs and hierarchy provided to us by the firm goes beyond typical definitions of occupations. This allows us to control much more precisely for the nature of the job. We also do not only observe earnings but the detailed variables determining compensation, including performance ratings.

Personnel Data We were provided with an anonymized monthly panel of all personnel records between January 2014 and March 2019. The data includes information on employees' compensation (base salaries and bonus payments), performance ratings, occupation, hierarchical rank, location, tenure, and some sociodemographic characteristics such as gender, age, or nationality.[8] Importantly, the data also indicate the identity of each worker's superior, to which we refer as *manager* or *boss*. Therefore, we can trace out the organizational hierarchy and identify employees' coworkers, superiors, and subordinates. Employees can be superiors and subordinates at the same time as the firm has many hierarchical layers.

We observe ten thousands of full-time employees.[9] The unadjusted gender gap (the average difference between male and female outcomes) in base salaries (before taxes) is 3917€, or 7.6%. One would typically control for experience, location, and job characteristics to determine the adjusted gender pay gap. Such an adjustment yields a gender gap in base salaries of 1.7%. 26 404 workers are paid a bonus. In this set of workers, the gender gap in annual bonus payout (before taxes) is 2375€, or 20.3%. Controlling for experience, location, and job characteristics results in an adjusted bonus gap of 4.6%.

Job Definitions Jobs are classified into 109 different occupations, for example *Electrical Engineering*, *Scientific Technical Assistance*, *Fire Brigade*, or *Web Design*.[10] In addition, jobs are classified by hierarchical rank on a scale from one to ten, representing a range from low-skilled helpers to executives. Ranks one to three are to a large extent blue-collar production jobs. While workers of different hierarchical rank can work in the same occupation, occupations only comprise a limited number of ranks. Starting at rank four, white-collar occupations are more

[8]The number of employees reporting education and previous employers is very small.
[9]We cannot report the exact number to protect the identity of the firm.
[10]We cannot show a full list of occupations as it could reveal the identity of the firm.

Table 1: Gender Distribution across Hierarchical Ranks

Rank	Share [%]	Salary [€]	Bonus [€]	Any Bonus [%]	Share Male [%]	Salary Gap [€]	Bonus Gap [€]
1	0.5	18 002.58	13 036.89	33.67	63.85	−5324.59	5792.14
2	7.65	27 131.86	4007.53	53.26	66.3	5958.01	2095.94
3	14.76	32 181.96	2479.71	54.02	67.62	2395.46	454.9
4	25.54	32 771.42	3002.1	47.4	57.1	−860.15	−162.59
5	27.79	44 937.26	5931.84	44.28	57.01	654.7	138.78
6	17.25	76 957.14	14 907.22	71.98	61.8	3002.29	131.61
7	3.71	117 899.9	31 514.63	80.15	68.5	−8527.77	−135.85
8	2.41	154 211.52	57 869.84	81.39	75.94	−5702.43	−1890.47
9	0.34	227 647.17	137 310.0	74.71	87.77	−16 322.27	−24 453.82
10	0.05	335 444.2	276 739.82	69.79	72.92	59 631.59	17 396.89
All	100.0	50 090.26	10 781.41	54.27	61.16	3917.02	2374.62

Notes: The table displays mean values of base salaries and bonus payouts in € with base year 2010 for nine out of ten hierarchical ranks (1 being lowest and 10 highest). The table also displays the share of workers, the share of men, and the gender gaps (male outcome - female outcome) in base salaries and bonus payouts.

prevalent. We henceforth characterize a job by the combination of occupation and hierarchical rank.

From Table 1 we can see that the majority of workers works on jobs of intermediate hierarchical rank. In general, higher ranks pay higher salaries and bonuses, but not all workers receive bonuses. While participating in a bonus program seems to be more common at high ranks, a number of workers opts out. At very high ranks, other long term incentives also play a greater role. The share of men at low ranks is relatively large as many production-related occupations are ranked here. Women represent around 40% of the workforce in the middle range of the hierarchy. But the higher the rank, the lower becomes the share of women. While there is no clear pattern of raw gender pay gaps at separate hierarchical levels, it seems that men face an advantage at the most common ranks in the firm.

Salaries, Bonus Payments and Performance Ratings According to the firm, conditional on individual productivity, experience, and location, employees working in the same job should be compensated equivalently. It might well be the case that a certain occupation pays more at a lower rank than another occupation at a higher rank. Each job has a salary band set by the human resource department which is only known by the worker's manager and not part of the data we obtain. Managers and workers negotiate a base salary within such a band. Usually, pay raises within the same job are only negotiated once a year, namely when an employee's performance is evaluated.

The contract also specifies a bonus target, which is the amount that will be paid out in addition to the base salary as an annual bonus. The target is expressed as a percentage of the base salary. For example, if the employee's target is 5% and the base salary is 50 000€, she can expect annual earnings of 50 000€ + 2500€ = 52 500€.

However, the bonus is supposed to incentivize effort. Workers showing satisfactory but not outstanding performance are paid as just described. Less is paid out as a bonus if the employee performs poorly, and more is paid out if the employee does especially well. This means that workers with a higher base salary, higher bonus target, or higher performance will receive a larger annual bonus. Workers' effort has a significant influence on the amount eventually paid out as a bonus. Workers know the function $f(\text{rating})$, which maps their grading into a factor multiplying base salary and bonus target. In principle, earnings can be expressed as the sum of base salary and the performance-dependent component, i.e. the product of base salary, target and a function of performance.

$$\text{Earnings} \approx \text{Base Salary} + \text{Base Salary} \times \text{Target} \times f(\text{rating})$$

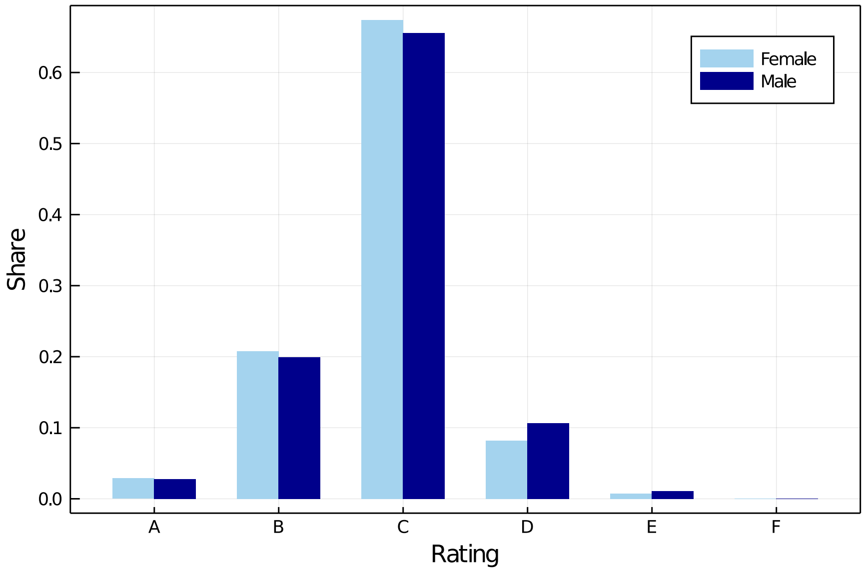
Performance ratings are handed out by the employee's direct superior once per year, evaluating the previous twelve months. An evaluation scheme of six grades is applied across all jobs and countries. The firm considers a ranking to be high if an employee achieves at least the second-best grade. A *high* ranking will ceteris paribus result in a bonus payout greater than the contracted target. As an employee's output is hard to measure, the mapping from effort to performance ratings cannot be contracted.[11] Hence, performance ratings are potentially subject to conscious or unconscious gender biases of the manager (e.g. Bordalo et al., 2019). Through their performance evaluations, managers thus have a substantial impact on the total earnings of their subordinates.

Figure 1 displays the distribution of performance ratings for men and women. The majority of workers receives a C, which implies no adjustment to the contracted bonus. A high performance rating is achieved by workers receiving ratings A or B. The graph also shows that in the raw data women are more likely than men to receive a high rating.

Observed bonuses are not equivalent to Base Salary $\times$ Target $\times f(\text{rating})$. There are several reasons for this. First, department-wide achievements also affect bonus

[11] Employees for which individual output can easily be measured are sales workers. They receive a separate sales bonus in addition to the general bonus which reflects the generated revenue. We do not have access to these data.

FIGURE 1: Distribution of Ratings by Gender



Notes: The figure plots a histogram of annual performance received by male and female workers. The best rating is A, the worst rating is F.

payout. Second, we are not provided with the mapping for workers with changes in workplace characteristics. Third, performance ratings are very detailed, while we only use a simple approximation, an indicator for receiving a high rating. Importantly, it holds that all else equal, workers with high performance should receive a larger bonus.

Sample Description We focus on full-time employees aged 25 to 60 and for which we observe gender, superior, job, age, and tenure. We aggregate the data to annual frequency for 2014-2019 as bonus payments and performance ratings are only determined once per year. Monetary variables are converted to Euros with 2010 as the base year. The resulting dataset is summarized in Table 2.[12]

Base salaries are on average 50 000€. We observe positive bonus payouts only for a subset of workers because not every worker receives performance pay and due to data limitations. The size of bonus payments is significant with a mean annual payout of almost 11 000€. Approximately 20% of workers receive a high performance rating, so are entitled to a bonus payout greater above their contracted bonus target. 13% of workers underperform, implying a below-target bonus payout. Some workers receive a rating even though their contracts do not include

[12]Extreme values are omitted for confidentiality reasons.

TABLE 2: Descriptive Statistics

	Mean	SD	10th Perc.	Median	90th Perc.	Observations
Salary [€]	50 090.26	53 096.49	10 077.67	40 404.73	94 234.79	178 377
Bonus [€]	10 781.41	20 324.33	1289.45	4233.43	24 812.78	96 803
High Performance	0.22	0.42	0.0	0.0	1.0	154 790
Low Performance	0.13	0.33	0.0	0.0	1.0	154 790
Bonus Target [%]	11.82	8.81	4.0	10.0	22.51	108 839
Male	0.61	0.49	0.0	1.0	1.0	178 377
Age	41.53	9.24	29.0	41.0	55.0	178 377
Tenure	9.82	9.19	1.0	7.0	24.0	178 377
Span of Control	1.16	3.77	0.0	0.0	5.0	178 377
Coworkers	9.65	20.59	1.0	5.0	19.0	178 377
New Manager in Same Job	0.25	0.44	0.0	0.0	1.0	128 521
New Manager in New Job	0.07	0.25	0.0	0.0	0.0	128 521
Male Manager	0.72	0.45	0.0	1.0	1.0	178 377
Male & Male Manager	0.49	0.5	0.0	0.0	1.0	178 377
Male & Female Manager	0.12	0.33	0.0	0.0	1.0	178 377
Female & Male Manager	0.23	0.42	0.0	0.0	1.0	178 377
Female & Female Manager	0.16	0.36	0.0	0.0	1.0	178 377
Age of Manager	44.97	8.08	34.0	45.0	56.0	178 377

Notes: Extreme values omitted for confidentiality reasons. Unbalanced panel based on ten thousands of workers and the years 2014-2019. Monetary variables normalized to € in 2010.

performance pay. 60% of employees are male and the average age is 42 years. The span of control measures the number of direct subordinates.

Identifying each worker's manager is key to studying managers' impact on gender gap. We do so by matching each worker to his or her direct superior. Each employee has on average 9.7 coworkers who work under the same manager. Employees are more likely to have a change in their manager due to managers rotating than due to a job change of the worker. One quarter of employees stay in their current job but work for a new manager. Managers are more likely to be male and on average three years older than workers.

The data reveal that male and female workers are sorted to different managers based on gender. The share of male workers sorted to a male manager is 80%. Women are more likely to work for female managers as the share of female workers sorted to a male manager is only 59%.

3 Empirical Strategy

In the first part of the empirical analysis, we examine how the sorting of workers to managers can explain gender gaps. Evidence for the impact of managers on worker productivity has been provided by Frederiksen et al. (2019) or Lazear et al.

(2015). For example, women may work for managers who are less productive. This could happen if male workers have stronger social networks within the firm which provide them with better information about managers. In Table 2 we saw that workers are sorted to managers based on gender. If female managers are less productive (as suggested by Azmat and Ferrer, 2017) and manager productivity affects worker productivity, female workers are disadvantaged.

There are other explanations why managers could matter. Male employees are often less reluctant to negotiate (e.g. Babcock et al., 2003). This could drive them towards more generous managers who are open to negotiation. Similarly, the fact that women tend to shy away from competition (Niederle and Vesterlund, 2007) could drive female workers to work more often for managers who create less competitive work environments, with the effect that workers are on average less productive. Women might be also driven to managers who—at the cost of lost productivity—offer a more family friendly environment, for example by allowing for more flexible work hours or permitting working from home on a regular basis (Goldin and Katz, 2015). This explanation would imply that women might actually prefer to work for "worse" bosses, i.e. bosses creating a environment which makes workers less productive.

In the second part of the analysis, we hold these manager effects fixed and study whether there is evidence that managers affect their *within-team pay* gaps. Observing any residual gender gap within teams does not necessarily imply that managers are to blame for gender pay gaps. But if within-team gaps vary across managers with different characteristics, we can conclude that managers do affect workplace equity.

3.1 Explaining Gender Gaps

We aim to answer the question what portion of gender gaps can be explained by observable characteristics. In particular, we want to quantify the contribution of the matching of managers and workers to gender gaps. To do so, we implement traditional Kitagawa-Oaxaca-Blinder-decompositions of differences between male and female workers in log salaries, log bonus payouts, high performance indicators, and contracted bonus targets (Kitagawa, 1955; Oaxaca, 1973; Blinder, 1973).

The decomposition classifies differences between two groups into a composition component that accounts for different characteristics, e.g. tenure or occupation, and an unexplained, or wage structure, component. Such Kitagawa-Oaxaca-Blinder-decompositions are commonly used in the estimation of gender gaps (e.g.

Bertrand et al., 2010; Blau and Kahn, 2017; Card et al., 2016; Juhn and McCue, 2017).

The unexplained component is often interpreted as a measure of discrimination, as it implies differences in pay or other outcomes for observationally identical workers. However, discrimination might also stem from different characteristics, i.e. the explained part of the gender gap. Women might be discriminated against by being allocated to worse-paying occupations. By controlling for the type of occupation, we take this allocation as given while it could already be the result of discriminatory treatment. It is also not clear that all unexplained differences are the result of discrimination. If men perform better than women (as found by Azmat and Ferrer, 2017), productivity differences contribute to the residual term.

The Kitagawa-Oaxaca-Blinder-decomposition is implemented as follows. Each worker i is either male m or female f and observed in year t. We estimate ordinary least squares (OLS) regressions for both genders separately.

$$Y_{it}^m = X_{it}^m \beta^m + u_{it}^m \tag{1}$$

$$Y_{it}^f = X_{it}^f \beta^f + u_{it}^f \tag{2}$$

Y_{it} is the outcome of interest of worker i in year t. X_{it} is a vector of variables observed at the worker level, including a constant. β^m and β^f are the gender-specific returns to these characteristics. u_{it} is the error term.

We obtain the estimates of returns $\widehat{\beta}^m$ and $\widehat{\beta}^f$ from OLS. We then calculate means of the outcomes and characteristics for both genders, denoted by a bar over the respective term. The difference of the means of equations (1) and (2) is the observed gender gap.

$$\overline{Y}^m - \overline{Y}^f = \overline{X}^m \widehat{\beta}^m - \overline{X}^f \widehat{\beta}^f = (\overline{X}^m - \overline{X}^f)\widehat{\beta}^m + \overline{X}^f(\widehat{\beta}^m - \widehat{\beta}^f) \tag{3}$$

The residuals drop out when taking the mean. The first term of the decomposition in equation (3) is the difference in male and female outcomes due to different characteristics, based on male coefficients. The second term is the unexplained difference in outcomes due to different returns for men and women. One could perform the decomposition using the coefficients on female returns as well. However, here we are interested in how the outcomes of women would change if the firm is required to treat women like men.

We decompose log base salaries, log bonus payouts, high performance indicators, and log bonus targets. Due to the richness of the firm's personnel data, we can include a wide range of variables in X_{it}. For age and tenure, we create bins for every six years of age. We include indicators for each year and each country. Job characteristics are controlled for by including the combination of occupation and hierarchical rank. As we are particularly interested in the role of bosses, X_{it} also includes an indicator for worker i's boss at time t.

The high resolution of worker-level controls comes at a cost. The matrices X^m and X^f, which respectively collect the vectors $X^m_{i,t}$ and $X^f_{i,t}$, need to have full rank. This is not the case if, for example, there is a certain job which is only done by men. In such a case the column of the matrix X^f indicating working for this manager would always be zero and hence perfectly correlated with the column indicating the constant. We therefore only include observations with a characteristic observed among men and women.

Another requirement for full rank matrices is that the different categorical variables are connected. This is identical to the condition explained by Abowd et al. (2002), that fixed effects in an AKM-model (Abowd, Kramarz, and Margolis, 1999) are only identified within a connected set. A set of observations is unconnected if a categorical variable is nested in another categorical variable. Consider an example where we include a constant, occupation, and location. Assume that engineers and accountants always work in Spain, cleaners always work in France, and there are no other occupations or countries. When comparing a worker in France to a worker in Spain it is unclear whether their pay difference is due to location or occupation. But if accountants work in both countries, they identify differences due to location. Once these differences are determined, residual differences in pay can be attributed to occupations. Note that even in this case we still require a linear restriction due to the inclusion of a constant. For this reason, we only keep the largest connected set of categorical variables for men and women. In practice, we iterate over the algorithm proposed by Abowd et al. (2002) for different combinations of categorical variables until the matrices X^m and X^f are full rank and only include observations with a characteristic observed both among men and women.

Assuring that matrices are full rank reduces the sample size. To maintain a constant size of data, we also impose that workers participate in bonus schemes and that bonus targets and performance ratings are observed. The resulting dataset consists of 59 813 observations based on 20 048 workers and 4327 managers from 58 countries and 421 jobs. Appendix Table A.1 shows that in this dataset workers earn a bit more which is due to the fact that some low-rank jobs without performance pay are excluded. Besides that, the subset of data used for estimation is very similar.

3.2 Understanding Residual Gender Gaps

Residual gender gaps could be interpreted as productivity differentials between men or women. In the decomposition, managers can contribute to gender gaps through the channel that male and female workers work for different managers. But it does not tell us anything about how individual managers treat men and women who actually work for them. For example, these residual gaps could persist if the majority of bosses for some reason favor male workers. At the firm, 72% of managers are male.

Illustration of Within-Manager-Gender Gender Gaps Figure 2a is an illustration of how gender gaps could look like, separating gaps at male and female managers. The light dots indicate the earnings of women, the dark dots earnings of men. The filled dots on the left plot earnings at female managers, the filled dots on the right at male managers. The labels MF, FF, etc. also refer to the four possible combinations of worker and manager gender. For example, MF stands for male workers working for female managers. Focusing on female managers only, the difference between MF and FF is the gender pay gap. Workers at male bosses earn more ($FM - FF$), but the size of the gender gap $MM - FM$ is equal to the gap under female managers. The gender pay gap $MF - FF$ is a quantity of interest, but it is unclear why this difference exists.

In the example from Figure 2a, all managers could be discriminating against women, or women could be less productive. In such a setting we cannot draw any conclusions on the impact of managers on gender gaps.

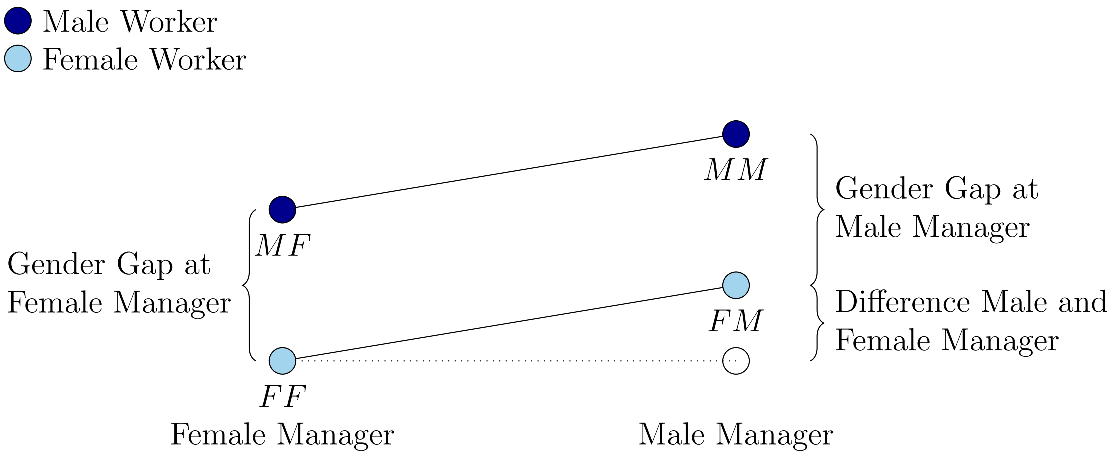
But if we find that there is variation in gender gaps across teams managed by managers of different gender, we know that manager gender and hence managers affect gender gaps. This is depicted in Figure 2b. In this example, the gender gap at male bosses is greater than the gender gap at female bosses. If the difference in gender gaps, ω, is significant, we can conclude that managers affect gender gaps.

Estimation To estimate the change in the gender gap depicted in Figure 2b, we run a difference-in-difference estimation for outcome Y of the following form.

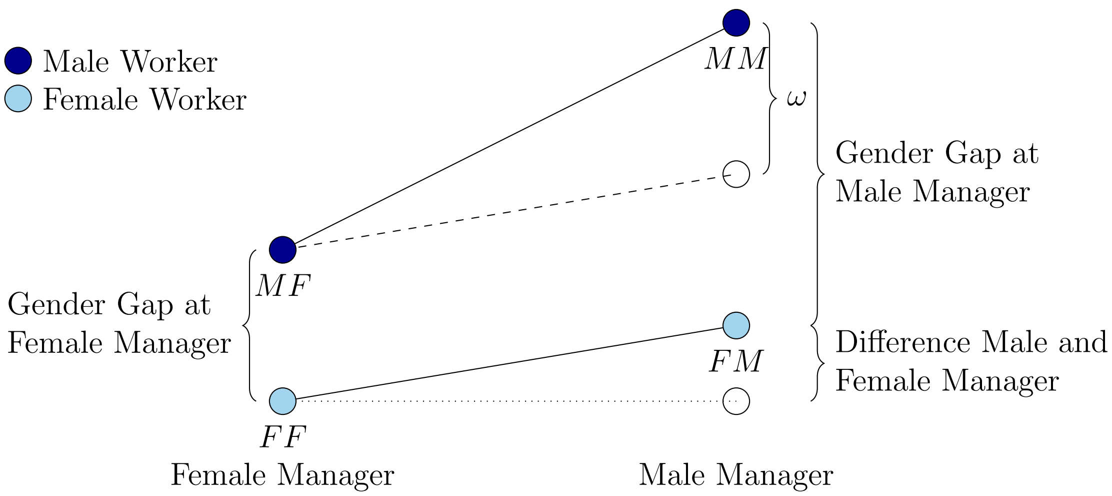
$$Y_{it} = \gamma_0 + \gamma_1 \times male_i + \gamma_2 \times male_{M(i,t)} + \omega \times male_i \times male_{M(i,t)} + X_{it}\beta + \epsilon_{it} \quad (4)$$

Figure 2: Illustration of Gender Gaps

(a) Equal Gender Gaps at Male and Female Managers



(b) Different Gender Gaps at Male and Female Managers



Notes: These figure provides a graphical illustration of gender gaps under male and female managers. FF stands for a female worker working for a female manager, MF for a male worker working for a female manager, FM for a female worker working for a male manager, and MM for a male worker working for a male manager. ω is the difference in gender gaps between male and female managers, i.e. $\omega = (MM - FM) - (MF - FF)$.

$male_i$ is a dummy taking value 1 if worker i is male. Its coefficient represents the gender gap under female managers, i.e. $MF - FF$ in Figure 2b. $male_{M(i,t)}$ is a dummy taking value 1 if the manager M of worker i at time t is male. Its coefficient can be interpreted as the difference in earnings among women when working for a male instead of a female manager, i.e. $FM - FF$ in Figure 2b. $X_{i,t}$ controls for age-bin, tenure-bin, year, country, and job as before. We are interested in the difference-in-differences coefficient ω on the interaction of the dummy $male_i$ with the dummy $male_{M(i,t)}$. This product is 1 if worker and manager are male and 0 otherwise. As shown in Figure 2b, ω is the difference in gender gaps between male and female managers. A positive ω indicates that the gender gap moves in favor of men when the manager is male.

Replacing all gender dummies by $female_i = 1 - male_i$ etc., results in exactly the same estimate of ω, but now on the product of dummies $female_i \times female_{M(i,t)}$.[13] The natural interpretation would be as follows. The inverse gender gap (female outcome - male outcome) increases if the manager is female. This shows that we only can quantify by how much the gender gap changes, but not whether male or female managers are to blame.

A major problem when estimating Equation (4) can be unobserved heterogeneity of workers and managers. If workers are sorted to managers based on these unobserved characteristics, the estimate of ω is biased. For example, if good male workers tend to work for good male managers, or good female workers often work for good female managers, identification is compromised. Therefore, we introduce in Equation (5) a worker fixed effect, α_i, and a manager fixed effect, $\Psi_{M(i,t)}$, for i's manager M at time t.

$$Y_{it} = \omega \times male_i \times male_{M(i,t)} + \alpha_i + \Psi_{M(i,t)} + X_{it}\beta + \epsilon_{it} \tag{5}$$

Estimating ω in Equation (5) yields the change in within-manager pay gaps, adjusted for worker quality, when the manager is male instead of female. Intuitively, this does the following. We residualize each worker's outcome based on the controls X_{it} and remove the worker mean. Then, we calculate the within-manager pay gap based on all workers who worked for the manager. Again, the level of the

[13] This can be shown by a simply replacement of variables:

$$\begin{aligned}
&\gamma_0 + \gamma_1\ male_i + \gamma_2\ male_{M(i,t)} + \omega\ male_i \times male_{M(i,t)} + \dots \\
&= \gamma_0 + \gamma_1\ (1 - female_i) + \gamma_2\ (1 - female_{M(i,t)}) + \omega\ (1 - female_i) \times (1 - female_{M(i,t)}) + \dots \\
&= (\gamma_0 + \gamma_1 + \gamma_2 + \omega) - (\gamma_1 + \omega)\ female_i - (\gamma_2 + \omega)\ female_{M(i,t)} + \omega\ female_i \times female_{M(i,t)} + \dots
\end{aligned}$$

gap has no interpretation, because we subtract the mean from each worker's outcome. ω is the mean difference of the adjusted within-manager pay gap between male and female managers.

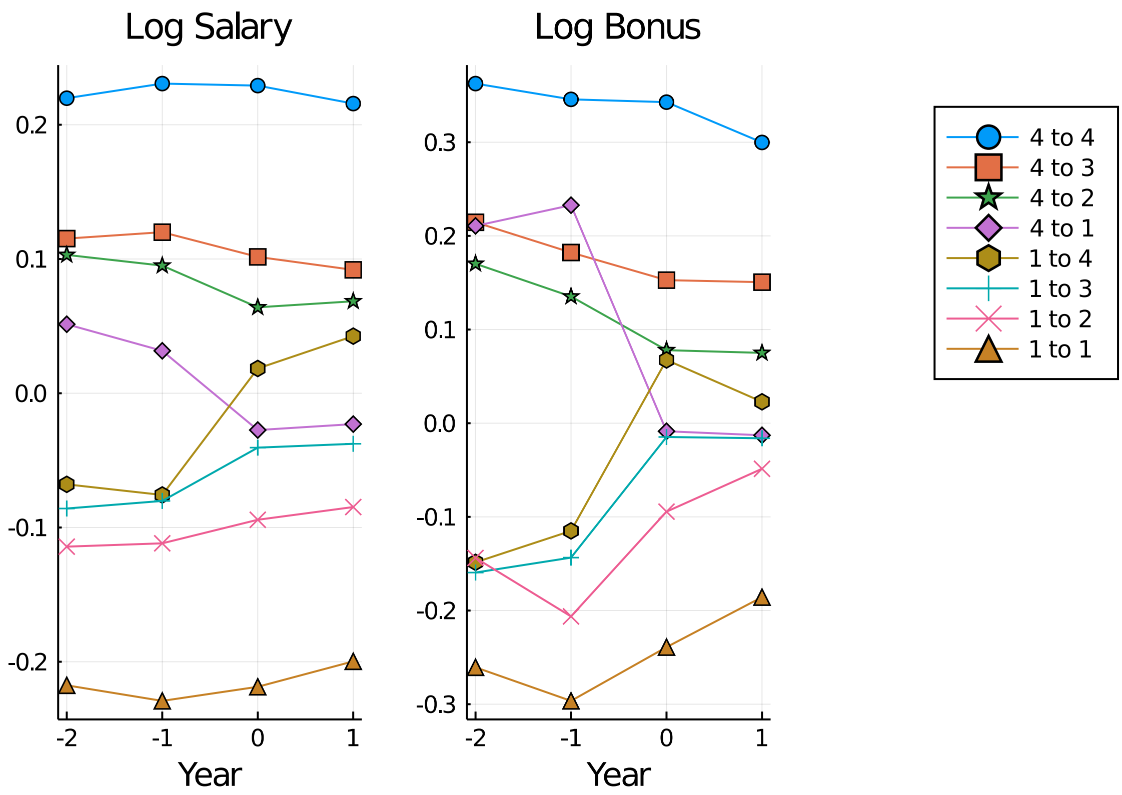
Identification Identification of ω in Equation (5) comes from "movers", i.e. workers who work for different managers. There are two reasons why a worker experiences a manager change. First, workers who switch their job will face a new manager.[14] Second, workers who do not change positions receive a new manager if the previous manager rotates to another job or leaves the firm. In the present setting, 32% of workers observe a change in manager in a given year, and almost 80% of these switches are due to managers rotating jobs.

We require an exogeneity assumption regarding the changes of managers. Sorting of workers to managers based on time-varying performance would bias estimations of equation (5). The fact that the majority of changes is due to managers rotating limits this concern because managers would need to be assigned based on the potential future performance of workers. From our interviews with the human resources department of the firm this is extremely unlikely. Usually, managers only get to know their subordinates after having started a new position. However, one might still worry that moves of workers correlate with time-varying performance or that workers only move if they get a better deal. While one cannot prove exogeneity, we examine whether there is evidence that sorting could bias the estimation results. As suggested by Card et al. (2013) in a setting where workers move across firms, we implement event studies on pay for workers changing managers.

To do so, we classify managers by the average of salaries or bonuses. To account for job characteristics, we first residualize these outcomes, taking into account job characteristics, location, tenure, age, and year. Then, we calculate the leave-one-out mean of the residual to avoid selection based on worker i's own productivity This is the average residual observed under i's current manager $M(i,t)$, excluding the contribution of i. The leave-one-out means are then used to classify each worker-year observation into one of four quartiles. Next, we calculate the average residuals of workers two years before and two years after changing managers. We do so for salaries and bonuses of workers in all 16 possible transitions, e.g. workers changing from a category 4 to a category 1 manager, workers changing from a category 4 to a category 3 manager, etc. For clarity, we focus on workers who previously worked for category 4 or category 1 managers. Note that we include changes in manager due to job changes of workers and due to manager rotation.

[14] Excluding the possibility that boss and worker jointly switch teams.

FIGURE 3: Mean Log Pay of Manager Changers, by Quartile of Mean Co-Worker Pay



Notes: These figures plot average residual base salaries and bonus payments in the two years before and after manager changes. Based on Card et al. (2013), workers are classified into 16 groups, of which eight are displayed. Workers are grouped by the quartile of their coworkers' pay before and after the manager change.

Figure 3 shows that the groups have different pay levels before (years -2 and -1) and after changing managers (years 0 and 1). For example, salaries of workers with coworkers in the fourth quartile who move to a quartile 1 manager have lower salaries prior to a change compared to workers who change from quartile 4 to another quartile 4 manager. Moving to a manager with higher-paid coworkers, e.g. from quartile 1 to quartile 4, increases pay. Workers who stay in the same quartile have relatively constant pay, although bonus pay seems to increase quite a bit for workers switching from a quartile 1 to another quartile 1 manager. Workers who change from a quartile 4 manager to a lower quartile manager lose pay, with larger losses for more extreme changes.

Pay changes in Figure 3 look symmetric for workers moving between quartile 1 and quartile 4 managers. This suggests that a simple additive model is a reasonable approximation of base salaries and bonus payments. It implies that workers do not only change managers if higher residual pay is expected.

The pay profiles in Figure 3 also look relatively flat before and after changing manager. While there is some variation in pre-change pay, for example among workers moving from bonus quartile 1 to 4, these changes are small compared to the jumps we observe. This suggests that a static model as in equation (5) should be a sufficient approximation.

4 Results

4.1 Decompositions

In the first set of results, we look at the impact of men and women doing different jobs and in particular working for different managers. The decomposition of gender pay gaps requires that male and female workers identify the same set of characteristics and full-rank matrices for each gender. Therefore, we reduce the data to a dual-connected set, as described in Section 3. We also impose that for a given observation we observe base salary, bonus payout, performance ratings, and targets. While this excludes workers who do not have performance pay in their contract, this has the advantage that different results for the outcomes are not driven by sample composition.

Table 3 displays the gender pay gap decomposition based on 59 813 observations. The raw gender pay gap in salary is 12 log points (13%). The raw gap in bonuses is even larger, with a difference between men's and women's payouts of 22 log points (24%). While the raw pay gaps are large, between 80 and 90% can be explained by different observed characteristics of men and women. The residual gender gap is 1.1 log points for base salaries and 3.8 log points for bonuses.

The Kitagawa-Oaxaca-Blinder decomposition in Table 3 shows the relative importance of the different characteristics explaining the gap. Age and tenure differences between men and women exist but are of small magnitude. Also, the fact that the gender distribution of the workforce might not be uniform over countries is not of primary importance. Job characteristics, i.e. the combination of hierarchical rank and occupation, explain between 55 and 60% of the gender gaps in salary and bonus. This means that if women worked in the same occupations and hierarchical levels as men, and earned the same returns from these jobs as men, the gender pay gap in salaries would be reduced by more than half.

Table 3: Gender Gap Decomposition

	Salary		Bonus Payout	
	Log points	Share explained	Log points	Share explained
Age	0.75	6.1%	0.93	4.2%
Tenure	0.16	1.3%	0.25	1.1%
Manager	3.13	25.4%	4.16	18.7%
Job	6.59	53.5%	13.57	61.1%
Year	-0.23	-1.8%	-0.83	-3.7%
Country	0.84	6.8%	0.38	1.7%
Total explained	11.24	91.2%	18.45	83.1%
Total unexplained	1.08	8.8%	3.75	16.9%
Total gap	12.32	100.0%	22.20	100.0%

Notes: The table displays Kitagawa-Oaxaca-Blinder-decompositions of the gender gap in Log Salary and Log Bonus Pay based on 59 813 observations. Age and tenure are summarized in six-year bins. Jobs are the combination of hierarchical rank and occupation.

The sorting of workers to managers matters. 25% of the gender pay gap in base pay and 19% of the gap in bonuses can be explained by the fact that men work for managers who have more positive impacts on pay. This is true conditional on workers doing the same job, i.e. working in the same occupation within the same hierarchical rank. While we cannot tell why women tend to work for bosses who are less generous or have less favorable impacts on productivity, we can see that managers are not perfectly substitutable but differ in terms of productivity or styles. This also means that firms seeking to reduce gender pay gaps need to carefully consider if and how to better match women to high-impact managers. Should women prefer to work for managers whose style implies a productivity reduction, for example due to flexible work hours, female workers might in spite of a financial cost prefer the current allocation to managers (Goldin and Katz, 2015).

The Role of Child Care A large part of gender pay gaps has been attributed to reduced working hours due to child care obligations (Kleven et al., 2019a,b). We neither observe family status nor overtime work. By limiting the data to full-time workers only and controlling granularly for the nature of the job, much of the variation in actual hours worked is already taken into account. However, to examine the role of child care in our setting, we expand the decompositions in several dimensions.

First, we repeat the pay decomposition for workers aged 44 and younger and workers aged 45 and older. Here one would expect that older workers are less likely to be affected by small kids at home. While child birth may have a lasting effect on careers of older workers as well, our approach already takes into account that parents might climb up the hierarchy more slowly. Appendix Table A.2 shows that the adjusted salary gap among younger workers is actually zero, and smaller than among older workers. The adjusted bonus gap is around 5% for both groups. This suggests that differences in unobserved actual hours worked do not play a role for the gender gap in this sample. As the sample is limited to full-time workers only and due to the exact controlling for job fixed effects, most differences in work hours are probably already accounted for.

To examine this further, we recalculate pay decompositions while including all workers in the data and controlling for contracted working hours. As Appendix Table A.3 shows, a significant part of the gender pay gap can be explained by differences in working hours. 34% of the pay gap in base salary of 13.7 log points is attributed to this channel. Unexplained gender pay gaps are larger in this full sample, relative to full-time workers only. This finding suggests that gender differences in working hours do matter, but are largely taken into account already by limiting observations to full-time employees.

Full-time workers might differ in their accumulated working hours. In particular, workers with children might have worked fewer hours in the past. Workers can also have spells during which they did not work at all, for example because of child birth. We treat these spells as having worked zero hours. Having worked part-time in the past could be interpreted as a measure of experience, less flexibility, or reduced likelihood of working overtime because of child care obligations. Appendix Table A.4 decomposes full-time workers' pay while controlling in addition for accumulated full-time equivalent months. As we need to observe every worker's full employment history at the firm, the sample size is reduced. The unexplained gender pay gap is similar to our baseline estimate from Table 3. Differences in accumulated full-time equivalent months do not contribute to gender gaps. Once more, this could be because workers sort into jobs with different requirements of flexibility or because the firm requires certain experience for working in particular positions.

These extensions demonstrate that it is unlikely that the unexplained part of the gender pay gap documented in Table 3 can be attributed to child care obligations.

Table 4: Gender Gap Decomposition

	High Performance		Bonus Target	
	Percentage points	Share explained	Log points	Share explained
Age	-0.93	46.7%	0.27	9.5%
Tenure	-0.00	0.0%	-0.13	-4.6%
Manager	2.12	-106.0%	-3.44	-121.9%
Job	0.71	-35.3%	6.61	234.6%
Year	-0.06	2.9%	-0.08	-2.8%
Country	-0.30	14.9%	-2.44	-86.7%
Total explained	1.54	-76.8%	0.79	28.1%
Total unexplained	-3.54	176.8%	2.03	71.9%
Total gap	-2.00	100.0%	2.82	100.0%

Notes: The table displays Kitagawa-Oaxaca-Blinder-decompositions of the gender gap in the probability of a high performance rating and contracted Log Bonus Targets based on 59 813 observations. Age and tenure are summarized in six-year bins. Jobs are the combination of hierarchical rank and occupation.

Sources of Gender Bonus Pay Gaps Bonuses depend on base salary, performance ratings, and contracted bonus targets. We have seen that a gap in base salaries exists and can be explained by sorting to jobs and managers. Here we study whether sorting with regard to contracted bonus target or performance rating matters as well.

Table 4 reports that the raw gender gap in performance is -2 percentage points. The penultimate line shows that the adjusted gender gap is even more negative (-3.5 percentage points). This is mainly driven by the fact that women tend to work for managers handing out worse ratings. This means that if women had the same characteristics as men and were to earn the same returns on these characteristics as men, their performance ratings would be even *better*.

It is a striking result that gender performance gaps are negative, i.e. favor women, while the unexplained gap in salaries and bonus payouts is positive. If performance ratings are a good proxy for actual performance, these residual gaps are difficult to reconcile with the explanation that men are more productive. Previous work by Azmat and Ferrer (2017) shows that female lawyers perform worse than their male colleagues. Our results demonstrate that one cannot generalize their finding to other settings.

How can it be that women earn lower bonuses, despite the fact that their ratings are better? Bonuses depend on base salaries and contracted bonus targets. As these gaps benefit men—the unexplained gap in targets is 2.0 log points and the unexplained gap in base salaries is 1.1 log points—the eventual payout still favors men.

Women do not sort to more generous or high-impact managers as can be seen from the detailed results of the decomposition in Table 4. Instead, men work for managers who hand out better ratings. If women worked for the same managers and benefited from them in the same way as men, the probability to receive a high performance rating would go up by two percentage points.

Table 4 also indicates that women are sorted to jobs with significantly lower bonus targets. However, women actually tend to work for managers who negotiate higher bonus targets. This means that while women might shy away from competition (as found by Niederle and Vesterlund, 2007), it does not imply that they work for managers where performance pay plays a smaller role.

Are Women's Better Ratings Explained by Lower Costs? One explanation for negative performance gaps is that managers might be more willing to hand out good ratings if they are less costly. We observed that women earn lower salaries and negotiate lower bonus targets. Managers could therefore use performance ratings to compensate women for negotiating lower salaries and targets.

To check this, we once more decompose the gender gaps in performance ratings, taking salary and target as predetermined variables and including them in the controls. We find in Appendix Table A.5 that the unexplained gender gap opens even more in favor of women. This suggests that women do not simply receive better ratings because they cost the manager less.

4.2 Within-Manager Gender Gaps

Having documented that the sorting of women to managers contributes to gender pay gaps, we now ask whether managers affect residual gender pay gaps.

Based on the same data used in the Kitagawa-Oaxaca-Blinder decomposition we estimate equation (5) on salaries, bonus payouts, performance ratings, and bonus targets. The number of observations contributing to the estimates is slightly reduced relative to the sample in the decomposition due to the inclusion of worker fixed effects. If a worker is only observed for a single period she cannot contribute to the identification of ω, the coefficient on the term of interest, $male_i \times male_{M(i,t)}$.

In addition to this fully saturated specification, we estimate two less granular versions on the same observations. First, as specified in Equation (4), we do not account at all for unobserved heterogeneity at the worker and manager level. This allows us to include dummies for the worker and manager being male, respectively. In an intermediate step, we add manager fixed effects. A dummy indicating the gender of the worker can then still be estimated. Third, we estimate the fully saturated Equation (5).

Table 5 shows the results. The coefficients from the first row reports the adjusted gender gap when working under a female manager. The coefficient from the second row is the difference in outcomes of women when they work under a male instead of a female manager. The third row estimates the difference between the gender gap under male and female managers. Before turning to more granular estimations, we look at columns 1, 4, 7, and 10, which report the coefficients from estimating Equation (4).

The gender salary gap under female managers is 2.3 log points. Women who work for male managers earn 1.9 log points higher salaries. Men only earn 1.6 log points higher salaries, but the difference to women is insignificant. This means that the estimated gender pay gap at male managers is smaller than at female managers by 0.3 log points, but this is highly insignificant.

Turning to bonuses, we find that gender gaps are 4.1% larger when the manager is male. The other coefficients imply that there is no statistical gender bonus gap under female managers and no advantage for women who work for male managers instead of female managers.

The increase in gender bonus gaps when the manager is male should be explained by higher salaries, performance ratings, or bonus targets. However, as we can see from the third row in columns 1, 7, and 10 this is not the case. The reason for this is that the high performance indicators are noise measures of actual performance ratings, which are more nuanced. We cannot reconstruct the exact mapping from more detailed performance ratings to bonuses. Also, omitted variable bias in unobserved worker or manager characteristics could invalidate the estimation approach.

In columns 2, 5, 8, and 11 we control for unobserved manager characteristics. Three observations can be made in comparison to the version without manager effects. First, the gender gap under female workers in salaries and ratings is almost unchanged. Second, the bonus gap under female workers now is higher and significant at 2.8 log points. Third, differences in gender gaps are all insignificant and smaller.

While the gender gap at female managers is an interesting statistic, we are looking for a causal interpretation of the effect of manager gender on gender gaps.

Table 5: Effects of Having a Same-Gender Superior

	log(Salary)			log(Bonus Payout)			High Performance			log(Bonus Target)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Male	0.023***	0.026***		0.014	0.028***		-0.037***	-0.034***		0.008	0.008	
	(0.006)	(0.005)		(0.012)	(0.010)		(0.008)	(0.009)		(0.008)	(0.006)	
Male Mngr.	0.019**			0.018			-0.005			0.003		
	(0.007)			(0.013)			(0.008)			(0.010)		
Male $\times$ Male Mngr.	-0.003	-0.003	0.002	0.041***	0.017	0.051***	0.014	0.006	0.027*	0.005	0.007	0.005
	(0.007)	(0.006)	(0.003)	(0.014)	(0.012)	(0.015)	(0.010)	(0.011)	(0.015)	(0.009)	(0.007)	(0.005)
Job FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tenure FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
Worker FE			Yes			Yes			Yes			Yes
N	55,464	55,464	55,464	55,464	55,464	55,464	55,464	55,464	55,464	55,464	55,464	55,464
R^2	0.903	0.954	0.995	0.816	0.875	0.939	0.073	0.191	0.563	0.861	0.934	0.988

Notes: Standard errors are in parentheses and clustered at the worker and manager level. *** denotes significance at 1%, ** at 5%, and * at 10%. Age and tenure are summarized in six-year bins. Jobs are the combination of hierarchical rank and occupation.

To ensure that workers are comparable, we add worker fixed effects in the complete specification of Equation (5) in columns 3, 6, 9, and 12. This proves critical for the estimation of the coefficient of interest.

Working for a male manager increases bonuses by 5.1 log points relative to women when controlling for worker and manager fixed effects. Put differently, the within-manager gender gap increases by 5% if the manager is male. Due to symmetry, this also implies that the within-manager gender gap falls by 5%, i.e. moves in favor of women, if the manager is female. There is no evidence that the manager's gender matters for gaps in base salaries or bonus targets. Instead, the advantageous position of men at male managers is driven by changes in performance ratings. The performance gap increases by 2.7 percentage points, i.e. moves in favor of men, when the manager is male. This represents more than 10% relative to the observed probability of receiving a high rating. The finding that gender gaps open up when the manager is male relates to Hospido and Sanz (2019) and Mengel et al. (2019) who document differences in gender gaps for different decision-maker genders in academic settings and thereby challenges findings by Card et al. (2020) who cannot document such differences.

Heterogeneity in the Impact of Manager Gender on Gender Gaps We also allow the effect of male bosses on the gender gap to vary along other dimensions. Table 6 displays these results. Each panel and column refers to a separate regression. All estimates of manager gender impacts on base salaries are insignificant. The effects of manager gender on the bonus gap do not differ by worker or manager characteristics. However, some interesting patterns emerge.

Younger workers seem to be more affected by the differential gender gaps. This could be because younger workers are found at lower ranks. But as panel B shows, if anything the opposite is true. It seems that at higher ranks the gender of the manager plays a larger role for gaps. In panel C it looks like the effects of manager gender are larger when the team is mostly male. This observation supports the interpretation that male bosses cater to the needs and preferences of male workers. Panels D to F look at characteristics of managers. The results for age and hierarchical rank follow a similar pattern as for workers. Because the cultural background of managers could impact their treatment of workers of different gender, we allow the effect to vary by the region of origin. We, therefore, classify managers as "western" if they have a European or Anglo-Saxon nationality. However, the point estimates look very similar. Overall, there is little statistical variation in the effect of managers, suggesting that the effect of manager gender on the gender gap is an issue across the entire firm.

Other Manager Characteristics It could be that manager characteristics apart from gender are the actual fundamental drivers of within-manager gaps. Note that even if this was the case, it is already clear that managers do matter. Here we examine whether gender indeed drives this finding.

We repeat the estimation of Equation (5) for all four outcomes considered, but in addition interact the dummy $male_i$ with manager characteristics correlated with manager gender. We allow gender gaps to vary by managers' age, tenure, origin, and hierarchical rank. If managers can experience a change in their characteristics, for example in hierarchical rank, the manager fixed effect does not absorb it. In this case, in addition to $male_i \times rank_{M(i,t)}$ we include $rank_{M(i,t)}$ as a regressor, etc.

Comparing the results from Table 7 with the original results from Table 5 shows that even if we control for the interaction between worker gender and various manager characteristics, the estimated coefficient on $male_i \times male_{M(i,t)}$ in the first row is almost identical. This suggests that omitted variable bias is not driving our finding but that indeed manager gender affects within-manager gender gaps.[15]

Table 7 also reveals that older managers close gender gaps in base salaries and contracted targets, relative to younger managers. The estimation also suggests that gender gaps in performance rating are greater when the manager is "western", suggesting that coming from a culturally more progressive society does not guarantee a reduced impact of managers on gaps. The finding could also mean that managers from a minority group are more concerned about the interests of other minorities.

Allowing for Differential Returns for Men and Women In the estimation of Equation (5), returns from male managers can differ between men and women while all other characteristics are assumed to have equal effects on men's and women's outcomes. This simplification could lead to bias if the differential returns capture differential returns from other characteristics. For example, if male bosses are more likely to work in engineering, and men have, for whatever reason, higher

[15]With a p-value of 12%, the coefficient on $male_i \times male_{M(i,t)}$ in Table 7 is statistically insignificant when considering gaps in the probability of receiving a high performance rating. This again might be because the grading is more complex than just an indicator for high ratings. Furthermore, while effects on base salary and contracted bonus targets remain insignificant, these can of course contribute to the effect on bonus payments in column 2.

Table 6: Effects of Having a Same-Gender Superior: Heterogeneity

	log(Salary)	log(Bonus Payout)
Panel A: Age		
Male × Male Mngr.	0.003	0.062***
	(0.004)	(0.021)
Male × Male Mngr. × > 44 years	−0.003	−0.027
	(0.005)	(0.028)
N	55,464	55,464
Panel B: Hierarchical Rank		
Male × Male Mngr.	0.003	0.052
	(0.004)	(0.037)
Male × Male Mngr. × Medium Rank	−0.002	−0.011
	(0.006)	(0.040)
Male × Male Mngr. × High Rank	0.005	0.070
	(0.011)	(0.058)
N	55,464	55,464
Panel C: Team Composition		
Male × Male Mngr.	−0.003	0.045**
	(0.004)	(0.020)
Male × Male Mngr. × Majority Male	0.007	0.014
	(0.005)	(0.024)
N	55,016	55,016
Panel D: Manager Age		
Male × Male Mngr.	0.003	0.049**
	(0.004)	(0.019)
Male × Male Mngr. × > 44 years	−0.002	0.006
	(0.006)	(0.024)
N	55,464	55,464
Panel E: Manager Hierarchical Rank		
Male × Male Mngr.	−0.011	−0.177
	(0.020)	(0.167)
Male × Male Mngr. × Medium Rank	0.012	0.215
	(0.020)	(0.168)
Male × Male Mngr. × High Rank	0.013	0.256
	(0.021)	(0.168)
N	54,654	54,654
Panel F: Manager Region		
Male × Male Mngr.	0.002	0.065*
	(0.007)	(0.034)
Male × Male Mngr. × Western	−0.001	−0.018
	(0.008)	(0.038)
N	55,464	55,464

Notes: Standard errors are in parentheses and clustered at the worker and manager level. *** denotes significance at 1%, ** at 5%, and * at 10%. Age and tenure are summarized in six-year bins. Jobs are the combination of hierarchical rank and occupation.

Table 7: Effects of Having a Same-Gender Superior: Alternative Channels

	log(Salary)	log(Bonus Payout)	High Performance	log(Bonus Target)
	(1)	(2)	(3)	(4)
Male × Male Mngr.	0.001	0.055***	0.024	0.004
	(0.003)	(0.016)	(0.015)	(0.006)
Male × Mngr. Age ≥ 45	-0.006*	-0.020	0.012	-0.009**
	(0.003)	(0.013)	(0.013)	(0.004)
Male × Mngr. Tenure ≥ 10	-0.001	0.003	-0.000	-0.002
	(0.003)	(0.014)	(0.013)	(0.005)
Male × Mngr. Western	0.011	-0.012	0.066*	0.010
	(0.009)	(0.036)	(0.034)	(0.010)
Male × Mngr. High Rank	0.002	0.014	0.015	-0.005
	(0.005)	(0.020)	(0.020)	(0.008)
Job FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes
Tenure FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	Yes
N	54,784	54,784	54,784	54,784
R^2	0.995	0.937	0.565	0.988

Notes: Standard errors are in parentheses and clustered at the worker and manager level. *** denotes significance at 1%, ** at 5%, and * at 10%. Age and tenure are summarized in six-year bins. Jobs are the combination of hierarchical rank and occupation.

returns than women when working in engineering, we would blame managers for these differential returns.

In Appendix Table A.6 we repeat the estimation of Equation (5) but interact all variables except worker and manager effects with a gender dummy. The effect of managers on gender gaps is unchanged. This adds to confidence that we are indeed estimating the gender-differential effect of bosses.

4.3 Why Does Manager Gender Matter?

Three main mechanisms could explain why the gender pay gap moves in favor of men when managers are male. First, the sorting of more productive men to male managers could result in an observed gender gap. Second, within-gender complementarities might make male workers relatively more productive than women when working under a male manager. Third, (unconscious) discrimination of workers of the other gender could drive our findings. Whatever explanation holds true, as long as women are underrepresented in managerial positions, these explanations would imply structural disadvantages for female workers We now evaluate which of these mechanisms is likely to explain the effect of manager gender.

Sorting Workers are not allocated randomly to managers. Managers might be better informed about the quality of a worker of the same gender. This could for example imply that a male manager's male workers are on average better than female workers. While such a mechanism could exist in the firm, it cannot explain our results. In specification (5), we control for unobserved heterogeneity of workers. Doing so fully takes into account time-invariant ability differences. This means that our results hold true conditional on the sorting of workers to managers.

Within-Gender Complementarities A second explanation could be complementarities within gender. While there is ample evidence that diverse teams are more fact-focused, process facts more carefully, and are more innovative (e.g. Díaz-García et al., 2013; Herring, 2009; Levine et al., 2014; Nathan and Lee, 2013; Phillips et al., 2009), one could think that homogeneity can also benefit employee performance. For example, a competitive worker might be more productive in a competitive environment, while a cooperative worker might be more productive in a cooperative environment. If the distribution of styles differs for men and women, men should be more productive when working with men and we would observe a wider gender gap due to productivity.

While we have no measure of productivity available, we can test for the plausibility of this mechanism. Under the assumption that within-gender complementarities also would exist with respect to coworkers of the same gender, we can test for complementarities by studying the effect of male coworkers on the gender pay gap. We therefore repeat the estimation of Equation (5) for the share of male coworkers working for the same manager. The interaction of male-dummies for worker and manager is replaced by the interaction of a male-dummy for the worker and the share of male coworkers. We include the share of male coworkers because in contrast to manager gender it is not absorbed by the manager fixed effect. We still include worker fixed effects, manager fixed effects, and all other controls. This differs from Panel C of Table 6 as here we directly estimate the effect of male coworkers instead, not the heterogeneous effect of a male managers leading majorly male teams.

Table 8 contains only one significant coefficient, indicating that bonuses are higher when working in predominantly male teams. But, if anything, bonus

Table 8: Effects of Having more Same-Gender Coworkers

	log(Salary)	log(Bonus Payout)	High Performance	log(Bonus Target)
	(1)	(2)	(3)	(4)
Male × Share of Male Coll.	0.001	-0.040	0.006	-0.001
	(0.006)	(0.028)	(0.027)	(0.011)
Share of Male Coll.	0.004	0.045**	-0.004	0.006
	(0.006)	(0.023)	(0.022)	(0.009)
Job FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes
Tenure FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	Yes
N	55,016	55,016	55,016	55,016
R^2	0.995	0.939	0.564	0.988

Notes: Standard errors are in parentheses and clustered at the worker and manager level. *** denotes significance at 1%, ** at 5%, and * at 10%. *Share of Male Coll.* is the share of colleagues, defined as workers with the same superior, who are male. Age and tenure are summarized in six-year bins. Jobs are the combination of hierarchical rank and occupation.

payments are lower for men compared to women when working with more male coworkers. Under the assumption that within-gender complementarities also need to exist with respect to coworkers, the results imply that such complementarities do not exist with respect to manager gender. Therefore, we take this as supporting evidence that complementarities within gender are highly unlikely to substantially explain the favorable outcomes of men (women) under men (women).

Discrimination and Biased Beliefs Managers who are uninformed about the productivity of their subordinates might be more likely to resort to (unconscious) biases when evaluating or negotiating with workers. Discrimination due to biased beliefs (Bohren et al., 2019) implies that decision-makers discriminate according to their biased priors if they are uninformed. If they are provided with previous evaluations of work quality by other decision-makers, discrimination is reduced and eventually flips if much previous information is available.

We suggest that a related mechanism can drive discrimination in our setting. Instead of collecting information from previous evaluators, one can easily think that decision-makers are less likely to discriminate according to their preexisting biased beliefs as they learn about the worker's true quality. So while Bohren et al. (2019) relate a reduction in discrimination to better information, one can also expect that a reduction in discrimination is related to better knowledge of the worker.

Besides learning about the true quality of workers, managers learning about their workers also could exhibit less discrimination for a separate reason. It could be the case that managers are less aware of the needs of workers of the other gender. For example, male managers could be less considerate of child care obligations of female workers. Over time, they could learn about their workers' needs and reshape the work environment such that all workers can show their best.

Note that this does not necessarily mean that only male managers discriminate. Female managers could be discriminating as well, so that we estimate the additional advantageous treatment of men. Theoretically, it could also be the case that male managers do not discriminate at all, and female managers favor female workers. We do not consider this a likely scenario, as previous research showed that women if anything tend to discriminate against women (e.g. Bagues and Esteve-Volart, 2010) and bias in evaluations has been found in other settings to be driven by men (Hospido and Sanz, 2019; Mengel et al., 2019)

Whether discrimination takes more direct forms, e.g. biased ratings, or indirect forms, e.g. biased work environments, we would expect in both cases that discriminating is reduced when managers are more knowledgeable about their workers. To test this, we group observations by a number of variables capturing aspects of information.

First, we split managers into a group with less than ten and a group with more than ten years of tenure at the firm. One would expect that these managers are more experienced and therefore less likely to fall back to preexisting biases, or less aware about the needs of workers of the other gender. Second, we examine whether managers of larger teams (five or more subordinates) show stronger effects of manager gender on gaps. Managers of larger teams might find it harder to observe the true effort of each worker and to cater to specific needs. Similarly, a manager who works at a different location than the subordinate and who only communicates remotely might find it harder to evaluate workers or build a connection with workers who are less alike themselves. Finally, we allow effects to change with the time a worker and manager have worked together. We do so by grouping relationships into a group with two or less and a group with more than two years of joint work. Over time, one would expect that superiors learn more and build connections with workers. Note that this measure could be biased if workers who feel discriminated against are more likely to leave their team.

Table 9: Effects of Information

	log(Salary)	log(Bonus Payout)
Panel A: Manager Tenure		
Male × Male Mngr.	−0.001	0.058***
	(0.004)	(0.021)
Male × Male Mngr. × $\geq$ 10 yrs Mngr. Tenure	0.006	−0.013
	(0.005)	(0.027)
N	55,450	55,450
Panel B: Team Size		
Male × Male Mngr.	0.002	0.057***
	(0.003)	(0.017)
Male × Male Mngr. × Small Team	−0.002	−0.022
	(0.005)	(0.023)
N	55,464	55,464
Panel C: Location		
Male × Male Mngr.	−0.000	0.096***
	(0.007)	(0.032)
Male × Male Mngr. × Same Location	0.001	−0.054
	(0.008)	(0.034)
N	54,326	54,326
Panel D: Joint Time		
Male × Male Mngr.	0.001	0.057***
	(0.003)	(0.017)
Male × Male Mngr. × > 2 Years Joint	0.001	−0.040
	(0.005)	(0.028)
N	49,338	49,338

Notes: Standard errors are in parentheses and clustered at the worker and manager level. *** denotes significance at 1%, ** at 5%, and * at 10%. Age and tenure are summarized in six-year bins. Jobs are the combination of hierarchical rank and occupation.

Table 9 shows the results. Each column of each panel refers to a separate regression. Sample sizes vary because some variables are not observed for all workers and managers. For salary, the effect of manager gender on pay gaps remains statistically insignificant. For bonus payments, one can observe a pattern that could be taken as support of the findings of Bohren et al. (2019), i.e. that better information leads to less discrimination. The coefficients are not statistically distinguishable at conventional levels. However, in all cases it seems that gender effects are larger in magnitude when information is harder to obtain. In particular, manager gender effects on pay gaps are larger when managers are less experienced, manage larger teams, work at different locations and know workers for a shorter amount of time. While none of these differences are statistically significant, all coefficients are negative and, in the case of location and joint time, close to significance with respective p-values of 12.0 and 15.8%, respectively. Proximity could also have led to the opposite effect on gender gaps if closer ties between managers and workers facilitate favoritism, an observation made by Cullen and Perez-Truglia (2019). Of course, such an effect might exist but seems to be more than netted out by managers accumulating additional information about workers.

The observation that overall the effect of manager gender on pay gaps seems to fall when the manager should be better informed supports the interpretation that some form of (unconscious) discrimination is an important driver of the results. While the observations here are in favor of discrimination by initially biased managers, they also contradict the mechanism discussed previously. If gender-specific complementarities would play a role, it is unclear why they should fall with better informed managers.

5 Conclusion

Using novel personnel data from a large company we examine gender gaps in wages and performance, and we show that they are affected by managers. Our analysis yielded three main findings.

First, a significant part of the gender gap can be explained by the sorting of male and female workers to different types of managers. Men are more likely to work for "better" managers, i.e. managers whose workers receive higher salaries, bonuses, and performance evaluations. The observation that women tend to work for "worse" managers means that firms seeking to improve gender equity need to find out what makes a "good" manager and why women tend to work for managers with a lower impact. While our research cannot determine which underlying manager characteristics drive wage inequality or why workers are sorted as they are, our results imply that firms should not only foster the occupational upgrading of female employees, but also consider how female workers can work for "better" bosses. However, women might actually prefer to work for "worse" managers if these offer more family-friendly environments (Goldin and Katz, 2015).

Second, we show that the gender pay gap cannot be explained by the notion that men outperform women. On the contrary, women actually receive significantly better ratings than men. Yet, on average, they earn less. This is a striking result as it implies that adjusted gender pay gaps should be even larger. It also challenges the notion that women's performance is worse due to being less ambitious or competitive (Azmat and Ferrer, 2017; Niederle and Vesterlund, 2007). In spite of the positive impact of ratings on bonus pay, bonus pay gaps still favor men because the performance effect is outweighed by differences in salaries and targets. Firms often resort to performance ratings determined by superiors if actual output cannot be quantified, as is typical in complex organizations characterized by division of labor. Future research should examine whether male and female superiors differ in what aspects of worker performance they value most when determining ratings. If firms interpret performance ratings as good proxies of actual performance, gender equity is not achieved when women earn the same as men. If anything, a negative gender performance gap means that women should earn more than men.

Third, we show that manager gender matters as male managers cause within-team bonus gaps to increase. This is driven by the fact that performance ratings are relatively more favorable towards men when the manager is male. As manager gender affects pay gaps, the over-representation of men in management position puts women at a disadvantage. Therefore, our research has important implications for the discussion of gender quotas. The basic requirement for such quotas to work is that having more female managers indeed improves gender equality. In contrast to quotas applying at the executive level only (Bertrand et al., 2019; Maida and Weber, 2019), our findings imply that quotas across all hierarchical ranks can be effective. Future research would need to consider other requirements that need to be fulfilled such that gender quotas across all ranks are indeed a suitable policy.

Digging deeper, we find suggestive evidence that discrimination due to biased beliefs could drive the findings, as manager gender tends to matter less with more knowledge about the workers. Alternatively, managers might learn about workers' needs and improve upon their initially biased work environments. This observation can inform alternative pathways for promoting gender equity. Organizing employees into smaller and more stable teams in closer physical proximity could be a feasible measure to reduce gender gaps. In addition, many firms train their staff to be more aware of gender-related biases. While the success of such diversity programs is found to vary significantly (Chang et al., 2019), they seem to be a necessity to make managers more aware of their gender-related biases.

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A Additional Tables

Table A.1: Descriptive Statistics

	Mean	SD	10th Perc.	Median	90th Perc.	Observations
Salary [€]	64 315.32	75 438.37	23 323.65	56 252.3	114 753.28	59 813
Bonus [€]	12 293.32	21 707.14	1393.49	4816.59	28 924.78	59 813
High Performance	0.25	0.43	0.0	0.0	1.0	59 813
Low Performance	0.1	0.3	0.0	0.0	1.0	59 813
Bonus Target [%]	12.36	8.68	4.0	11.0	25.0	59 813
Male	0.58	0.49	0.0	1.0	1.0	59 813
Age	42.65	9.04	30.0	43.0	55.0	59 813
Tenure	10.73	9.24	2.0	8.0	25.0	59 813
Span of Control	1.64	4.55	0.0	0.0	6.0	59 813
Coworkers	8.33	9.6	2.0	5.0	18.0	59 813
New Manager in Same Job	0.24	0.43	0.0	0.0	1.0	46 534
New Manager in New Job	0.07	0.25	0.0	0.0	0.0	46 534
Male Manager	0.72	0.45	0.0	1.0	1.0	59 813
Male & Male Manager	0.45	0.5	0.0	0.0	1.0	59 813
Male & Female Manager	0.13	0.34	0.0	0.0	1.0	59 813
Female & Male Manager	0.27	0.44	0.0	0.0	1.0	59 813
Female & Female Manager	0.15	0.36	0.0	0.0	1.0	59 813
Age of Manager	45.92	7.93	35.0	46.0	56.0	59 813

Notes: Extreme values omitted for confidentiality reasons. Unbalanced panel based on 20 048 workers and the years 2014-2019. Monetary variables normalized to € in 2010.

Table A.2: Gender Gap Decomposition for Younger and Older Workers

(a) 44 and younger

	Salary		Bonus Payout	
	Log points	Share explained	Log points	Share explained
Age	0.40	6.2%	0.60	4.7%
Tenure	-0.01	-0.2%	-0.04	-0.3%
Manager	1.50	23.2%	4.39	34.9%
Job	3.87	59.9%	1.93	15.3%
Year	-0.13	-2.0%	-0.44	-3.5%
Country	0.95	14.8%	1.06	8.4%
Total explained	6.58	101.9%	7.50	59.6%
Total unexplained	-0.12	-1.9%	5.09	40.4%
Total gap	6.46	100.0%	12.59	100.0%

(b) 45 and older

	Salary		Bonus Payout	
	Log points	Share explained	Log points	Share explained
Age	0.11	0.6%	0.13	0.3%
Tenure	-0.00	-0.0%	0.16	0.4%
Manager	3.93	22.7%	4.85	13.1%
Job	13.21	76.4%	28.98	78.0%
Year	-0.29	-1.7%	-0.91	-2.5%
Country	-0.93	-5.4%	-1.42	-3.8%
Total explained	16.03	92.7%	31.78	85.5%
Total unexplained	1.27	7.3%	5.37	14.5%
Total gap	17.30	100.0%	37.15	100.0%

Notes: The tables display Kitagawa-Oaxaca-Blinder-decompositions of the gender gap in Log Salary and Log Bonus Payout based on 48 537 observations. Age and tenure are summarized in six-year bins. Jobs are the combination of hierarchical rank and occupation.

Table A.3: Gender Gap Decomposition Including Part-Time Workers

	Salary		Bonus Payout	
	Log points	Share explained	Log points	Share explained
Working hours	4.67	34.1%	1.93	7.5%
Age	0.56	4.1%	0.62	2.4%
Tenure	0.04	0.3%	-0.04	-0.2%
Manager	1.45	10.6%	4.52	17.5%
Job	5.72	41.8%	13.08	50.7%
Year	-0.25	-1.8%	-0.88	-3.4%
Country	-0.18	-1.3%	-0.54	-2.1%
Total explained	12.01	87.7%	18.69	72.5%
Total unexplained	1.68	12.3%	7.10	27.5%
Total gap	13.69	100.0%	25.79	100.0%

Notes: The table displays Kitagawa-Oaxaca-Blinder-decompositions of the gender gap in Log Salary and Log Bonus Payout based on 66 040 observations. Age and tenure are summarized in six-year bins. Jobs are the combination of hierarchical rank and occupation.

Table A.4: Gender Gap Decomposition Controlling for Accumulate Full-Time-Equivalent Months

	Salary		Bonus Payout	
	Log points	Share explained	Log points	Share explained
FTE months	-0.00	-0.0%	0.12	0.6%
Age	0.50	4.1%	0.51	2.4%
Tenure	-0.03	-0.2%	0.41	2.0%
Manager	1.37	11.2%	2.63	12.5%
Job	7.38	60.0%	12.21	58.1%
Year	-0.18	-1.5%	-0.25	-1.2%
Country	1.37	11.2%	0.42	2.0%
Total explained	10.42	84.7%	16.06	76.3%
Total unexplained	1.88	15.3%	4.98	23.7%
Total gap	12.30	100.0%	21.04	100.0%

Notes: The table displays Kitagawa-Oaxaca-Blinder-decompositions of the gender gap in Log Salary and Log Bonus Payout based on 24 389 observations. Age and tenure are summarized in six-year bins. Jobs are the combination of hierarchical rank and occupation.

Table A.5: Gender Gap Decomposition Controlling for Salary and Target

	High Performance	
	Percentage points	Share explained
Salary	1.62	-88.6%
Bonus Target	0.04	-2.1%
Age	-0.81	44.4%
Tenure	-0.03	1.5%
Manager	1.80	-98.7%
Job	-0.56	30.9%
Year	-0.04	1.9%
Country	-0.20	10.9%
Total explained	1.82	-99.7%
Total unexplained	-3.64	199.7%
Total gap	-1.82	100.0%

Notes: The table displays Kitagawa-Oaxaca-Blinder-decompositions of the gender gap in the probability of a high performance rating based on 59 813 observations. Age and tenure are summarized in six-year bins. Jobs are the combination of hierarchical rank and occupation. Salary and bonus target are measured in logs.

Table A.6: Effects of Having a Same-Gender Superior: Gender-Interacted Controls

	log(Salary)	log(Bonus Payout)	High Performance	log(Bonus Target)
	(1)	(2)	(3)	(4)
Male × Male Mngr.	-0.001	0.053***	0.026*	0.003
	(0.003)	(0.016)	(0.015)	(0.005)
Job × Gender FE	Yes	Yes	Yes	Yes
Year × Gender FE	Yes	Yes	Yes	Yes
Age × Gender FE	Yes	Yes	Yes	Yes
Tenure × Gender FE	Yes	Yes	Yes	Yes
Country × Gender FE	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	Yes
N	55,412	55,412	55,412	55,412
R^2	0.995	0.940	0.569	0.989

Notes: Standard errors are in parentheses and clustered at the worker and manager level. *** denotes significance at 1%, ** at 5%, and * at 10%. Age and tenure are summarized in six-year bins. Jobs are the combination of hierarchical rank and occupation.