Misreporting of Mandatory ESG Disclosures: Evidence from Gender Pay Gap Information★

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Abstract

We examine misreporting of gender pay gap information. Beginning in 2017, the UK government mandated that UK employers report gender employment ratios and pay gaps. The mandate does not include an audit requirement and has received little regulatory enforcement. Nonetheless, supporters of the mandate argue that reputation and legal costs should prevent misreporting. We find that a large number of employers misreport as evidenced by their reporting a set of disclosures that in concert are mathematically impossible. We also find that a disproportionate number of employers report perfectly-balanced gender statistics, consistent with some firms intentionally misreporting. We document a link between misreporting and firms' broader ESG considerations: firms involved in an ESG controversy are more likely to report perfect gender statistics, and firms reporting no gap in their median pay receive higher social pillar ESG ratings. Our results suggest that gender pay gap reporting mandates are less effective in the absence of enforcement, and that stakeholders and researchers should exercise caution when using self-reported ESG information either directly, or indirectly via ESG scores, to measure ESG performance.

Keywords: Corporate social responsibility (CSR), Environmental, social, and governance (ESG), mandatory disclosure, enforcement, voluntary disclosure, gender pay gap, gender representation
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1. Introduction

We examine whether employers misreport information about gender pay equity. These disclosures reflect an important class of Environmental, Social, and Governance (ESG) information, with regulators, investors, academics, and the broader public increasingly seeking to understand and close the pay gap.[1] While many countries have attempted to close gender pay gaps with legislation, such as the 1963 Equal Pay Act in the US and the 1970 Equality Act in the UK, a common criticism of these laws is that enforcement is difficult because firms need not publicly provide or even internally compile gender pay information.[2] In response to these criticisms, in 2017 the UK began requiring employers to publicly disclose detailed information about their gender pay gaps. Politicians and the media lauded the legislation as an example of how ESG disclosure and "regulation by shaming" could bring about real change in firms' pay practices.[3] However, absent strong public enforcement mechanisms, penalties for misreporting, or any audit requirement, firms may misreport. This misreporting would undermine the effectiveness of gender pay gap disclosure as a policy tool and, more generally, the inferences researchers can draw from ESG disclosure initiatives and the quality of stakeholder decisions based on ESG disclosures.

There are several reasons to suspect employers may misreport their gender diversity statistics. First, given the absence of enforcement or penalties for misreporting, employers may invest little in ensuring accurate reporting and may misreport due to sloppiness. Second, employers may intentionally misreport. Employers that report favorable gender pay information, and ESG information more generally, can potentially benefit from greater access to and lower costs of capital, increased sales to socially-conscious customers,

[1] See, e.g., Krentz et al. (2019), UNESCO (2019), Blundell (2020), Duchini et al. (2020), LaViers and Sandvik (2021). The term "gender pay gap" refers to a number, typically the median wage, which quantifies the difference in pay between men and women within a reference group (e.g., within a company). Gender pay gaps may result from women holding a smaller proportion of the higher-paying positions within the company, and/or receiving less pay for doing the same work as men. The latter concept—equal pay—is related to, but narrower than the gender pay gap.

[2] `www.nytimes.com/2017/04/06/business/britain-salary-gender-gap.html`

[3] `www.theguardian.com/society/2017/apr/06/gender-pay-gap-law-could-have-significant-impact-say-experts`
`www.nytimes.com/2018/04/04/business/britain-gender-pay-gap.html`

and a greater ability to attract and retain employees sensitive to such information.[4] These benefits may motivate some employers to misreport their gender pay statistics in an attempt to pool with employers that truthfully report strong gender pay performance. Prior work applies similar arguments to the misreporting of financial information, and documents evidence of misreporting and noncompliance with financial reporting mandates (see, e.g., Beyer et al., 2010, for a review of the literature). Anecdotal evidence also suggests that some employers may misreport ESG information; consumers, investors, and nonprofit organizations have recently filed lawsuits against employers for false or misleading ESG disclosures.[5]

To document whether some employers misreport ESG information, we examine the most comprehensive gender pay gap disclosure mandate to date. All UK employers with 250 or more employees must disclose the median (and mean) gender pay gap, defined as the difference in pay between the median (mean) male and female, scaled by the median (mean) male pay. Additionally, each employer must provide a percentage breakdown of the men and women employed in each pay quartile. Using the combination of gender statistics reported by individual UK firms, along with the distributions of reported values across the full population, we document significant irregularities. In 4.8% of disclosures, internal inconsistencies between the metrics render the combination of the reported median pay gap and the quartile breakdowns mathematically impossible. For example, employers may disclose quartile breakdowns indicating that the median woman falls in the lower middle quartile of the overall pay distribution and the median man falls in the top middle quartile. If that same employer reports a negative median pay gap, which indicates that the median man makes less than the median woman, the combination of the metrics would be mathematically impossible.

[4]E.g., Luo and Bhattacharya (2009), Servaes and Tamayo (2013), Cheng et al. (2014), Friedman and Heinle (2016), Blundell (2020), Chen et al. (2020), LaViers and Sandvik (2021).

[5]While the existence of ESG misreporting litigation is anecdotally consistent with misreporting, no widespread academic empirical evidence exists regarding potential misreporting and it is difficult to draw inferences from existing litigation because this a relatively new area of the law and because of the disperse outcomes of the relatively few cases that have completed. Courts have dismissed some of these cases on the grounds that contentious ESG disclosures were in fact statements of opinion (e.g., Ruiz v. Darigold, Inc./Nw. Dairy Ass'n, No. C14-1283RSL, 2014 WL 5599989, at *2 (W.D. Wash. Nov. 3, 2014)). Discovery is proceeding in others (e.g., Gardner v. Starkist Co., No. 19-CV-02561-WHO, 2021 WL 303426, at *5 (N.D. Cal. Jan. 29, 2021)). Finally, in some others defendants have settled with litigants (e.g., for $25 million in Vale S.A. Securities Litigation 1:15-CV-9539 (GHW) (S.D.N.Y.)). Most of these lawsuits are ongoing (e.g., Gardner v. Starkist Co., No. 19-CV-02561-WHO, 2021 WL 303426, at *5 (N.D. Cal. Jan. 29, 2021)).

We find the rate of impossible disclosures increases from 2017 to 2018, consistent with a lack of discipline for accurate reporting. The rate of impossible disclosures also persists in 2019, when the UK's Equality and Human Rights Commission (EHRC) made reporting voluntary for one year in response to the COVID-19 pandemic.

Given the high prevalence of mathematically impossible disclosures, and the fact that identifying them requires no additional information beyond the publicly disclosed statistics, it appears that employers experience few forces disciplining inaccurate reporting. Indeed, the EHRC has faced significant criticism for taking a "light-touch" enforcement approach.[6] While the EHRC has broad de jure oversight over all aspects of the reporting process, the EHRC's de facto primary concern is the timeliness of submissions rather than their accuracy. For example, 50 of the 51 enforcement actions listed on the EHRC's website as of June 2021 are sanctions for late reporting (EHRC 2021), and a 2018 Guardian article explicitly stated that the EHRC did not fact-check the data.[7]

The lack of strong enforcement of reporting accuracy may allow some employers to strategically misreport their gender pay gap information. While assessing the intent behind disclosure is difficult, we triangulate employers' intentions using several approaches. We begin by evaluating the prevalence of perfectly-balanced average gender pay gaps (0.0%) and perfectly-balanced gender ratios (50.0%/50.0%). Perfectly-balanced average gender pay gaps and gender ratios are desirable because they indicate the greatest possible diversity, do not risk making either gender feel underrepresented or dominated by the other, are typically seen as "the target" or "ideal," and are the ultimate goal of gender equality mandates.[8] Consequently, when a firm chooses to misreport, its strongest incentive is to misreport its gender statistics as perfectly-balanced. We focus on firms reporting no pay gap between the *mean* woman and man rather than the *median* be-

[6] `www.theguardian.com/society/2019/feb/28/lack-of-sanctions-makes-a-mockery-of-gender-pay-gap-reports`

[7] `www.theguardian.com/news/2018/feb/28/what-you-need-to-know-about-gender-pay-gap-reporting`

[8] E.g., UNESCO (2019); `https://www.sodexo.com/inspired-thinking/research-and-reports/gender-balance-study-2018.html`. Last accessed November 7, 2021.

cause idiosyncratic variation in labor market dynamics and negotiations anywhere in the pay distribution will cause firms to deviate slightly from a perfect 0.0%, gender pay gap. In contrast, misreporting firms can always choose to report 0.0% pay gaps. Consistent with widespread intentional misreporting, we find an unusually large number of employers report 0.0% pay gaps and 50.0/50.0 gender ratios. Based on fitting a smooth curve to the reporting distribution in the neighborhood of the targets, we estimate that one-third to one-half of the employers reporting no mean pay gap are likely misreporting.[9]

To explore whether a lack of enforcement relates to misreporting, we construct a novel dataset of gender pay gap restatements. We show that while restatements occur in over 3% of reports of 2017 and 2018 gender pay gap data, there is considerable clustering of the restatement timing—many restatements occur on the same date as the employer's subsequent year disclosure. This clustering suggests that a large portion of restatements are employer-initiated, rather than initiated by third parties, and is therefore consistent with weak discipline for inaccurate reporting (either by EHRC or the public at large). We compare restatement rates for impossible disclosures and find that when the marquee metric, the median pay gap, is not favorable for the employer (i.e., women earn less then men), the employer is more likely to restate. However, if the impossible disclosure's median pay gap is more favorable for the employer (i.e., women earn more than men), the employer is relatively less likely to restate their statistics even though they must be erroneous. This asymmetry is further consistent with at least some firms intentionally misreporting.

Having established the prevalence of misreporting, we investigate which types of employers are more or less likely to misreport. We find that smaller firms, as measured by the number of employees, are more likely to misreport. We find no evidence that misreporting relates to firm profitability or whether the firm's equity is publicly traded. Across all measures of misreporting, firms that include an optional link to a discussion of their gender pay gap performance are less likely to misreport. We also find a negative relation between

[9] Given our empirical approach does not identify employers that choose to misreport close to perfectly-balanced gender pay gaps or ratios, or simply report better than actual performance but still well shy of the ideal performance, our estimates can be considered lower bounds for the prevalence of overall strategic misreporting.

misreporting and financial audit quality (as proxied by an audit from a big four firm). However we find a mixed relation between CSR audits and misreporting. While we find that CSR audits relate to lower levels of egregious impossible reporting, we find no relation between CSR audits and reporting perfectly-balanced gender statistics. These relations are consistent with the broader literature that suggests CSR audits are lower quality and provide only superficial assurance.[10]

We next turn to firms' potential motives for misreporting. We first examine whether recent involvement in an ESG controversy relates to misreporting. ESG controversies may cause employers to misreport gender statistics in an attempt to sugarcoat their poor performance or distract stakeholders from problem areas. Alternatively, in the absence of misreporting, employers involved in an ESG controversy should be less likely to report perfectly-balanced gender statistics because of their poor ESG performance. Consistent with the former explanation, and inconsistent with truthful reporting of gender pay gaps or ratios, we find that firms Refinitiv identifies with poor ESG controversy scores are more likely to report perfectly-balanced gender statistics.

Given the link between ESG controversies and misreporting, we examine whether employers benefit from misreporting. Intentional misreporting implies a pooling equilibrium where misreporting employers pool with truthfully-reporting good types in an attempt to enjoy some benefit. Because ESG ratings agencies consider gender balance, including the information reported via the UK mandate, one potential benefit of reporting perfectly-balanced gender statistics is higher ESG scores, which prior work suggests attracts investment and corporate customers (Hartzmark and Sussman, 2019; Darendeli et al., 2021). Consistent with potential benefits to misreporting, we find that employers reporting 0.0% median pay gaps are more likely to enjoy increases in the Social Pillar component of their ESG scores (we estimate a similar-in-magnitude effect for reporting 0.0% mean pay gaps, though that estimate is not statistically significant). These findings

[10]CSR audits require non-accounting expertise, and hence may be low-quality, particularly as they are currently purely voluntary (Christensen et al., 2021). Consistent with this idea, Moroney and Trotman (2016) find in an experimental setting that differences in auditor liability, lack of guidance or experience, and different justifications between CSR versus financial audits cause auditors to apply tighter materiality thresholds to financial statement audits than to CSR audits.

add to a growing body of evidence that ESG ratings may not be reliable indicators of ESG performance (Christensen et al., 2021; Basu et al., 2021; Raghunandan and Rajgopal, 2022; Thomas et al., 2022).

Our study makes several contributions to both academic literature and practice. First, our evidence can inform how regulators design gender pay gap reporting mandates, and ESG reporting mandates more broadly. Without accurate reporting, it is unlikely that firms will be held accountable for their gender pay gaps. This is a particularly timely point as the UK gender reporting mandate includes a provision for re-evaluation in 2022, and regulators in other countries are evaluating and/or considering implementing their own reporting mandates and enforcement regimes, both with respect to gender pay statistics and workplace diversity statistics more generally. For example, the US Equal Employment Opportunity Commission has required public firms to provide it with gender pay statistics (Component 2 of Form EEO-1), although firms need not publicly disclose this data for now. Similarly, one of the top priorities of current Securities and Exchange Commission (SEC) Chair Gary Gensler is a potential new rule on disclosing workforce diversity metrics (Johnson, 2021). While a complete accounting of the costs and benefits of any regulatory intervention is beyond the scope of any one study, our results suggest that in the absence of strong enforcement and oversight, many employers will misreport the required information, undermining the reliability and usefulness of mandated reports. More generally, as regulators worldwide introduce a number of reporting mandates related to gender pay and ESG performance more generally (e.g. US Government Accounting Office, 2020), misreporting likely undermines the ability of these mandates to improve performance.[11]

Second, our study has immediate implications for the increasing number of stakeholders, including

[11] In this regard, our study also relates to the literature on greenwashing, which “has usually been defined as a gap between symbolic and substantive actions” (Siano et al., 2017, p. 27) or as the act of “disseminating a misleading picture of environmental friendliness or other [socially responsible behavior], or one that is accurate in some dimensions but serves to obscure less savoury ones” (Benabou and Tirole, 2010, p. 11). Greenwashing can occur when employers are unable to fulfill well-intentioned promises to improve ESG performance (e.g. Siano et al., 2017). Greenwashing can also occur when employers strategically disclose information, for example by using boilerplate language to conceal or distract from poor ESG action or inaction (e.g. Cho et al., 2009; Crilly et al., 2016; Raghunandan and Rajgopal, 2021a). We add to this literature by documenting evidence of employers misreporting their ESG performance, while prior work documents evidence of employers using cheap talk or selective reporting to distract from poor ESG performance. Consequently, we document evidence of a relatively extreme form of greenwashing.

researchers, that use self-reported ESG information either directly, or indirectly via ESG scores. As Christensen et al. (2021) highlight, gender pay gap disclosures are a powerful setting to study broader questions about the effects of mandatory ESG disclosure. However, our evidence that many firms misreport their gender pay gap statistics suggests that taking the data at face value may bias inferences. Given the increasing frequency of ESG disclosure mandates worldwide, our study also highlights an important practical issue: disclosure alone may not be sufficient to induce real change in firms without sufficient monitoring and enforcement of accurate reporting. Our results also suggest that researchers and stakeholders should exercise caution when using self-reported ESG metrics, or ratings scores based on self-reported ESG metrics, in the absence of strong enforcement. This evidence also suggests that inferences about ESG performance drawn from secondary sources, such as in Chen et al. (2018) or Bonetti et al. (2021), are particularly valuable.[12]

2. Background and Related Literature

2.1. UK gender pay gap disclosure mandate

Gender pay gaps and differences in workforce participation are salient measures of gender inequality.[13] Despite efforts to equalize opportunities between genders, gender differences in pay and workforce participation persist. In an attempt to close these gaps and equalize workforce participation, many governments are forcing employers to disclose gender representation statistics. We examine one such disclosure mandate in the UK.

In 2017, the UK government enacted the Equality Act 2010 (Gender Pay Gap Information) Regulations 2017. The Act required all employers registered in Great Britain with at least 250 employees to publish

[12]Chen et al. (2018) find that Chinese stock exchanges' ESG reporting mandates reduce wastewater and SO_2 emissions levels at cities more affected by the mandate. Bonetti et al. (2021) find that the disclosure of fluids used in hydraulic fracking well drilling improves water quality at nearby wells. In both settings, the entity recording and reporting the outcome variable is not the employer required to provide ESG information and consequently the information is less likely to be manipulated.

[13]While related, the gender pay gap is a distinct concept from equal pay. Equal pay refers to women and men earning the same amount for completing the same job. The gender pay gap refers to women and men receiving different pay regardless of the jobs they perform. While a gender pay gap may be a result of a firm not providing equal pay, it may also stem from men dominating high-paying positions in the organization.

gender pay and employment information on their corporate websites and submit the required metrics to the Government Equalities Office (GEO).[14] Employers must publish the data every year within 12 months of the relevant snapshot date. The publication must be accompanied by a written statement signed by a person specified in paragraph 14(2) or 14(3) of the Regulations which confirms that the information is accurate.[15] The GEO also makes this information publicly available on a dedicated website.[16]

The regulations require employers to publish the overall average and median gender hourly gap in pay, and the proportion of men and women in each quartile of the wage distribution. The reporting requirement does not depend on organization type: publicly listed firms in the UK, British subsidiaries of foreign firms, private for-profit firms, governmental organizations, and charities must all file gender pay gap reports if they employ at least 250 individuals based in the UK. Disclosure is based on a "snapshot date" of March 31 (for governmental entities) and April 5 (for private firms and charities) of each year (i.e., reported figures reflect the composition of the firm's workforce as of the snapshot date). Firms must then report these figures within twelve months of the snapshot date. Full data is available for firms' gender pay gaps for 2017, 2018, and 2020. Full figures are not available for 2019 because the EHRC allowed employers to opt out of reporting their 2019 data due to the Covid-19 pandemic, with the understanding that reporting would return to mandatory in future years.

Figure 1 illustrates the relevant calculations for a simulated firm.[17] Specifically, the average pay gap is calculated by taking the difference between the average man's and the average woman's pay, scaled by the average man's pay. The median pay gap is calculated analogously using the median man and median woman's pay. Firms report their gender statistics via the GEO portal, and are required to populate all fields.

[14]While the rules were intended to apply across the entire UK, they were never established for Northern Ireland.

[15]E.g., if the employer is "the members or officers of an unincorporated body of persons other than a partnership, the written statement must be signed by a member of the governing body or a senior officer" paragraph 14(2)(e).

[16]`https://gender-pay-gap.service.gov.uk/`

[17]The regulations also require firms to report the percentage of men and women who receive bonuses, along with the average and median gender bonus pay gap for those employees receiving bonuses. Because we do not examine bonus pay gaps we do not illustrate their calculation.

They cannot report only a subset of the required information. Firms populate the fields themselves and there are no default values. Therefore, an unusually large number of reported values, such as 0.0% pay gaps, are not due to default reporting.

The regulations do not impose penalties on employers that do not improve their gender representation over time. However, the EHRC can seek a court order requiring that employers comply with the Act.[18] Although the EHRC can seek a court order to require that employers report some information, in practice it has little ability to ensure and enforce the accuracy of the information reported (Whincup, 2016). The EHRC has opened only one investigation for inaccurate reporting, and to the best of our knowledge levied no enforcement actions.[19] In total, EHRC enforcement does not appear to meaningfully constrain misreporting.

2.2. Related literature and hypotheses

Several existing studies also examine the UK reporting mandate, or are motivated by the reporting mandate. Using linked Annual Survey of Hours and Earnings data, Blundell (2020) and Duchini et al. (2020) find that employers just above the 250-employee threshold decrease their pay gaps after the mandate goes into effect, relative to employers just below the threshold. In a registered report project, LaViers and Sandvik (2021) plan to conduct a hypothetical choice experiment to examine whether job-seekers respond to gender diversity disclosures. Raghunandan and Rajgopal (2021b) find that the mandate only modestly decreased the pay gap of small employers, while having no impact on employers with more than 500 employees. We build on these studies by examining reported gender statistics for evidence of misreporting, which may undermine the ability of the mandate to accomplish its stated goal of increasing gender equality.

We predict that some employers will unintentionally misreport their gender statistics due to the lax over-

[18]Failure to comply with the court order can result in unlimited fines, and the EHRC publishes information on investigations into noncompliance on its website. For the 2018 reporting period, 47 organizations failed to report their gender representation; `https://www.equalityhumanrights.com/en/pay-gaps/gender-pay-gap-our-enforcement-action`. Last accessed November 23, 2021.

[19]`https://www.equalityhumanrights.com/en/pay-gaps/gender-pay-gap-our-enforcement-action`. Last accessed November 23, 2021. The employer in question reported perfectly-balanced gender ratios across all four pay quartiles and perfectly-imbalanced pay ratios (i.e., the employer reported half of its employees were women and that these women made £0 for every £1 that men made).

sight of accurate reporting. We also predict that some employers will strategically, intentionally misreport their gender statistics. A large prior literature documents that employers misreport their financial performance due to the benefits of reporting strong financial performance (see Beyer et al., 2010, for a review of the literature). Another large literature documents that employers benefit from reporting strong ESG performance, including with respect to gender diversity (see Christensen et al., 2021, for a review of the literature). Given that reporting strong ESG performance benefits employers, and that firms misreport their performance when there are benefits to doing so, it seems natural that some employers will misreport their gender pay gaps. Moreover, we argue that in the UK gender pay gap setting, misreporting is particularly likely given that there is little to no enforcement of reporting accuracy (Whincup, 2016; Christensen et al., 2021).

In most empirical settings, documenting evidence of intentional misreporting is challenging because in order to obtain benefits misreporting employers must be able to pool with truthfully-reporting employers (Fischer and Verrecchia, 2000). Accounting researchers have traditionally overcome these challenges in one of three ways: (i) focusing on ex-post revealed misreporting (e.g., misreporting revealed via enforcement actions), (ii) relying on private data (Bens et al., 2011, e.g., to identify selective reporting as in), or (iii) inferring misreporting from the distributional properties of the quantity being misreported (e.g. Burgstahler and Dichev, 1997, in the context of the zero-earnings discontinuity). Approaches (i) and (ii) are challenging in the ESG setting, for example because ESG reporting is relatively novel and few enforcement actions exist. Consequently, we follow approach (iii) and identify a set of firms that are highly likely—but not guaranteed—to have misreported based on the statistical improbability of their disclosures. In particular, we examine whether a disproportionate number of employers report perfectly-balanced gender statistics (i.e., 50/50 gender ratios and 0.0% pay gaps).

Perfectly-balanced gender ratios or no pay gaps imply no preference for, or bias in favor of, either gender, do not risk leaving either gender feeling underrepresented, and are often discussed as the ideal or target.[20] Employers pursuing perfect gender ratios and pay gaps likely do so with some "error," for example due to the whims of the labor market (e.g., members of a given gender may depart the employer with greater frequency in a given period, leading to slightly imbalanced gender ratios). Consequently, truthfully-reporting employers are likely to achieve and report near perfectly-balanced gender statistics with some frequency (e.g., they are likely to report 49/51 or 51/49 gender balance). In contrast, misreporting employers do not suffer from this issue and can always choose to report perfectly-balanced gender statistics. Therefore, finding a disproportionate number of employers reporting perfectly-balanced gender statistics suggests that some are likely misreporting.[21]

3. Empirical Evidence on Gender Pay Gap Misreporting

3.1. Disclosure Sample

Our main sample consists of gender statistics reported to the GEO. The GEO collects annual reports from employers via an online portal and makes those reports available to interested parties either through an employer-specific search or a bulk download.[22] Our sample comprises all reports from 2017 through 2020 (for ease of exposition, we refer to reports by the snapshot year rather than the year of the disclosure; i.e. 2017 reports have a snapshot date of early 2017 but the reporting deadline was early 2018).

Table 1, Panel A presents sample descriptive statistics, separated by year. In each of the mandatory reporting years, just over 10,000 employers submitted reports. When reporting became voluntary for the 2019 snapshot, volume fell by nearly 40%. For the 2020 snapshot, firms were not required to disclose quartile

[20]E.g., `https://www.sodexo.com/inspired-thinking/research-and-reports/gender-balance-study2018.html`. Last accessed November 7, 2021.

[21]An issue with this approach is that misreporting employers may also misreport near perfectly-balanced gender statistics (e.g., they can also choose to report 49/51 or 51/49 gender balance). They also may misreport by simply shifting to meet an unspecified industry goal, to exceed the performance of key peers, or hide performance deterioration relative to the prior period. Our approach is unable to detect these kinds of misreporting. Consequently, our approach entails a higher type II error rate (i.e., it is biased towards accepting the null hypothesis of no misreporting). We believe a higher type II error rate is acceptable in this setting, due to type I errors being potentially more costly because they can encourage greater enforcement of reporting accuracy.

[22]In the online appendix, we include screenshots for the data entry process on the GEO portal. Disclosure data can be downloaded from `https://gender-pay-gap.service.gov.uk/`

statistics if a considerable number of employees were on a coronavirus-related furlough; hence the number of observations is not the same across measures for this year. Multiple dimensions suggest a considerable compensation gap exists between men and women. In terms of average hourly pay, the mean reported gap is roughly 14% with some evidence of skew. Reported median hourly pay gaps are slightly smaller, suggesting that men disproportionately appear in the high end of the reported pay distribution. The reported percent of women in each quartile of the pay distribution further supports this pattern. For the majority of employers, women disproportionately appear in the lowest quartile of the reported pay distribution, and men disproportionately appear in the upper pay quartiles.[23]

In Table 1, Panel B, we present transitions in the mean value of each disclosed statistic across reporting years. The reported average pay gap did not significantly change between years. The median pay gap increased by approximately one percentage point from 2018 to 2019, and did not revert in 2020. These patterns differ from the national gender pay gap figures published by the UK Office for National Statistics, which reported that the median pay gap decreased from 18.4% to 17.8% economy-wide over the same period.[24] There are several potential explanations for this discrepancy. First, the economy-wide statistics include small employers whereas the firm-level pay gap data primarily includes employers with more than 250 employees.[25] Second, the statistics presented in Table 1 equal-weight employers. If the gap for large employers is greater than for smaller employers, it would likely drive the economy-wide figures being higher than the aggregates of the firm disclosure. Third, the firm disclosures only capture within-employer

[23]For brevity, we do not tabulate the percent men in each pay quartile because for all observations the reported percent men and percent women in a pay quartile total 100%. We also do not tabulate summary statistics related to bonus pay. While the data are interesting and employers may potentially misreport them, it is highly likely that discontinuous jumps occur in these distributions that are unrelated to misreporting. For example, employers likely often award a flat bonus across-the-board, either to all employees or the bonus-eligible subset. In this instance, there would be no bonus gap. Because we do not know how often employers engage in this type of bonus structure, we cannot examine this distribution for evidence of misreporting.

[24]`https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/bulletins/genderpaygapintheuk/2020`

[25]The ONS conducted an ad hoc calculation of the gender pay gap economy-wide by different employer size bands (`https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/adhocs/008137genderpaygapbybusinesssize`), and while very small employers (1-9) employees had smaller gaps than larger employers, there is relatively little difference in the 10-49, 50-249, and 250+ employee bands.

pay gaps, which may mask across-employer differences. For instance, if one firm employs 10 men and 10 women at the same pay rate of £10 per hour, and a second firm employs 15 men and 5 women at the same pay rate of £20 per hour, both employers individually have no gender pay gap. However, when employees are combined across the two employers, the median male would earn £20 whereas the median female would earn £10, for a combined gap of 50%. Thus, aggregating employer-level disclosures does not necessarily speak to the gender pay gap of the UK economy as a whole. Finally, the GEO data may be biased by misreporting, while the UK Office for National Statistics data – which is derived from payroll tax records – is less likely to be so.

The percentage of women in each quartile of the distribution increases over time. While changes are smoother across time for the quartiles compared to the median pay gap, the bulk of the shift happened in 2019. This likely reflects the temporary shift from mandatory to voluntary reporting for 2019: when given the option to voluntarily disclose their gender pay gap information, employers with a higher proportion of female employees were more likely to submit reports. However, average reported pay gaps did not change and median pay gaps actually increased, suggesting any increase in female representation in the upper pay quartiles was equally or more than offset by increases in the lower pay quartiles.

The GEO records all data points to one decimal place. Additionally, the guidance for reporting employers lists example calculations with rounding to one decimal place, and the system requires disclosure to one decimal place (e.g., an employer wishing to report no pay gap cannot input a pay gap of 0 and must input a pay gap of 0.0). Nonetheless, as Table IA.1 in the internet appendix illustrates, a zero tenths digit is far more common than any other value, suggesting employers round to the nearest integer percentage value. We take this rounding into account when we conduct our distributional tests of misreporting.

Table 1, Panel C presents descriptive statistics of sample covariates and additional outcome variables of interest.

3.2. Impossible Disclosures

We first explore GPG reporting quality by identifying disclosures where the combination of disclosed values is mathematically impossible. Specifically, we determine if the median woman earns strictly more or less than the median man based on the reported median pay gap. We then use the gender breakdown in each pay quartile to also infer if the median woman earns strictly more or less than the median man. If the two approaches produce conflicting results, we label the disclosure mathematically impossible.[26]

Table 2 presents statistics on employers' reporting of mathematically impossible disclosures. Depending on the year, 4.3%-5.1% of disclosures are mathematically impossible. These high rates suggest low reporting quality in gender pay gap disclosures. Moreover, disclosure quality does not appear to improve over time as the reporting regime becomes more familiar. In fact, the rates of impossible disclosures were higher in 2018 and 2020 than in 2017 (χ^2 test of equal proportions statistics of 8.2 and 7.5 respectively). The decline in the impossible disclosure rate in 2019 is consistent with firms that choose to voluntarily report gender pay gap statistics being more likely to report accurate figures. However, the impossible disclosure rate is still quite large and insignificantly different from 2017 (χ^2 = 0.09).

Assessing intent from this evidence is difficult. Impossible disclosures may result from the employer attempting to strategically misreport more attractive gender pay gap results, or they may reflect simple sloppiness. While either scenario undermines the usefulness of these disclosures, to try to tease apart these possibilities we break down the impossible disclosures based on the sign of the stated median pay gap. The columns labelled $MedianGap_{i,t} < 0$ and $MedianGap_{i,t} > 0$ correspond with the employer reporting that the median woman earns more than and less than the median man respectively, but with contradictory

[26]For example, consider a hypothetical firm disclosing that 20.0% of employees in the the lowest pay quartile, 25.0% in the lower middle quartile, 30.0% in the upper middle quartile and 20.0% in the top pay quartile are women. These statistics imply that the workforce is 23.75% women, and because by definition there are an equal number of employees in each pay quartile, the median woman earns more than the median employee, and hence more than the median man. If the firm simultaneously reports a positive median pay gap (i.e., the median man is earning more than the median woman), then at least one of the employer's disclosures (i.e., the median pay gap or the quartile breakdowns) must be incorrect. While we know that the disclosed combination of measures is mathematically impossible, we cannot with certainty tell which measure(s) provided by the employer is(are) erroneous.

quartile distributions. We find that 27.7%-36.3% of impossible disclosures report a negative median pay gap, showing the median female earning more than the median male. In comparison, for all non-zero median pay gap disclosures, only 13.1%-15.4% report a negative pay gap, and these proportions are significantly different in every year (χ^2 test statistics of 135.52, 105.97, 54.02, and 76.36 for years 2017, 2018, 2019, and 2020, respectively).

Assuming reporting a negative median gender pay gap is preferable to reporting a positive one, the difference between impossible disclosures and the overall non-zero pay gap population is consistent with at least some intentional misreporting in the impossible disclosures. If the impossible disclosures were purely a result of sloppiness, we would expect the proportions to be similar. However, we note this inference is based on strong assumptions. First, it assumes a strictly negative median pay gap is desirable. Second, it assumes that consumers of the GPG information pay attention to the median pay gap and not the quartile distributions, or that they cannot reliably identify impossible disclosures. Given the mean and median are the marquee measures and virtually all media reporting on GPG disclosures focus solely on these statistics, this assumption is likely reasonable. It is curious, however, that an employer might intentionally misrepresent the median gender pay gap but leave the quartile distributions untouched; if the employer is already intentionally misreporting one figure, misreporting the others may make detection of the misreporting more difficult. That said, the quartile distributions may have low visibility and hence not increase the probability of detection. Additionally, employers may perceive a higher penalty for being caught misreporting multiple figures rather than just one. While subject to a number of caveats, there is circumstantial evidence that a portion of the impossible reports are likely intentional misreporting.

3.3. Restatements

To further probe the quality of GPG disclosures and the likely intent behind misreporting, we examine restatements of gender pay gap information. Employers may restate their reported numbers by logging in to the UK's Gender Pay Gap Reporting Service website and updating their prior disclosures.[27] While employers do not formally announce these restatements, we are able to detect them by comparing historical downloads of data posted on the GPG reporting service website with current data. Specifically, for the 2017 reporting year we compare the employer's first disclosure in either September 2017 or April 2018 with the same year's data downloaded in April 2022.[28] For 2018 reporting year data, we compare a download from April 2019 to an April 2022 download.

Table 3, Panel A tabulates the frequency of restatements by type. Restatements were quite common in the first reporting year, with over five percent of reports having at least one figure restated. By 2018, the restatement rate fell considerably to 1.51%. This drop may be consistent with a learning explanation—with a year of practice, employers made fewer mistakes the second year around. It could also be consistent with a shift (real or perceived) in the forces providing discipline for truthful reporting. An unlikely explanation is that 2017 observations simply have been around longer than 2018 and hence have more opportunity to have been restated. To rule out this explanation, in the third set of columns we exclude 2017 restatements made between April 2021 and April 2022, effectively equalizing the time period during report could potentially be restated. Inconsistent with the longer period for firms to restate 2017 data driving our results, only 12 restatements for the 2017 reporting-year were made over three years after the original report.

Across the different metrics firms report, there is little difference in the restatement rate. The highest-profile measure, the median hourly pay gap, does not have a markedly higher restatement rate than the other measures. This finding is consistent with there being limited pressure from the public to correct misreporting. Further bolstering this idea, in Panel B companies often batch their efforts and issue restatements on the

[27]The employer is required to submit a brief explanation for the restatement. This explanation is not publicly reported on the website, and we have been unsuccessful in obtaining these explanations via Freedom of Information requests.

[28]The September 2017 download is after the 2017 "snapshot" date but well before the reporting deadline; the April 2018 download is just after the reporting deadline. Thus, our 2017 restatement sample includes firms that reported early, and then potentially restated before the deadline. In the internet appendix we report results only using differences between the April 2018 download and the April 2022 download. While the number of restatements is necessarily smaller, the results are qualitatively the same. Early versions of the data did not include the GEO's employer identifier—instead we must match observations based on the Companies House registration number. As a result, our restatement sample only includes employers that are registered with Companies House.

same day they report the subsequent year's disclosure (29% for 2017 and 46% for 2018). It seems unlikely that firms respond to external pressure by waiting to the next reporting date to restate. Instead, batching restatements suggests that firms either realize their prior mistake as part of calculating the current report, or that they attempt to conceal the restatement by waiting until they release a new number. In either case, they are likely not responding to external pressure.

To further triangulate on the intent behind misreporting, in Panel C we assess the relation between impossible disclosures and restatements. We regress an indicator for whether an employer restated its gender pay gap information in a specific year on an indicator for whether the firm made a mathematically impossible disclosure. We base our measures of misreporting on the original, pre-restatement report, so that these tests capture whether likely misreporting relates to restatements. In column (1), we find that employers are 2.3 percentage points more likely to restate mathematically impossible reports. In column (2), we decompose the impossible restatements based on the sign of the median pay gap. If a large portion of restatements are firm-driven, we expect firms to restate unintentional errors at a much higher rate than intentional misreporting. We see results consistent with this expectation; of the impossible reports, those with a negative median pay gap (median woman earns more than median man, and hence more likely to be intentional) are not associated with a higher restatement rate whereas positive pay gap disclosures have a 3.3 percentage point higher restatement rate.

For an employer's disclosure to be impossible, the median pay gap number or the quartile distributions must be erroneous. In columns (3) and (4) we isolate these components of the restatement. We find that impossible reports with a positive median pay gap, which are less likely to be intentional, are more strongly correlated with restating one of the quartile metrics. This may be a result of employers devoting more care to the higher profile measure. Conversely, for misreporting that is more likely to be intentional—disclosures where the median pay gap is negative—we find a negative correlation with restating the mean and no relation with restating the quartiles. This finding matches our expectations; if employers intentionally misreport the median gap, they are unlikely to restate it.

3.4. Distributional Indications of Intentional Misreporting

Our analyses thus far have centered on gender pay gap reports that we can clearly identify as misreported due to internal inconsistencies. In many cases, however, the existence of misreporting may be less obvious to identify. Thus, we next turn to the incidence of likely (rather than definite) misreporting. Our approach to detecting likely misreporting is to examine the distributions of all gender pay gap reports for anomalies. Figure 2 presents histograms of the for 2017 data. Panel A summarizes the mean and median pay gaps and Panel B summarizes the four pay quartiles. The other reporting years are qualitatively similar, so we exclude them for brevity. For clarity given the frequent rounding of reported statistics, these histograms only include reported values ending in a zero tenths place. For the mean pay gap and, especially, the median pay gap, the modal reported value is 0.0%.

Common reporting of no gap in the median base pay is not surprising given how the median is calculated; discrete pay bands and even moderately consistent female representation across the pay bands can result in the median man and woman earning the same. However, having no gap in the *mean* base pay is a much less likely scenario mathematically, given every employee's pay throughout the entire distribution contributes to the average. Turning to quartile reporting in Panel B, we observe similar distributional jumps around equal gender representation. In all four quartiles, the modal report is 50.0%. Again, having 50.0% female representation is not impossible, but the likelihood of it being so much more prevalent than nearby values is improbable.

We next formalize the intuition in the preceding paragraph by estimating the incidence of misreporting perfectly-balanced gender statistics (i.e., 0.0% average pay gaps or 50.0% women in a pay quartile). Our approach assumes that in the neighborhood of a perfectly-balance gender statistic, the probability distribution should be smooth. Under this assumption, deviations occur if a significant number of firms misreport that they have perfect gender balance. We estimate the following models for each metric-year using ordinary least squares (OLS) regression:

$$Count_x = \beta_0 + \beta_1 x + \beta_1 x^2 + \beta_3 x^3 + \beta_4 \mathbb{I}\{x = Target\} + \varepsilon_x \tag{1}$$

where x is a reported value for the metric, expressed as an integer (e.g. for a 2.0% average pay gap, x would be 2) and $Count_x$ is the number of employers reporting x for the given metric-year. In other words, we fit a smooth cubic function to the distribution of frequencies but permit a jump at the target value.[29] Given that a single cubic function likely does not describe the entire distribution, we fit it locally using only values of x in a 20 percentage point neighborhood of the target (i.e. $-10 \leq x \leq 10$ for the average pay gap and $40 \leq x \leq 60$ for the quartile representation metrics). β_4 is thus our estimate of the abnormal number of employers reporting the target exactly, relative to our assumed smooth function.[30]

Figure 3 illustrates the estimation process graphically. The higher dark bars at each integer reporting value illustrate the prevalence of employer rounding. To accommodate this rounding we undertake two estimation approaches. First, we fit the model only using employers that report a whole integer percentage value, as pictured by the green open points in Figure 3. Second, we round reports to the nearest integer percentage value, and estimate the models on frequencies of these rounded reports. Table 4 reports estimates for the average pay gap metrics; Table IA.2 in the internet appendix reports estimates for the quartile female representation metrics. For 2017, our fitted cubic suggests that absent misreporting, 39 employers would report a 0.0% average pay gap exactly and 201 employers would report an average pay gap that rounds to 0.0% (the intercept values). Locally the distribution is increasing ($\beta_1 > 0$) and concave ($\beta_2 < 0$), which is consistent with fitting to the left side of a bell-shaped curve. Based on integer reports only, we estimate 35 employers misreport, which is highly statistically significant (t-statistic: 7.5). Based on rounding the

[29]Given the shape of the distributions, cubic functions (i.e., a third order polynomial) appear to fit well without overfitting. Inferences are unchanged if we choose different orders for the polynomial.

[30]Before estimating the quartile specifications, we recenter representation metrics on 0 by subtracting 50 from x; doing so means the intercept predicts the number of employers reporting the target exactly, absent misreporting.

reports, our estimate increases to 64 employers, though the statistical significance is lower (t-statistic: 1.9). Given the expected frequencies of reporting no pay gap, these values are economically large. Relative to the total sample of 10,560 employers, these estimates represent a misreporting rate 0.3%-0.6% for the average pay gap metric alone. Additionally, because this procedure captures only one type of misreporting (moving to a specific sample-wide target value for the whole sample as opposed to generic shifts, moving closer but not exactly to the target, or moving to other targets), our estimates are almost certainly lower bounds for total misreporting.

The estimated number of employers misreporting modestly increased in 2018. A number of factors could explain this increase. First, the overall sample grew by 2.5%, so we would naturally expect some growth in employers that report the target exactly. However, the increase appears too large to be solely due to sample growth. Second, overall pay gaps may be improving, consistent with the growth in the intercept. Third, more employers may have chosen to misreport because they revised their perceived probability of detection and/or the penalty for misreporting downward after observing essentially no enforcement actions for 2017 reports. Similarly, more employers may have chosen to misreport because they revised their perceived benefits of reporting perfectly-balanced gender statistics upwards. Anecdotally, employers with "good" gender pay gaps were covered positively by the business press, while particularly poor performance was also highlighted in a negative light.[31]

The prevalence of likely misreporting was similar after the shift to voluntary disclosure in 2019. That employers would misreport their average pay gap even when reporting was voluntary likely indicates that the perceived benefits of misreporting outweigh the perceived costs, even relative to choosing not to disclose. Once a mandatory reporting regime returned for 2020, the rate of misreporting increased considerably. We also detect statistically and economically significant rates of likely misreporting of the quartile representation

[31] See, e.g., https://www.theguardian.com/society/2018/apr/05/the-uk-companies-reporting-the-biggest-gender-pay-gaps.

metrics in Table IA.2, but for brevity avoid a detailed discussion of those results.

In total, we find strong evidence that an anomalously large number of employers report perfectly-balanced gender statistics. We interpret this evidence as likely intentional misreporting. However alternate explanations may exist for this phenomenon. First, the data may be erroneous. While we cannot completely rule out that errors in the GEO's systems drive our results, we view this scenario as unlikely. Employers have the option to provide a link to a supplementary, free-form report that expounds on their gender pay gap efforts. We pulled a small sample of these reports and manually compared the information contained in them to the information in the dataset. While we occasionally noted discrepancies, they did not appear systematic, as they occurred both when the employer reported the target exactly, and when they reported another number. Second, the methodology for calculating the metrics might provide employers with sufficient flexibility to measure in a way that results in reporting the target exactly. While observing that employers exploit this reporting flexibility would be interesting in and of itself, we believe the required methodology considerably constrains employers such that our results are not due to strategic measurement choices. For instance, employers have no flexibility on which workers they can include in their calculations or what constitutes pay, and the directions specifically articulate how to deal with potentially problematic scenarios such as a large group of employees earning the same hourly pay.[32] While we cannot ascertain whether any particular firm's misreporting is intentional (the employer knew the correct value but chose to report a different value) or unintentional (the employer made a mistake in calculating), we do note that the GEO instructions are extremely detailed and provide step-by-step example calculations. Moreover, as we describe in subsequent sections, we empirically document a relation between misreporting and firms' strategic incentives to misreport, consistent with employers intentionally misreporting.

[32]For instance, if an employer has a large group of employees that are paid the same hourly rate but who span a quartile break, the employer could strategically push the women in that group towards one quartile in an effort to balance the representation metrics. However, the guide for disclosures (`https://www.gov.uk/guidance/the-gender-pay-gap-data-you-must-gather`) states that employers should allocate men and women in the same ratio across quartile breaks in this scenario.

3.5. Implausible 0.0% Median Pay Gap Reports

In this section, we build on evidence that firms intentionally misreport their mean pay gap by documenting evidence that they misreport their median pay gap. Roughly 8% of disclosures report 0.0% median pay gap, which, as illustrated by Figure 2, Panel A, is the modal response. While at first glance this pattern may seem suspicious, achieving a 0.0% pay gap between the *median* man and woman is not as improbable as a 0.0% gap between the *mean* man and woman. If the employer uses discrete pay bands, it is possible that multiple employees (men and women) earn the same pay as the median employee. Using the gender breakdowns by pay quartiles, we develop a proxy for the implied size of the pay band required to make the employer's set of disclosed measures internally consistent. Specifically, we measure the imbalance between the number of high-pay and low-pay women, or $WomenTilt_{i,t}$, as the unsigned difference between 0.5 and the fraction of women in the first and second pay quartiles out of total women. For firms that report no median pay gap, larger values of $WomenTilt_{i,t}$ imply that the firm pays an unusually large number of employees the same amount or that the firm is misreporting their median pay gap (or gender representation statistics).

To illustrate why a 0.0% median pay gap and a large imbalance between the number of high-pay and low-pay women would require a large band of employees earning the median pay, consider a hypothetical firm illustrated in Figure 4. The firm discloses 0.0% median pay gap, and pay quartiles 1-4 comprised of 52.3%, 20.0%, 15.4% and 9.2% women, respectively. For ease of exposition, assume the firm has 260 employees; thus the quartile distributions indicate a total of 63 women and 197 men. Because there is no gap between the median woman and median man, the 32nd most paid woman must be earning the same as the 99th most paid man. The quartile disclosures thus require this woman to be located in the first quartile and this man in the third quartile, implying that everyone in the second quartile is paid the same. Further, the disclosure rules stipulate that whenever firms have a band of employees earning the same pay spanning a quartile break, the employer must allocate men and women from the same band to each side of the break in the same proportion. Specifically, the 1:4 ratio of women and men from the second quartile must extend into the top of the first quartile and the bottom of the third. Thus, for this firm's disclosures to be internally consistent, a minimum of 100 of its employees (38.5%) must be paid the same amount as the median employee.

While a 0.0% median pay gap and high values of $WomenTilt_{i,t}$ are mathematically possible, the larger amount of pay "lumpiness" required to make such reports internally consistent is increasingly improbable. Consequently, we assume that firms reporting a 0.0% median pay gap are more likely misreporting as $WomenTilt_{i,t}$ increases. Unlike our other methods of detecting likely misreporting, there is no natural cutoff in $WomenTilt_{i,t}$ representing a discrete jump in misreporting likelihood. Thus, we cannot use this approach to quantify this type of misreporting. However, we can use this approach to correlate factors associated with misreporting. Given a 0.0% median pay gap is desirable, it is reasonable to assume this type of misreporting is likely intentional.

4. Employer Characteristics Associated with Misreporting

In order to better understand which firms misreport and their motivations for doing so, we examine a number of factors that may be relevant to the decision to misreport. We begin by descriptively examining whether employer characteristics relate to the propensity for misreporting. These characteristics include employer size, whether the employer provided an explanatory report discussing its gender ratios, and employer type (governmental/non-profit entity, for-profit private, UK listed firm, subsidiary of foreign listed firm). We also examine whether the employer's financial auditor is a member of the Big Four (i.e., Deloitte, EY, KPMG, and PwC). We do not make predictions for the relation between these variables and the likelihood of reporting perfectly-balanced gender statistics.

We begin in Table 5 by regressing measures of misreporting on the employer characteristics noted above. While we view these results as largely descriptive, they bolster the validity of our measures and help provide insight to the nature of the misreporting. In odd-numbered columns we use only the variables we can obtain from the gender pay gap dataset; in even-numbered columns, we link the GPG data with Bureau van Dijk's ORBIS database to obtain additional firm information. We link these data using Companies House registration numbers, and hence are left with a smaller sample restricted to business employers.

Several themes emerge from the results. Larger employers and those that receive a financial audit from a Big 4 auditor are less likely to misreport. While the latter association may suggest that financial audits improve the quality of GPG reporting, the correlation may also reflect sophistication or the attention the firm pays to the reporting process. We find no evidence that misreporting is associated with the employer's financial performance (ROA) or whether the firm's equity is publicly traded. However, we do observe some associations between misreporting and firms that are funded in part by long-term debt, and if the employer is a registered company (as opposed to government entities and some non-profits). We also find a strong link between late submission and impossible reports, but virtually no link to the other measures of misreporting. This relation suggests that employers that do not devote care to the GPG reporting process are more apt to report impossible figures—likely unintentionally. That the other measures of misreporting do not correlate with late submissions suggests they are due to intentional misreporting, rather than sloppiness, to a greater degree. Employers that provide a link to an expanded discussion of their GPG statistics and plans for achieving gender equity are less likely to misreport, potentially because employers that place more importance on gender equity issues are more likely to author a report. More directly, the expanded gender discussion could make it harder to misreport—either because the process of authoring the discussion helps the employer catch errors, or because a discussion highlights inconsistencies and makes misreporting easier to detect.

4.1. Auditing and Likely Misreporting

Building on the findings linking big four financial auditors with lower rates of misreporting, we next investigate a more directly-related form of auditing: corporate social responsibility (CSR) audits. While prior work suggests financial statement audits constrain financial misreporting (see DeFond and Zhang, 2014, for a review), CSR audits may not constrain misreporting for several reasons. For example, CSR audits are frequently conducted by accountants despite requiring specialized non-accounting expertise. CSR audits are also largely voluntary (Christensen et al., 2021). Further, Moroney and Trotman (2016) find that differences in auditor liability, lack of guidance or experience, and different justifications between CSR versus financial audits cause auditors to apply tighter materiality thresholds to financial statement audits than to CSR audits.

In Table 6, we investigate whether firms that choose to undergo a CSR audit are less likely to misreport. We regress measures of misreporting on indicators for whether the firm underwent a CSR audit along with other firm characteristics. We obtain CSR audit information from Refinitiv.[33] We also control for *FinancialAuditBig4*. We find that CSR audits are negatively associated with impossible reports, but find no evidence of a negative association with reporting a precisely 0.0% mean pay gap or 50.0% women in any pay quartile. Importantly, this null result is unlikely to reflect significant noise or lack of power. The coefficients on *CSRAudit* in columns (3)-(6) are economically small, typically a fraction of the magnitude of those on *FinancialAuditBig4*, but the standard errors for the two coefficients are the same. In other words, the confidence interval of the estimate around *CSRAudit* is roughly the same as that around *FinancialAuditBig4*, just centered on a much smaller (near-zero) value. This finding is consistent with and without other controls, and if we redefine $CSRAudit_{i,t}$ to only indicate if the firm received its CSR audit from a big four auditor (untabulated). In columns (7) and (8), we limit our sample to employers reporting 0.0% median pay gaps and regress $WomenTilt_{i,t}$ on our auditing variables. Contrary to their constraining misreporting, we find that CSR audits are positively associated with this likely more intentional misreporting.

The negative association between CSR audits and mathematically impossible reports along with the insignificant and positive associations between CSR audits and other indicators of misreporting provides

[33]Refinitiv's ESG data is at the ISIN-level whereas gender pay gaps are at the employer level (legal entity, or BvD identifier). For some employers there is a one-to-one match from the BvD identifier to the ISIN, whereas other reporting employers are part of a larger umbrella organization. For these employers, we take advantage of the ownership information in Orbis to identify ISINs from majority-holding parents or grandparents to obtain the relevant CSR Audit information.

some insight into the likely channels by which CSR audits influence GPG reporting. In particular, the results are consistent with CSR audits being associated with more sophistication in the GPG calculation and disclosure process, and thereby negatively relating to unintentional misreporting resulting from sloppiness. This negative relation may arise because the CSR auditor catches problems in the employer's calculation of GPG information. Alternatively, it may arise because firms that devote care to the GPG disclosure process may be more likely to undergo a CSR audit. However, we do not find evidence that CSR audits negatively relate to our measures of intentional misreporting, consistent with CSR audits being lower-quality and of limited value in assuring the content of GPG disclosures.

4.2. ESG controversies and Likely Misreporting

We next examine whether ESG controversies relate to gender pay gap misreporting, given that a firm's gender pay gap is one key measure of its ESG performance. To the extent that firms truthfully report their GPG statistics, we expect firms experiencing ESG controversies are less likely to have perfectly-balanced gender statistics, particularly if the controversies center on workforce diversity and equity issues. However, to the extent firms involved in ESG controversies do not report truthfully, we expect them to be more likely to report perfectly-balanced gender statistics in attempt to 'pinkwash' their poor performance elsewhere. Given the evidence we have previously documented suggesting widespread misreporting, we predict that involvement in an ESG controversy will positively relate to reporting perfectly-balanced gender statistics.

In Table 7, we investigate whether ESG controversies relate to misreporting. We regress an indicator for reporting either 0.0% mean pay gap or 50.0% women in any pay quartile on *ESGControversiesPreceding*.[34] The results in column (1) suggest that firms involved in an ESG controversy in the preceding year are 1.8 percentage points more likely to report perfectly-balanced gender statistics (t-statistic of 2.25). This relation

[34]Refinitiv provides an ESG controversy score on a scale of 0-100, with lower values indicating bigger controversies. Scores lower than 50 fall in the C and D range. We define *ESGControversiesPreceding* to take a value of one if the controversy score is 50 of less, and zero otherwise. We focus on these measures of likely misreporting as they are the most likely of our dichotomous measures to be intentional. If we include impossible reports in the dependent variable our results are qualitatively unchanged.

is consistent with firms using the disclosures of strong gender pay gap performance to greenwash problems elsewhere.

However, it is possible that firms with more ESG controversies are more likely to report perfectly-balanced gender statistics for some other reason. To further investigate whether firms respond to ESG problems by misreporting their gender statistics, in column (2) we conduct a falsification test. We add *ESGControversiesFollowing* (an indicator equal to one if the subsequent ESG controversies score indicates any major controversies). If firms respond to ESG problems elsewhere by misreporting their gender statistics, we would expect to see controversies lead disclosure of perfectly-balanced gender statistics, but would not predict perfectly-balanced gender statistics to lead controversies. Indeed, we find this to be the case. The magnitude on *ESGControversiesFollowing* in column (2) is less than one-tenth the coefficient on *ESGControversiesPreceding* and is statistically insignificant (t-statistic 0.25).

In column (3) we conduct a second falsification test, using firms that report economically equivalent GPG performance, but not the performance benchmark precisely. That is, after excluding observations reporting either 0.0% mean pay gap or 50.0% women in any pay quartile, the dependent variable is an indicator for an employer disclosing +/- 1.0 percentage points from these benchmarks. If the bad press of ESG controversies prompted firms to actually improve gender representation and equity, we would expect to see reporting economically equivalent to perfect reporting to load similarly as perfect reporting in column (1). If the controversies result in misreporting to greenwash, we expect to see no relation. We find results consistent with greenwashing. The coefficient in column (3) is roughly 13% the magnitude of the analogous coefficient in column (1), and is statistically insignificant (t-statistic: 0.19).

In total, the results of Table 7 suggest that firms involved in an ESG controversy are more likely to report perfectly-balanced gender statistics, consistent with these firms misreporting in an attempt to compensate for poor ESG performance elsewhere. However, given ESG controversies may be a result of firm choices and are not exogenously assigned, we are careful to avoid making definitive causal claims.

4.3. Likely Misreporting and ESG Scores

One potential benefit of misreporting gender statistics is attracting employees sensitive to gender imbalance. For example, Blundell (2020) finds that women are willing to accept lower pay to work for firms with low pay gaps. While we cannot directly measure this potential benefit in our setting, a correlated benefit that we can measure is receiving higher ESG scores. Prior work suggests that higher ESG scores attract inward investment (Hartzmark and Sussman, 2019) and corporate customers (Darendeli et al., 2021). ESG ratings agencies consider gender pay gaps and balance as part of an employer's social performance.[35]

In this section, we examine this possibility by testing whether employers reporting 0.0% gender pay gap statistics receive higher ESG scores. Specifically, we focus on the Social Pillar component of the ESG scores (given this pillar covers workforce diversity and equity issues). We estimate a fixed effects regression of the Social Pillar score immediately after the GPG disclosure on indicators if the firm disclosed a 0.0% pay gap, a pay gap between -1.0% and 1.0%, controls for having undergone a CSR audit, and having ESG controversies. With employer- and year-fixed effects, the specification is a generalized differences-in-differences. Our aim is to test if the Social Pillar Score is responsive to reporting a 0.0% pay gap precisely and/or reporting pay gap performance close to the 0.0% benchmark. We argue that the gender balance conditions within the firm are likely indistinguishable for employers that report pay gaps very close to 0.0% (between -1.0% and 1.0%) as employers reporting 0.0% precisely. Thus, if we detect a positive coefficient on reporting 0.0% precisely, the difference is likely a result of the GPG report.

The results in Column (1) of Table 8 suggest that reporting a median pay gap of 0.0% precisely is associated with a roughly two-point increase in the social pillar component score from Refinitiv (t-statistic: 1.70). This estimate is over-and-above simply reporting close to 0.0% pay gap. When we turn to the mean pay gap in Column (2), we find similar magnitudes but statistical insignificance (t-statistic: 1.02). Thus, we

[35] Some ratings agencies directly use the same information that we examine, including the agency that we use (Refinitiv, previously known as Asset4).

have weaker, but suggestive evidence that ESG scores are responsive to reporting 0.0% pay gaps precisely, potentially resulting in an incentive for employers to misreport their gender pay gap performance to "perfect" balance.

While the employer and year fixed effects rule out across-employer differences or secular shifts driving our results, to add further confidence in our findings liking reporting 0.0% median gender pay gaps to increased ESG scores we conduct a falsification test. In Column (3), we take the specification from Column (1) but replace the dependent variable with the last social pillar score reported *before* reporting the gender pay gap information. If the ESG score is sensitive to the GPG disclosure, we anticipate that there should be no significant relation to the lagged ESG score. Indeed, we find no relation between reporting a precisely 0.0% median pay gap and the lagged social pillar score. The coefficient estimate is roughly 5% the magnitude as in Column (1) and highly insignificant (t-statistic: 0.09). Thus, the sequence matters—higher social pillar scores and "perfect" gender pay gap reporting are not merely clustered in time, but rather gender pay gap reporting precedes more favorable ESG scores. While this evidence is suggestive that the ESG scores are directly sensitive to perfect reporting and hence contribute an incentive to misreport, we are cautious to avoid drawing definitive causal conclusions. Employers that report 0.0% pay gaps precisely may also take other concurrent steps to bolster their ESG scores that our regressions do not capture.

5. Conclusion

We examine misreporting of mandated gender pay gap disclosures in the UK. We find that approximately one out of twenty employers reports mathematically impossible gender statistics, consistent with widespread misreporting—intentional or otherwise. We find that restatements are relatively common in the first year of reporting, but the timing of when employers restate suggests a large portion of restatements are employer-driven, consistent with minimal external discipline of misreporting. Further, while we find that employers are more likely to restate mathematically impossible disclosures, they are less likely to restate those that indicate that the median woman earns more than the median man. We also find that a disproportionate number of employers report perfectly-equal pay gaps and perfectly-balanced gender ratios, including relative to those that report near perfectly-equal pay gaps and near perfectly-balanced gender ratios.

We identify employer characteristics associated with misreporting. We find a negative correlation between financial audit quality and misreporting, but no evidence that CSR audits constrain misreporting. Turning to potential motives for misreporting, we find firms incentivized to misreport due to recent involvement in ESG controversies are more likely to report perfectly-balanced gender ratios. Firms that report perfectly-balanced median pay gaps benefit from higher social pillar components of ESG scores.

Together, our results suggest that firms are willing and able to misreport gender pay gap information, a finding that has consequences for the gender pay gap setting and the ESG disclosure setting more generally. Consequently, our results suggest researchers and stakeholders should exercise caution when using self-reported ESG information, including indirectly via ESG scores, to draw inferences or make decisions. These results also carry potential policy implications. The UK gender reporting mandate includes a provision for reevaluation in 2022, and regulators in other countries, including the SEC in the US, are evaluating and/or considering implementing their own reporting mandates and enforcement regimes. We echo Christensen et al. (2021), p. 1229, that "...a combination of public and private enforcement similar to what we have for financial reporting is necessary for an effective [ESG reporting] enforcement regime."

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Figure 1

Illustration of Pay Gap and Gender Balance Calculations

This figure plots pay data for a simulated employer with 100 employees. To calculate the gender balance by quartile, the employer must sort employees by ascending pay and calculate the percentage of employees in each quartile. To calculate the average pay gap, the employer must identify the average man's pay and the average woman's pay, and calculate the difference between the two, scaled by the average man's pay on a percentage basis (positive numbers indicate the average man is paid higher than the average woman). The median pay gap is calculated similarly using the difference between median man and median woman, scaled by the median man and expressed as a percentage.

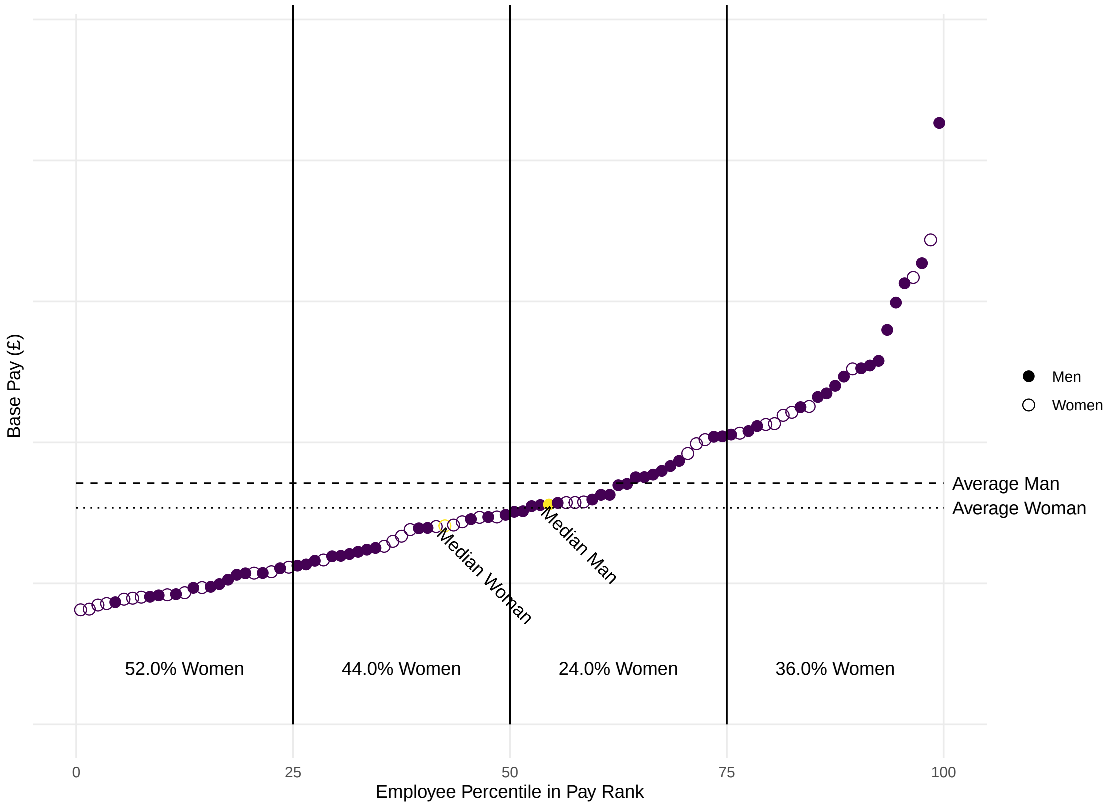

Figure 2
Frequency of Reported Values

This figure plots histograms of employers' 2017 reporting. Panel A presents employer counts by gender pay gap reported values, whereas Panel B presents counts by reported values of the percent of women employed in each pay quartile. For each histogram, we only tabulate reports with zero tenths values due to potential rounding.

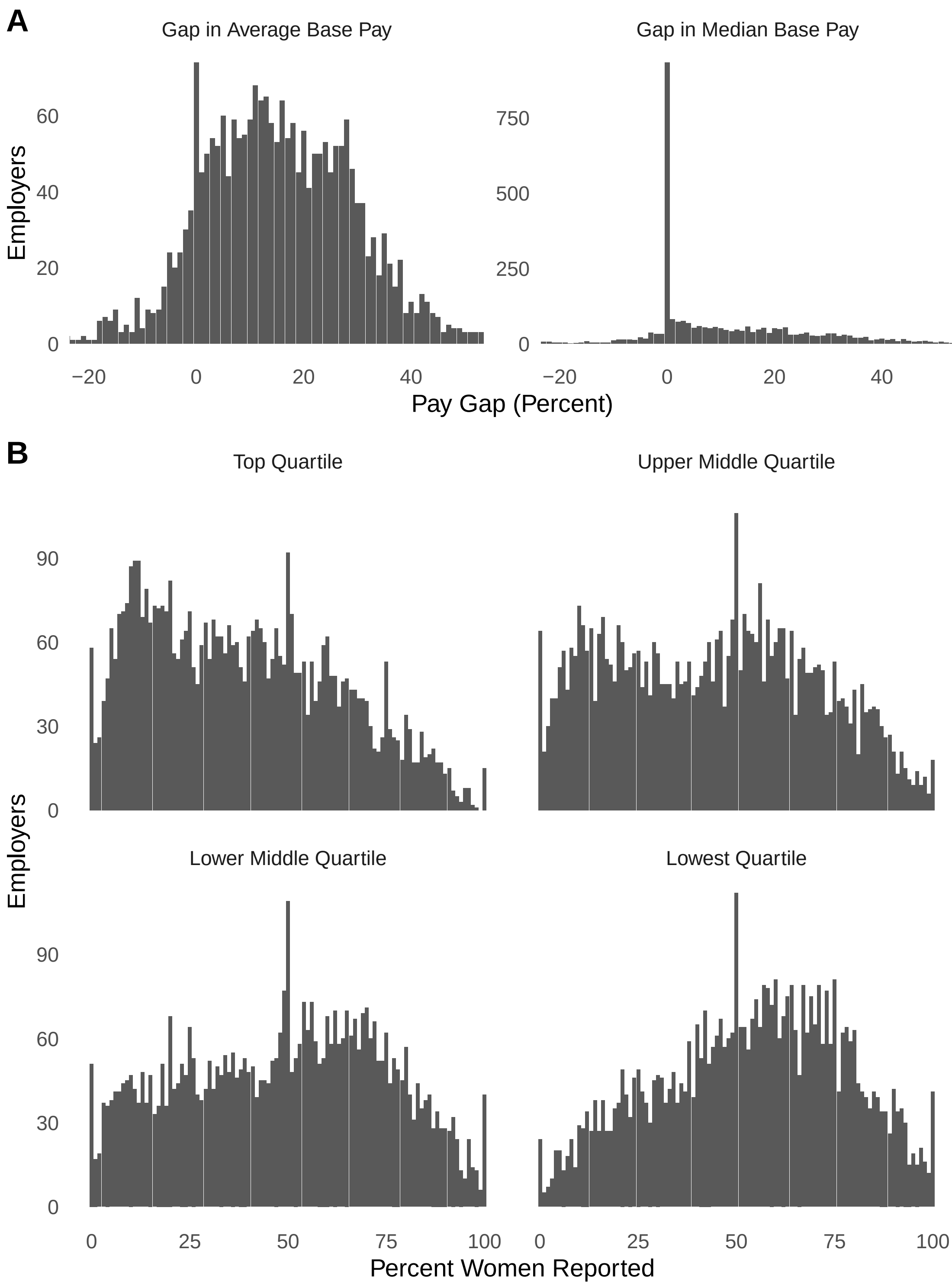

Figure 3

Estimating Frequency of Misreporting

This figure plots histograms of the mean pay gap by year. Dark bars are reported values ending in a zero tenths digit. Light bars are reported values with a non-zero tenths digit. The circles depict the fitted values generated by the models in the odd-numbered columns of Table 4.

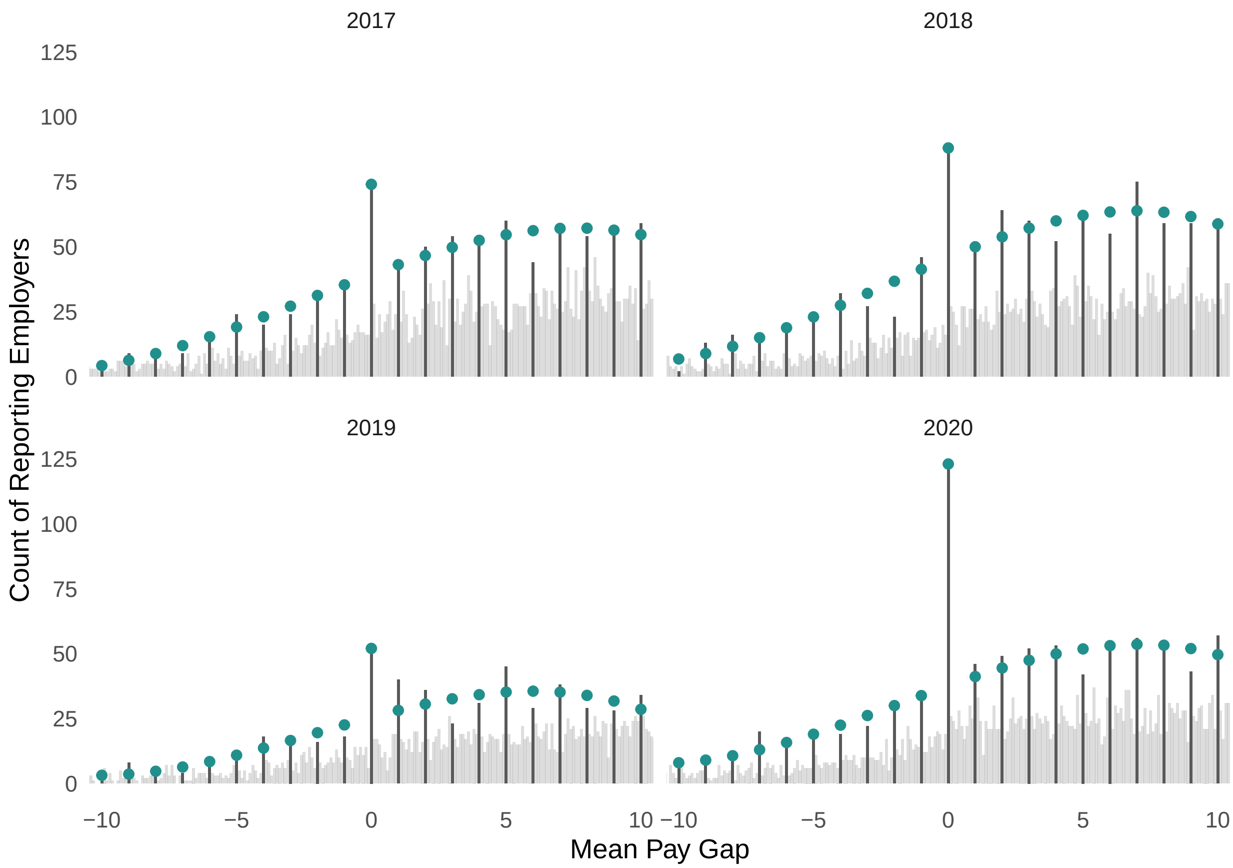

Figure 4

Example of Imbalance and 0.0% Median Pay Gap Implications

This figure plots the ordering of women and men employees for a hypothetical firm disclosing a 0.0% median pay gap, 52.3% women employees in the first pay quartile, 20.0% women in the second, 15.4% women in the third, and 9.2% women in the fourth. For ease of exposition assume the firm has 260 employees and each employee is ordered from lowest pay to highest pay. Thus, the 32nd woman and 99th man are the median paid employees for each gender. Outside of the pay band where all employees earn the same amount, for simplicity and without loss of generality we illustrate pay differences as linearly increasing based on rank order. Employees in the shaded gray box must be earning the same pay for the pay disclosures to be internally consistent.

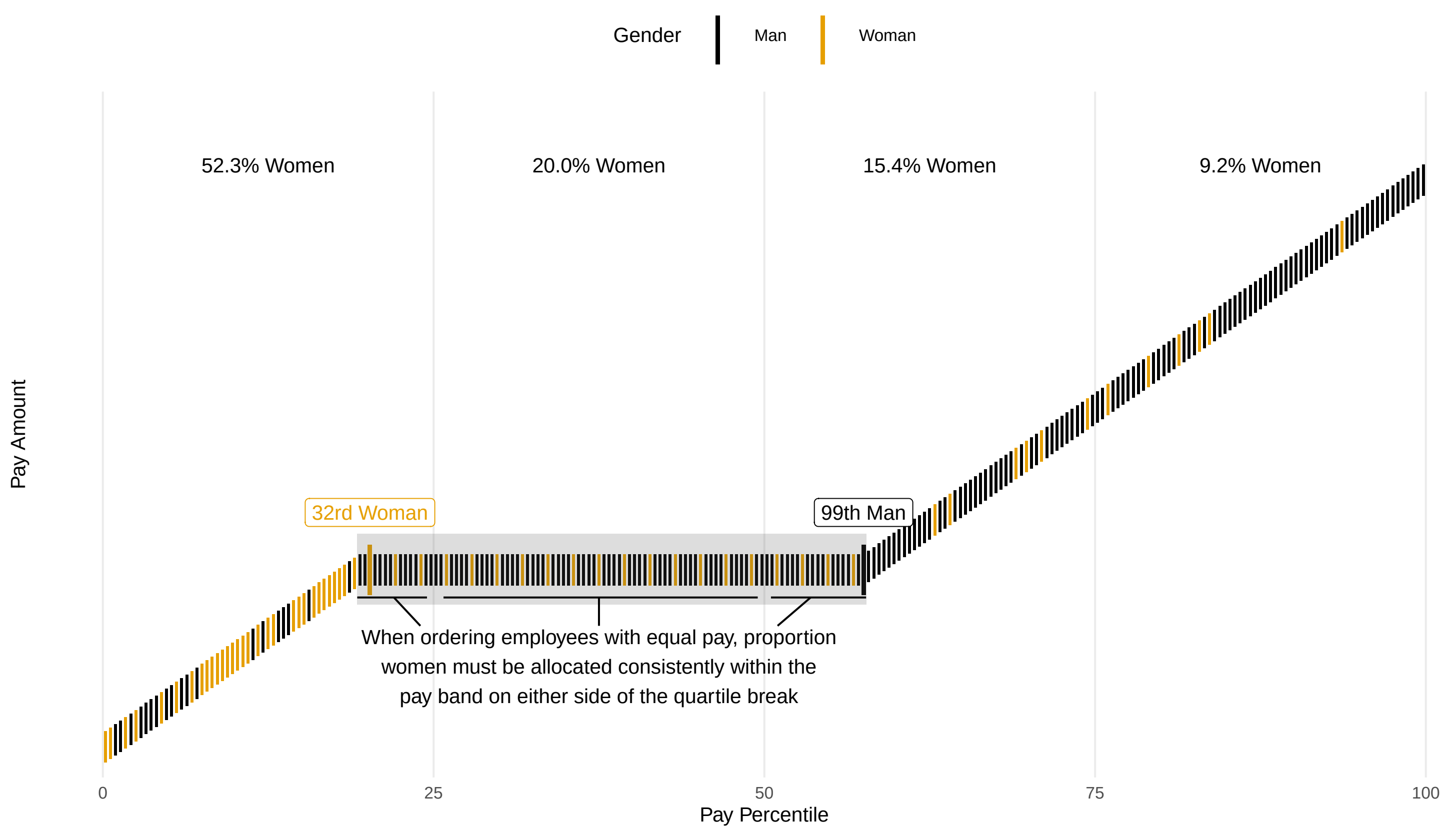

Table 1

Descriptive Statistics of Gender Pay Gap Disclosures

This table summarizes gender pay gap disclosure data. Panel A presents means, standard deviations, and inter-quartile ranges for the hourly pay gap and gender balance by quartile metrics for the entire population of disclosing employers, broken down by year. Panel B provide changes in the mean values across years along with t-statistics of the significance.

Panel A. Summary statistics by year

Statistic	Year	N	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
Gap in Average Pay	2017	10,547	14.3	14.9	5.0	13.4	22.9
	2018	10,813	14.2	14.2	4.9	13.2	22.4
	2019	6993	14.3	15.0	5.5	13.7	22.5
	2020	10,017	14.1	15.3	4.6	13.2	22.7
Gap in Median Pay	2017	10,547	11.8	15.8	0.7	9.3	21.0
	2018	10,813	11.9	15.5	0.9	9.6	21.0
	2019	6993	12.8	15.4	1.9	10.4	22.0
	2020	10,017	12.6	17.0	1.0	10.3	22.3
Lowest Quartile Percent Women	2017	10,547	53.7	24.1	35.7	55.7	73.0
	2018	10,813	53.9	24.1	35.5	55.4	73.0
	2019	6993	54.9	23.7	37.0	57.0	73.9
	2020	9851	54.6	24.3	36.0	56.3	74.0
Lower Middle Quartile Percent Women	2017	10,547	49.5	26.1	27.6	51.6	70.5
	2018	10,813	49.8	26.2	28.0	52.0	71.0
	2019	6993	50.5	25.7	29.4	53.0	71.0
	2020	9851	50.1	26.2	28.0	52.0	71.1
Upper Middle Quartile Percent Women	2017	10,547	45.1	26.2	21.5	46.0	66.0
	2018	10,813	45.6	26.3	22.0	47.0	67.0
	2019	6993	45.9	25.8	23.0	47.3	66.9
	2020	9851	45.6	26.1	22.6	46.6	67.0
Top Quartile Percent Women	2017	10,547	39.2	24.4	17.1	37.2	58.5
	2018	10,813	39.7	24.5	18.0	38.0	59.0
	2019	6993	40.1	24.0	18.8	38.6	59.1
	2020	9851	40.1	24.5	18.8	38.0	60.0

Panel B. T-tests of transitions in the mean values of disclosures

	Average Pay Gap			Median Pay Gap		
	2018	2019	2020	2018	2019	2020
2017	−0.2	−0.1	−0.3	0.1	1.0***	0.8***
	[0.8]	[0.4]	[1.4]	[0.5]	[4.0]	[3.7]
2018		0.1	−0.1		0.9***	0.7***
		[0.3]	[0.7]		[3.6]	[3.2]
2019			−0.2			−0.1
			[0.8]			[0.5]

	Lowest Quartile			Lower Middle Quartile			Upper Middle Quartile			Top Quartile		
	2018	2019	2020	2018	2019	2020	2018	2019	2020	2018	2019	2020
2017	0.2	1.2***	1.0***	0.4	1.0***	0.6*	0.5	0.8**	0.5	0.6*	1.0***	0.9***
	[0.7]	[3.4]	[2.8]	[1.0]	[2.6]	[1.7]	[1.3]	[2.0]	[1.3]	[1.7]	[2.6]	[2.7]
2018		1.0***	0.7**		0.7*	0.3		0.3	0.0		0.4	0.4
		[2.7]	[2.1]		[1.7]	[0.7]		[0.8]	[0.0]		[1.0]	[1.1]
2019			−0.3			−0.4			−0.3			0.0
			[0.8]			[1.0]			[0.8]			[0.0]

Panel C. Descriptive Statistics of Regression Variables

Variable	N	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
$\text{MeanGap}_{i,t} = 0.0\%$	37,840	0.009	0.093	0	0	0
$\text{MeanGap}_{i,t} \in [-1.0\%, 1.0\%]$	37,840	0.050	0.218	0	0	0
$\text{MedianGap}_{i,t} = 0.0\%$	37,840	0.083	0.276	0	0	0
$\text{MedianGap}_{i,t} \in [-1.0\%, 1.0\%]$	37,840	0.139	0.346	0	0	0
$\text{AnyQuartile}_{i,t} = 0.0\%$	37,677	0.039	0.195	0	0	0
$\text{AnyQuartile}_{i,t} \in [49.0\%, 51.0\%]$	37,677	0.046	0.210	0	0	0
$\text{RegisteredCompany}_{i,t}$	37,840	0.868	0.338	1	1	1
$\text{SubmittedLate}_{i,t}$	37,840	0.047	0.212	0	0	0
$\text{ExplanatoryLink}_{i,t}$	37,840	0.694	0.461	0	1	1
$\text{EmployerSizeGroupRank}_{i,t}$	37,840	2.818	1.009	2	3	4
$\ln(\text{Employees}_{i,t})$	27,967	6.423	1.057	5.781	6.209	6.889
$\text{FinancialAuditBig4}_{i,t}$	27,967	0.527	0.499	0	1	1
$\text{ROA}_{i,t}$	27,967	0.069	0.125	−0.001	0.044	0.109
$\text{PrivateFirm}_{i,t}$	27,967	0.986	0.119	1	1	1
$\text{LTDebt}_{i,t} > 0$	27,967	0.449	0.497	0	0	1
$\text{WomenTilt}_{i,t}$	3,074	0.032	0.046	0.005	0.015	0.040
$\text{CSRAudit}_{i,t}$	29,363	0.233	0.423	0	0	0
$\text{ESGControversiesPreceding}_{i,t}$	4,981	0.347	0.431	0	0	1
$\text{ESGControversiesFollowing}_{i,t}$	2,411	0.254	0.435	0	0	0
$\text{SocialPillarScore}_{t+1}$	2,544	65.701	19.856	52.419	68.105	82.367

Table 2
Mathematically Impossible Disclosures

This table presents the frequency of mathematically impossible disclosures by year. We consider a disclosure to be impossible if: the percentage of bottom pay quartile employees that are women + the percentage of bottom middle pay quartile employees that are women is greater than (less than) the percentage of top pay quartile employees that are women + the percentage of upper middle pay quartile employees that are women, and the median hourly pay gap reported is strictly negative (positive). We further break down the impossible reports based on whether the employer reports the median woman earning more than the median man ($MedianGap_{i,t} < 0$) or the median man earning more than the median woman (Median $\text{Gap}_t > 0$).

Year	All	Impossible Disclosures						All Non-zero $MedianGap_{i,t}$			
		Any		$MedianGap_{i,t} < 0$		$MedianGap_{i,t} > 0$		$MedianGap_{i,t} < 0$		$MedianGap_{i,t} > 0$	
		Count	Rate	Count	% of Impossible	Count	% of Impossible	Count	% of Non-zero	Count	% of Non-zero
2017	10547	452	4.3%	164	36.3%	288	63.7%	1484	15.4%	8130	84.6%
2018	10813	554	5.1%	175	31.6%	379	68.4%	1489	15.0%	8406	85.0%
2019	6993	307	4.4%	85	27.7%	222	72.3%	849	13.1%	5617	86.9%
2020	9851	503	5.1%	147	29.2%	356	70.8%	1334	14.7%	7853	85.3%

Table 3
Restatements

This table summarizes gender pay gap restatements of 2017 and 2018 data. We identify restatements by comparing the earliest employer-year disclosures from downloads of the gender pay gap data on September 2017 or April 2018 for 2017 reporting-year data and April 2019 for 2018 reporting-year data with the same reporting-year disclosures from an April 2022 download. Panel A reports the number of restated disclosures, broken down by disclosure type. Because disclosures from 2018 have less post-disclosure time than their 2017 counterparts, we also tabulate 2017 restatements that were restated before April 2021 (denoted with "shorter window") for cross-year comparison purposes. Panel B tabulates the timing of the restatement relative to the subsequent year's disclosure. The total number of restatements in this panel is smaller than the prior because some firms have no subsequent year GPG disclosure. Panel C presents OLS regressions of an indicator capturing if the disclosure was restated on indicators about the disclosure and characteristics of the discloser. Standard errors in parentheses are clustered by employer. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A. Frequencies of Restatements

	2017 Restatements		2018 Restatements		2017 Restatements (Shorter Window)	
Restatement Type	Count	Percent	Count	Percent	Count	Percent
Any	462	5.05%	143	1.51%	450	4.92%
Median Hourly Pay Gap	167	1.83%	45	0.48%	166	1.82%
Mean Hourly Pay Gap	183	2.00%	48	0.51%	182	1.99%
Top Quartile	194	2.12%	43	0.45%	194	2.12%
Upper Middle Quartile	203	2.22%	44	0.46%	202	2.21%
Lower Middle Quartile	203	2.22%	42	0.44%	202	2.21%
Bottom Quartile	199	2.17%	41	0.43%	197	2.16%
Total Employers	9141	100.00%	9463	100.00%	9141	100.00%

Panel B. Restatement Timing

	2017 Restatements		2018 Restatements		2017 Restatements (Shorter Window)	
Timing	Count	Percent	Count	Percent	Count	Percent
Before Subsequent Year Disclosure	290	64.88%	58	47.15%	290	66.67%
Same Day as Subsequent Year Disclosure	130	29.08%	57	46.34%	118	27.13%
After Subsequent Year Disclosure	27	6.04%	8	6.50%	27	6.21%
All Restatements	447	100.00%	123	100.00%	435	100.00%

Panel C. Restating Impossible Disclosures

	$\text{Restated}_{i,t}$		$\text{RestatedMedian}_{i,t}$	$\text{RestatedQuartile}_{i,t}$
	(1)	(2)	(3)	(4)
$\text{Impossible}_{i,t}$	0.023^{***}			
	(0.007)			
$\text{Impossible}_{i,t}$&Median $\text{Gap}_{i,t} > 0^{\dagger}$		0.033^{***}	0.011^{*}	0.033^{***}
		(0.010)	(0.006)	(0.008)
$\text{Impossible}_{i,t}$&Median $\text{Gap}_{i,t} < 0^{\ddagger}$		0.004	-0.008^{***}	0.010
		(0.009)	(0.0008)	(0.008)
$\text{ExplanatoryLink}_{i,t}$	0.010^{***}	0.010^{***}	0.004^{**}	0.002
	(0.003)	(0.003)	(0.002)	(0.002)
$\text{EmployerSizeGroupRank}_{i,t}$	0.004^{***}	0.004^{***}	0.0009	0.002^{**}
	(0.001)	(0.001)	(0.0009)	(0.0010)
$\mathbb{I}\{\text{Year}_t = 2018\}$	-0.023^{***}	-0.023^{***}	-0.010^{***}	-0.014^{***}
	(0.002)	(0.002)	(0.001)	(0.002)
(Intercept)	0.019^{***}	0.019^{***}	0.009^{***}	0.011^{***}
	(0.004)	(0.004)	(0.003)	(0.003)
Observations	18,161	18,161	18,161	18,161
R^2	0.007	0.008	0.003	0.007
Difference between † and ‡		0.028^{**}	0.019^{***}	0.023^{**}
		(0.013)	(0.006)	(0.012)

Table 4

Estimates of the Extent of Misreporting

This table presents OLS regressions fitting the function $Count_x = \beta_0 + \beta_1 x + \beta_1 x^2 + \beta_3 x^3 + \beta_4 \mathbb{I}\{x = Target\} + \varepsilon_x$ to the distribution of frequencies of reporting employers in the neighborhood of a target gender metric. Table 4 presents estimates using average pay gap in the neighborhood $x \in [-10\%, 10\%]$. x is the reported value and $count_x$ is the number of employers reporting x for the specified metric-year. For integer specifications we only count disclosures ending in zero tenths of a percent whereas for rounded specifications, we round disclosures to the nearest integer percent value prior to counting the frequency. The variable of interest is $\mathbb{I}\{x = Target\}$. Refer to IA.2 for estimates using the gender balance by pay quartile metrics for 2017, 2018, 2019, and 2020 respectively, in the neighborhood $x \in [40\%, 60\%]$. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A. Reporting 0.0% average gender pay gap based on hourly pay

Year:	2017		2018		2019		2020	
Count Based On:	Integer	Rounded	Integer	Rounded	Integer	Rounded	Integer	Rounded
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{I}\{x = 0.0\}$	34.70^{***}	63.91^{*}	42.25^{***}	67.66^{**}	26.56^{***}	50.13^{**}	85.42^{***}	141.2^{***}
	(4.63)	(33.38)	(7.15)	(24.03)	(6.33)	(20.44)	(5.33)	(24.73)
(Intercept)	39.30^{***}	201.1^{***}	45.75^{***}	210.3^{***}	25.44^{***}	128.9^{***}	37.58^{***}	191.8^{***}
	(1.52)	(10.95)	(2.34)	(7.88)	(2.08)	(6.70)	(1.75)	(8.11)
x	3.90^{***}	24.12^{***}	4.34^{***}	26.33^{***}	2.82^{***}	16.07^{***}	3.69^{***}	23.08^{***}
	(0.40)	(2.86)	(0.61)	(2.06)	(0.54)	(1.75)	(0.46)	(2.12)
x^2	-0.10^{***}	-0.27	-0.13^{**}	-0.31^{*}	-0.10^{**}	-0.14	-0.09^{**}	-0.38^{**}
	(0.03)	(0.22)	(0.05)	(0.16)	(0.04)	(0.13)	(0.04)	(0.16)
x^3	-0.01^{**}	-0.10^{**}	-0.02^{*}	-0.13^{***}	-0.01^{*}	-0.07^{**}	-0.02^{**}	-0.12^{***}
	(0.005)	(0.04)	(0.009)	(0.03)	(0.008)	(0.02)	(0.006)	(0.03)
Observations	21	21	21	21	21	21	21	21
R^2	0.966	0.938	0.935	0.969	0.866	0.949	0.970	0.961

Table 5
Firm Characteristics and Gender Pay Gap Misreporting

This table estimates employer-year level OLS regressions of likely misreporting on employer and disclosure characteristics. Odd-numbered columns use variables from only the GEO's GPG data; even-numbered columns are linked to Bureau van Dijk's ORBIS data. The dependent variable for columns (1) and (2) is an indicator if employer *i*'s disclosure in year *t* is mathematically impossible. In columns (3) and (4), the dependent variable is an indicator if the employer discloses a mean gender pay gap of 0.0% in year *t*. Columns (5) and (6) use an indicator for employer *i* in year *t* reporting 50.0% female representation in any pay quartile. All other variables are defined in Appendix A. Standard errors, clustered by employer are listed in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	$\text{Impossible}_{i,t}$		$\text{Mean Gap}_{i,t} = 0$		$\text{Any Quartile}_{i,t} = 50.0\%$		$\text{WomenTilt}_{i,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{RegisteredCompany}_{i,t}$	−0.0007		0.006***		0.003		0.012***	
	(0.004)		(0.001)		(0.003)		(0.002)	
$\text{SubmittedLate}_{i,t}$	0.039***	0.035***	0.005*	0.001	−0.006	−0.005	0.006	0.004
	(0.007)	(0.008)	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)	(0.005)
$\text{ExplanatoryLink}_{i,t}$	−0.019***	−0.017***	−0.009***	−0.009***	−0.009***	−0.007**	−0.006***	−0.008***
	(0.003)	(0.003)	(0.001)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
$\text{EmployerSizeGroupRank}_{i,t}$	−0.006***		−0.002***		−0.010***		−0.004***	
	(0.001)		(0.0006)		(0.001)		(0.001)	
$\ln(\text{Employees})_{i,t}$		−0.006***		0.0006		−0.004***		−0.003***
		(0.001)		(0.0006)		(0.001)		(0.001)
$\text{ROA}_{i,t}$		−0.015		−0.003		0.006		−0.004
		(0.010)		(0.004)		(0.010)		(0.009)
$\text{PrivateFirm}_{i,t}$		−0.008		0.0003		−0.013		−0.005
		(0.011)		(0.004)		(0.013)		(0.012)
$\text{LTDebt}_{i,t} > 0$		0.006**		−0.0004		0.007**		0.002
		(0.003)		(0.001)		(0.003)		(0.003)
$\text{FinancialAuditBig4}_{i,t}$		−0.021***		−0.009***		−0.006**		0.002
		(0.003)		(0.001)		(0.003)		(0.003)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37,677	27,836	37,840	27,967	37,677	27,836	3,074	2,145
R^2	0.005	0.008	0.004	0.006	0.004	0.003	0.022	0.014

Table 6

Audits and Likely Gender Pay Gap Misreporting

This table estimates employer-year level OLS regressions of indicators for gender pay gap misreporting on CSR auditing. Odd-numbered columns only include an indicator of whether or not the firm engages a big four financial auditor as a control; even number columns include other firm controls. The dependent variable for columns (1) and (2) is an indicator if employer *i*'s disclosure in year *t* is mathematically impossible. In columns (3) and (4), the dependent variable is an indicator if the employer discloses a mean gender pay gap of 0.0% in year *t*. Columns (5) and (6) use an indicator for employer *i* in year *t* reporting 50.0% female representation in any pay quartile. All other variables are defined in Appendix A. Standard errors, clustered by employer are listed in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	$\text{Impossible}_{i,t}$		$\text{Mean Gap}_{i,t} = 0$		$\text{Any Quartile}_{i,t} = 50.0\%$		$\text{WomenTilt}_{i,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{CSRAudit}_{i,t}$	-0.013^{***}	-0.010^{***}	-0.0005	0.00007	-0.001	0.0003	0.014^{***}	0.017^{***}
	(0.003)	(0.003)	(0.001)	(0.001)	(0.003)	(0.003)	(0.004)	(0.004)
$\text{FinancialAuditBig4}_{i,t}$	-0.025^{***}	-0.018^{***}	-0.011^{***}	-0.009^{***}	-0.011^{***}	-0.006^{**}	-0.005^{**}	-0.002
	(0.003)	(0.003)	(0.001)	(0.001)	(0.003)	(0.003)	(0.002)	(0.003)
$\text{SubmittedLate}_{i,t}$		0.035^{***}		0.001		-0.005		0.004
		(0.008)		(0.003)		(0.005)		(0.004)
$\text{ExplanatoryLink}_{i,t}$		-0.017^{***}		-0.009^{***}		-0.007^{**}		-0.008^{***}
		(0.003)		(0.002)		(0.003)		(0.003)
$\ln(\text{Employees})_{i,t}$		-0.006^{***}		0.0006		-0.004^{***}		-0.004^{***}
		(0.001)		(0.0006)		(0.001)		(0.001)
$\text{ROA}_{i,t}$		-0.016		-0.003		0.006		-0.007
		(0.010)		(0.004)		(0.010)		(0.009)
$\text{PrivateFirm}_{i,t}$		-0.014		0.0004		-0.013		0.011
		(0.012)		(0.004)		(0.013)		(0.013)
$\text{LTDebt}_{i,t} > 0$		0.006^{**}		-0.0004		0.007^{**}		0.003
		(0.003)		(0.001)		(0.003)		(0.003)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29,227	27,836	29,363	27,967	29,227	27,836	2,444	2,145
R^2	0.006	0.009	0.004	0.006	0.002	0.003	0.009	0.026

Table 7

ESG Controversies and Likely Gender Pay Gap Misreporting

This table estimates employer-year level OLS regressions of reporting a gender equity target on ESG Controversies. The sample includes all disclosures where the employer links to Bureau van Dijk's Orbis data and to the Refinitiv ESG controversies scores. $AnyTarget_{i,t}$ is an indicator if the average pay gap is reported as 0.0% or any of the quartile gender balance metrics are reported as 50.0%. $NearTarget_{i,t}$ is an indicator if the average pay gap $\in [-1.0\%, -0.1\%] \cup [0.1\%, 1.0\%]$ or any of the quartile gender balance metrics $\in [49.0\%, 49.9\%] \cup [50.1\%, 51.0\%]$. Column (3) excludes observations where $AnyTarget_{i,t}$ is true $ESGControversiesPreceding_{i,t}$ is an indicator equaling 1 if the most recent Refinitiv ESG controversy score received by the discloser prior to the gender pay gap report was less than 50 (letter scores C or D), and 0 if the score was over 50 (letter scores A or B). $ESGControversiesFollowing_{i,t}$ is calculated analogously based on the first Refinitiv ESG controversy score after the gender pay gap report. All other variables are defined in Appendix A. Standard errors, clustered by employer ISIN are listed in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	$AnyTarget_{i,t}$		$NearTarget_{i,t}$
	(1)	(2)	(3)
$ESGControversiesPreceding_{i,t}$	0.018**	0.023**	0.002
	(0.008)	(0.011)	(0.012)
$ESGControversiesFollowing_{i,t}$		0.002	
		(0.009)	
$SubmittedLate_{i,t}$	−0.007	0.013	−0.010
	(0.015)	(0.025)	(0.027)
$ExplanatoryLink_{i,t}$	−0.025***	−0.025*	0.016
	(0.010)	(0.014)	(0.013)
$\ln(Employees)_{i,t}$	−0.003	−0.001	0.003
	(0.003)	(0.004)	(0.005)
$ROA_{i,t}$	0.024	0.059	0.041
	(0.025)	(0.037)	(0.044)
$PrivateFirm_{i,t}$	−0.040**	−0.031	−0.034
	(0.020)	(0.022)	(0.031)
$LTDebt_{i,t} > 0$	−0.009	−0.007	−0.009
	(0.007)	(0.008)	(0.012)
$FinancialAuditBig4_{i,t}$	−0.013	−0.018	0.010
	(0.012)	(0.018)	(0.017)
Year Fixed Effects	Yes	Yes	Yes
Observations	4,981	2,411	4,795
R^2	0.008	0.009	0.002

Table 8

Likely Gender Pay Gap Misreporting and ESG Scores

This table estimates employer-year level OLS regressions of the Social Pillar component of Refinitiv ESG scores on reported gender pay gap metrics. The sample includes all disclosures where the employer links to Bureau van Dijk's Orbis data and to the Refinitiv ESG scores. $SocialPillarScore_{i,t+1}$ is the first social pillar component score for the employer subsequent to the gender pay gap report, whereas $SocialPillarScore_{i,t+1}$ is the last social pillar component score for the employer prior to the gender pay gap report. We obtain both of these variables from Refinitiv. $CSRAudit_{i,t}$ is an indicator if the employer underwent an CSR audit in for the reporting period immediately before the gender pay gap disclosure. $ESGControversiesPreceding_{i,t}$ is an indicator if the employer had an ESG controversies score of less than 50 in the report immediately before the gender pay gap disclosure. The regressions include employer fixed effects and year fixed effects. Standard errors, clustered by employer are listed in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	$\text{SocialPillarScore}_{i,t+1}$		$\text{SocialPillarScore}_{i,t-1}$
	(1)	(2)	(3)
$\text{MedianGap}_{i,t} = 0.0\%$	2.052^{*}		0.1126
	(1.210)		(1.246)
$\text{MedianGap}_{i,t} \in [-1.0\%, 1.0\%]$	−0.277		0.610
	(0.684)		(0.574)
$\text{MeanGap}_{i,t} = 0.0\%$		2.950	
		(2.892)	
$\text{MeanGap}_{i,t} \in [-1.0\%, 1.0\%]$		0.564	
		(1.03)	
$\text{CSRAudit}_{i,t}$	1.812	1.805	2.039
	(2.242)	(2.238)	(1.714)
$\text{ESGControversiesPreceding}_{i,t}$	−0.006	−0.030	0.300
	(0.465)	(0.463)	(0.434)
Employer Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	2,544	2,544	2,544
R^2	0.969	0.969	0.970

Appendix A. Variable Definitions

AnyTarget$_{i,t}$ an indicator if the average pay gap is reported as 0.0% or any of the quartile gender balance metrics are reported as 50.0%

CSRAudit$_{i,t}$ an indicator if the firm received a corporate social responsibility audit for year t per Refinitiv

Employees$_{i,t}$ Number of employees per Bureau van Dijk's Orbis

EmployerSizeGroupRank$_{i,t}$ takes the values 1-6 for employer i's size grouping rank from the GEO GPG data. The size groupings are < 250 employees, 250-499, 500-999, 1000-4999, 5000-19,999, and ≥ 20,000[36]

ESGControversiesFollowing$_{i,t}$ an indicator equaling 1 if the next Refinitiv ESG controversy score received by the discloser after to the gender pay gap report was less than 50 (letter scores C or D), and 0 if the score was over 50 (letter scores A or B)

ESGControversiesPreceding$_{i,t}$ an indicator equaling 1 if the most recent Refinitiv ESG controversy score received by the discloser prior to the gender pay gap report was less than 50 (letter scores C or D), and 0 if the score was over 50 (letter scores A or B)

ExplanatoryLink$_{i,t}$ an indicator that takes the value one if employer i provides a link to an explanatory report discussing its gender statistics for year t

Impossible$_{i,t}$ an indicator if the sign of the median pay gap conflicts with the sign implied by same employer-year quartile gender balance statistics. The sign of the median pay gap implied from the quartile statistics is positive if $Q1Women_{i,t} + Q2Women_{i,t} > Q3Women_{i,t} + Q4Women_{i,t}$, and negative if $Q1Women_{i,t} + Q2Women_{i,t} < Q3Women_{i,t} + Q4Women_{i,t}$

FinancialAuditBig4$_{i,t}$ an indicator equaling 1 if the firm was audited by one of the big 4 auditors (Deloitte, KPMG, EY, or PwC), 0 otherwise

LTDebt$_{i,t}$ an indicator if Orbis reports the firm has non-zero long-term debt financing, 0 otherwise

MeanGap$_{i,t}$ mean pay gap, calculated as the mean salary for men at employer i minus the mean salary for women, scaled by the mean man's salary

MedianGap$_{i,t}$ median pay gap, calculated as the median salary for men at employer i minus the median salary for women, scaled by the median man's salary

NearTarget$_{i,t}$ an indicator if the average pay gap $\in [-1.0\%, -0.1\%] \cup [0.1\%, 1.0\%]$ or any of the quartile gender balance metrics $\in [49.0\%, 49.9\%] \cup [50.1\%, 51.0\%]$

Q1Women$_{i,t}$ percent of the lowest pay quartile employees that are women disclosed by employer i in for year t

Q2Women$_{i,t}$ percent of the lower middle pay quartile employees that are women disclosed by employer i in for year t

Q3Women$_{i,t}$ percent of the upper middle quartile employees that are women disclosed by employer i in for year t

[36]A small number of employers list "Not Provided" for the size grouping; we exclude these observations from our estimation.

Q4Women$_{i,t}$ percent of the top pay quartile employees that are women disclosed by employer *i* in for year *t*

PrivateFirm$_{i,t}$ indicator equalling 1 if the employer's equity is not publicly traded, 0 if it is

Restated$_{i,t}$ an indicator if the employer restated any of the gender pay gap measures reported for year *t*

RestatedMedian$_{i,t}$ an indicator if the employer restated the median gender pay gap reported for year *t*

RestatedQuartile$_{i,t}$ an indicator if employer *i* restated at least one of the quartile gender balance measures reported for year *t*

RegisteredCompany$_{i,t}$ an indicator that takes the value one if employer *i* has a Companies House registration number (a company or limited partnership; other organizations such as charities, schools, and government entities do not register with Companies House)

ROA$_{i,t}$ profit or loss before taxes in year *t* scaled by end-of-year assets, winsorized at 1st and 99th percentiles. Financial data comes from Orbis

SubmittedLate$_{i,t}$ an indicator taking the value one if the employer *i* reported its statistics for year *t* after the deadline

SocialPillarScore$_{i,t}$ the social pillar component score for the employer from Refinitiv's ESG scoring

WomenTilt$_{i,t}$ Absolute value of difference between one-half and the ratio of women in the first two quartiles to women in the firm, calculated as: $\left|0.5 - \frac{\text{Q1Women}_{i,t}+\text{Q2Women}_{i,t}}{\text{Q1Women}_{i,t}+\text{Q2Women}_{i,t}+\text{Q3Women}_{i,t}+\text{Q4Women}_{i,t}}\right|$

Internet Appendix

Table IA.1

Frequency of Tenths Digits in Disclosures

This table presents the frequencies of each digit in the tenths place across reported measure. There is no difference across the quartiles or across years (untabulated). A zero in the tenths digit is more common for the median pay gap than for the mean pay gap because so many employers report a 0.0% median pay gap. If we exclude one full set of decimals around 0.0% (i.e. exclude observations in the [-0.5, 0.4] interval), 21.4% of median pay gaps have a zero in the tenths digit place (untabulated).

	Tenths Digit (%)									
	_.0	_.1	_.2	_.3	_.4	_.5	_.6	_.7	_.8	_.9
Mean Pay Gap	21.3	8.6	8.5	8.7	9.0	8.9	8.8	8.7	8.8	8.7
Median Pay Gap	27.3	8.2	8.1	7.7	8.0	8.1	8.2	8.2	8.1	8.2
Quartile Percentages	43.5	6.1	6.3	6.6	6.2	6.6	6.1	6.6	6.2	6.0

Table IA.2

Additional Estimates of the Extent of Misreporting

These are supplementary panels of Table 4, presenting OLS regressions fitting the function $Count_x = \beta_0 + \beta_1 x + \beta_1 x^2 + \beta_3 x^3 + \beta_4 \mathbb{I}\{x = 50.0\%\} + \varepsilon_x$ to the distribution of frequencies of reporting employers in the neighborhood of a target gender metric. Panel A, Panel B, Panel D, and Panel D present estimates using the gender balance by pay quartile metrics for 2017, 2018, 2019, and 2020 respectively, in the neighborhood $x \in [40\%, 60\%]$. x is the reported value and $count_x$ is the number of employers reporting x for the specified metric-year. For integer specifications we only count disclosures ending in zero tenths of a percent whereas for rounded specifications, we round disclosures to the nearest integer percent value prior to counting the frequency. The variable of interest is $\mathbb{I}\{x = 50.0\%\}$. For each panel, prior to estimation we subtract 50 from each value of x, recentering x on 0 such that the intercept can be interpreted as the expectation of the number of firms disclosing the benchmark absent misreporting. Standard errors are listed in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A. 2017 reporting 50.0% gender balance by quartile

Count Based On:	Reporting Integer Exactly				Rounded to Nearest Integer			
Quartile:	1st	2nd	3rd	4th	1st	2nd	3rd	4th
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{I}\{x = 50.0\}$	50.58***	50.40***	45.56***	39.53***	15.18	36.02*	34.38**	14.19
	(6.29)	(9.60)	(10.51)	(8.81)	(11.52)	(17.91)	(15.83)	(12.07)
(Intercept)	61.42***	58.60***	60.44***	52.47***	140.8***	127.0***	128.6***	122.8***
	(2.06)	(3.15)	(3.45)	(2.89)	(3.77)	(5.87)	(5.19)	(3.96)
x	0.91	1.52*	1.02	−1.70**	2.72**	2.79*	2.46*	−2.60**
	(0.54)	(0.82)	(0.90)	(0.76)	(0.99)	(1.54)	(1.36)	(1.04)
x^2	0.0944**	−0.08	−0.07	0.07	−0.00	−0.12	−0.16	0.02
	(0.04)	(0.06)	(0.07)	(0.06)	(0.08)	(0.12)	(0.10)	(0.08)
x^3	0.00	−0.01	−0.01	0.01	−0.01	−0.01	−0.02	0.03*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Observations	21	21	21	21	21	21	21	21
R^2	0.839	0.731	0.634	0.637	0.631	0.503	0.543	0.363

Panel B. 2018 reporting 50.0% gender balance by quartile

Count Based On:	Reporting Integer Exactly				Rounded to Nearest Integer			
Quartile:	1st (1)	2nd (2)	3rd (3)	4th (4)	1st (5)	2nd (6)	3rd (7)	4th (8)
$\mathbb{I}\{x = 50.0\}$	72.42***	50.08***	40.55***	57.37***	54.02***	20.10	24.49	27.28*
	(10.99)	(10.10)	(9.24)	(7.83)	(16.31)	(17.92)	(17.37)	(13.17)
(Intercept)	60.58***	54.92***	58.45***	53.63***	142.0***	123.9***	135.5***	127.7***
	(3.60)	(3.31)	(3.03)	(2.57)	(5.35)	(5.88)	(5.70)	(4.32)
x	1.8*	1.19	0.31	−1.31*	1.63	2.71*	1.40	−2.60**
	(0.94)	(0.87)	(0.79)	(0.67)	(1.40)	(1.54)	(1.49)	(1.13)
x^2	0.11	0.02	−0.03	0.01	−0.03	−0.02	−0.23*	−0.05
	(0.07)	(0.07)	(0.06)	(0.05)	(0.11)	(0.12)	(0.11)	(0.09)
x^3	−0.01	−0.01	0.00	0.02*	−0.00	−0.02	0.00	0.03*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	21	21	21	21	21	21	21	21
R^2	0.761	0.666	0.611	0.791	0.536	0.367	0.492	0.416

Panel C. 2019 reporting 50.0% gender balance by quartile

Count Based On:	Reporting Integer Exactly				Rounded to Nearest Integer			
Quartile:	1st (1)	2nd (2)	3rd (3)	4th (4)	1st (5)	2nd (6)	3rd (7)	4th (8)
$\mathbb{I}\{x = 50.0\}$	47.21***	33.64***	32.46***	26.32***	22.23**	22.12*	33.21**	16.29
	(6.50)	(6.77)	(6.33)	(7.46)	(10.37)	(11.72)	(14.14)	(16.31)
(Intercept)	38.79***	37.36***	37.54***	35.68***	91.77***	83.88***	83.79***	84.71***
	(2.13)	(2.22)	(2.08)	(2.45)	(3.40)	(3.84)	(4.64)	(5.35)
x	0.38	1.77***	0.52	−0.01	1.49	3.84***	1.23	−0.35
	(0.56)	(0.58)	(0.54)	(0.64)	(0.89)	(1.01)	(1.21)	(1.40)
x^2	0.09*	0.02	−0.02	0.01	−0.01	−0.03	−0.06	−0.01
	(0.04)	(0.04)	(0.04)	(0.05)	(0.07)	(0.08)	(0.09)	(0.11)
x^3	0.01*	−0.02*	−0.00	−0.00	0.01	−0.03*	−0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Observations	21	21	21	21	21	21	21	21
R^2	0.854	0.714	0.661	0.450	0.742	0.691	0.445	0.091

Panel D. 2020 reporting 50.0% gender balance by quartile

Count Based On:	Reporting Integer Exactly				Rounded to Nearest Integer			
Quartile:	1st (1)	2nd (2)	3rd (3)	4th (4)	1st (5)	2nd (6)	3rd (7)	4th (8)
$\mathbb{I}\{x = 50.0\}$	96.83***	112.8***	78.91***	80.56***	72.30***	89.51***	53.06***	57.15***
	(12.23)	(9.870)	(8.138)	(10.34)	(13.40)	(14.58)	(15.78)	(16.18)
(Intercept)	52.17***	41.15***	49.09***	44.44***	122.7***	105.5***	115.9***	105.8***
	(4.01)	(3.24)	(2.67)	(3.39)	(4.39)	(4.78)	(5.18)	(5.31)
x	0.53	0.05	0.62	−0.40	2.14*	1.24	0.80	−0.66
	(1.05)	(0.85)	(0.70)	(0.89)	(1.15)	(1.25)	(1.35)	(1.39)
x^2	0.09	0.15**	−0.02	0.05	0.10	0.09	−0.06	0.11
	(0.08)	(0.06)	(0.05)	(0.07)	(0.09)	(0.10)	(0.10)	(0.11)
x^3	0.01	0.01	−0.01	−0.00	−0.00	0.00	−0.01	−0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	21	21	21	21	21	21	21	21
R^2	0.819	0.896	0.866	0.800	0.761	0.750	0.464	0.497

Table IA.3

Placebo Tests of Restating Misreporting

This table presents supplemental analyses for Table 3, Panel C. The characteristics marked with ′ are based on the restated value of the disclosure. Standard errors in parentheses are clustered by employer. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	Restated$_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
Impossible$'_{i,t}$	0.002				
	(0.006)				
$\mathbb{I}$\{Impossible$'_{i,t}$ & Median Gap$'_{i,t} > 0.0\%$\}		−0.00001			
		(0.007)			
$\mathbb{I}$\{Impossible$'_{i,t}$ & Median Gap$'_{i,t} < 0.0\%$\}		0.007			
		(0.010)			
$\mathbb{I}$\{Mean Gap$'_{i,t} = 0.0\%$\}			−0.002		
			(0.011)		
$\mathbb{I}$\{Mean Gap$'_{i,t} \in [-1.0\%, -0.1\%] \cup [0.1\%, 1.0\%]$\}			−0.008		
			(0.005)		
$\mathbb{I}$\{Any Quartile$'_{i,t} = 50.0\%$\}				0.007	
				(0.007)	
$\mathbb{I}$\{Any Quartile$'_{i,t} \in [49.0\%, 49.9\%] \cup [50.1\%, 51.0\%]$\}				−0.001	
				(0.004)	
$\mathbb{I}$\{Median Gap$'_{i,t} = 0.0\%$\}					0.0004
					(0.005)
WomenTilt$'_{i,t}$					0.049***
					(0.016)
$\mathbb{I}$\{Median Gap$'_{i,t} = 0.0\%$\} × WomenTilt$'_{i,t}$					0.070
					(0.099)
ExplanatoryLink$_{i,t}$	0.009***	0.009***	0.009***	0.009***	0.009***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
EmployerSizeGroupRank$_{i,t}$	0.004**	0.004**	0.004**	0.004**	0.004***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Voluntary$_{i,t}$	−0.0007	−0.0008	−0.0006	−0.001	−0.0005
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$\mathbb{I}$\{Year$_t$ = 2018\}	−0.022***	−0.022***	−0.022***	−0.022***	−0.022***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
(Intercept)	0.021***	0.021***	0.021***	0.021***	0.015***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Observations	18,161	18,161	18,161	18,161	18,155
R^2	0.007	0.007	0.007	0.007	0.007