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# A Pay Scale of Their Own: Gender Differences in Variable Pay

# Abstract

In the United States and other large economies, women receive less variable pay than men, even within the same firms and job titles. We argue this disparity in pay partly reflects labor market sorting. Since women are less-represented in more variable-pay-intensive jobs, even within occupations, women accumulate less variable pay over time. Women apply relatively less often to and early in their careers separate faster from such roles. Compared with their male peers, women perceive variable-paying jobs as offering worse amenities, including culture, work-life balance, and paid family leave. Compensation schemes appear to induce disparities in pay through worker sorting.

JEL-Codes: J160, M520.

Keywords: gender gap, variable pay, job search, amenities.

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### 1 Introduction

Disparities in labor market opportunities afforded to men and women remain a central concern in economics and finance.<sup>1</sup> Although much progress has been made in understanding the gender pay gap, the role of selection toward and away from employment opportunities that rely on variable pay in exacerbating this disparity is not well-documented. Beyond bonuses constituting a meaningful device for firms to incentivize employee effort, illuminating the interplay between variable pay and gender is important for at least three reasons.

For one, variable compensation has become increasingly prevalent over time (Lemieux *et al.*, 2009) such that variable pay is now relevant to most U.S. workers. Grigsby *et al.* (2021) estimate that only one-quarter of U.S. workers receive all of their compensation through base pay and a 2023 Payscale survey found that among 5,000 U.S. firms, 78 percent compensate employees with variable pay.<sup>2</sup>

Two, policymakers will take legislative steps to address gender pay gaps, including by enacting pay transparency laws (e.g., Bennedsen *et al.*, 2022; Cullen, 2024). Such laws though typically overlook variable pay (e.g., California excluding bonuses from required pay scales in job ads) or take varied approaches to addressing variable pay (e.g., Colorado requiring job ads to describe variable pay practices or the United Kingdom requiring employers to publicly disclose their gender gaps in variable pay).

Three, there are stark differences in variable pay practices across employers and these differences appear to overlap with disparities in female representation. Although the extent to which firms use variable pay is seldom observed, U.K. firms with at least 250 employees are required to publicly disclose statistics on variable pay usage. From these data, we can calculate for 10,000 large U.K. firms, the fraction of employees who receive a bonus and the share who are female.<sup>3</sup> Two patterns stand out. First, firms differ drastically in bonus usage: Among large U.K. firms, while one-quarter compensate fewer than 10 percent of employees with bonuses, one-eighth compensate more than 90 percent of employees with bonuses. Second, high bonus usage is associated with starkly fewer female employees. While 62 percent of employees are female among the former category of low-bonus-usage firms, only 34 percent are female among the latter (Figure 1).

Given the growing prevalence, policy relevance, and observed differences in variable pay practices and female representation across employers, alongside the highly variable and

<sup>&</sup>lt;sup>1</sup>For instance, see Altonji and Blank (1999), Bertrand (2010), Goldin (2014), and Blau and Kahn (2017). <sup>2</sup>See https://www.payscale.com/research-and-insights/cbpr/.

<sup>&</sup>lt;sup>3</sup>Since firms disclose their statistics to the U.K. government, it is possible firms report disingenuously. Indeed, concerns have been raised regarding the gender gaps some firms disclose (e.g., Ehrenberg-Shannon *et al.*, 2017; Cox, 2019). While firms may have an incentive to untruthfully report statistics by gender, we see little incentive to lie about their overall use of bonuses or the share of employees who are female.

opaque nature of employee bonuses, we ask whether gender differences in labor market sorting, particularly into and out of variable-paying jobs, contribute to gender pay gaps; and if so, what aspects of variable-paying jobs help explain such sorting?

To answer these questions, we rely on data from Glassdoor, an online platform where workers can learn about the pay and job satisfaction that other workers report experiencing at their own employers. These matched employee-employer data on pay offer an ideal setting for examining gender gaps related to variable pay because workers: (i) separate variable pay from base pay when reporting total income, (ii) detail their employers and job titles, allowing us to test different mechanisms while considering variation between jobs *within* occupations, and (iii) can be linked to other Glassdoor data pertaining to job seeker applications, job amenities, and job tenure. Although such pay data are self-reported, this is a common feature among studies using surveys to analyze the magnitude of variable pay and gender (e.g., Chauvin and Ash, 1994; Grund, 2015; Reuben et al., 2024). To address concerns about external validity, we compare Glassdoor with the American Community Survey (ACS) and show that the two exhibit similar wage and employment patterns across industry-occupations. Additionally, in each cross-sectional analysis of wages and employment, we incorporate representative weights from the ACS. We further validate our dataset by providing evidence that there is no evidence for the systematic misreporting of base or variable pay by gender, and by comparing the gender gaps we uncover in Glassdoor to the ACS and to official statistics U.K. firms disclose to the U.K. government.

Beyond providing the first study of the relation between variable pay and the gender pay gap for a large sample of U.S. workers, we demonstrate that preferences play an important role. Women avoid applying to variable-paying jobs and express more dissatisfaction with amenities and work culture while in them—ultimately separating from them faster earlier in the life-cycle. Although conditional on receiving variable pay, income growth is similar for men and women, we show that women receive variable pay significantly less often in their careers, which compounds over time. This mechanism can help rationalize the "glass ceilings" observed for women in performance pay (de la Rica *et al.*, 2014) and the widening of the gender gap in performance pay with experience and hierarchy (Grund, 2015).

We show that jobs that rely on variable pay bundle risky compensation with amenities and a workplace culture that are less desirable to women. Because many factors drive variable pay beyond individual performance (i.e., team- or firm-level performance), the phenomenon we capture is related to but goes beyond female aversion to competition (e.g., Niederle and Vesterlund, 2007) or penalization when being evaluated (e.g., Sarsons *et al.*, 2021), which could impact future promotions (Benson *et al.*, 2019). Consequently, our analysis reveals a structural component of the gender gap that is not the product of women sorting into lowerpaying firms or occupations (Card *et al.*, 2016; Sorkin, 2017; Morchio and Moser, 2024), but rather less variable-pay-intensive jobs *within* firms and occupations.

As a preliminary exercise, we quantify gender gaps in the level and incidence of variable pay in our dataset to be 22 percent and 4.8 percentage points, respectively, after accounting for differences across employers and occupations — typical explanations for disparities in male and female earnings (e.g., Paglin and Rufolo, 1990; Card *et al.*, 2016; Sorkin, 2017).<sup>4</sup> In turn, variable pay accounts for roughly one-fifth of the overall pay gap within occupations. The variable pay gap is not explained by known drivers of the overall pay gap, such as experience, tenure, and education, nor does it seem to be related to differences in ability or social networks. A variable pay gap arises within each industry and occupation, each type of variable pay including stock and signing bonuses, and in other large economies. The ubiquity and size of the variable pay gap, coupled with its inability to be rationalized by typical explanations for the overall pay gap, motivates examining whether it is related to the characteristics of jobs that rely on variable pay.

Across the U.S. labor market, the most variable-pay intensive jobs tend to have the least female representation. For instance, registered nurses and administrative assistants exhibit low variable-pay usage and are predominantly female, whereas sales managers and investment banking analysts exhibit a high reliance on variable pay and are predominantly male. To capture variable-pay intensity across jobs, we introduce a novel continuous measure based on each worker's industry and job title — a degree of granularity that goes beyond occupations. On average, although women represent around 55 percent of workers in the least variable-pay-intensive jobs, they represent closer to 30 percent in the most intensive ones. Studying workers' resumes, which capture the history of workers' employment spells, we show the gender gap in representation within variable-paying roles widens over the life cycle. The first job on male employees' resumes is 0.1 standard deviations more variable-pay intensive than that of female employees; by the eighth job, the gap is 0.2 standard deviations. Because variable pay is persistent and employees in such jobs more often receive variable pay and receive more of it when they do, women accumulate less variable pay over time.

Why are women under-represented in variable-pay-intensive jobs? Our evidence is consistent with, even *within* occupations, women actively selecting out of such roles and learning about their preferences for such roles over time. For instance, although sales assistants

<sup>&</sup>lt;sup>4</sup>Previous related work has been limited to: a subset of workers, e.g., business school graduates and MBA recipients (Chauvin and Ash, 1994; Reuben *et al.*, 2024), executive directors (Kulich *et al.*, 2011), and the chemical sector (Grund, 2015); outside the United States, e.g., New Zealand (Fabling *et al.*, 2012), Spain (de la Rica *et al.*, 2014), or the United Kingdom (Manning and Saidi, 2010); and small-sample U.S. surveys such as the National Longitudinal Survey of Youth 1997 (NLSY97) or the Panel Study of Income Dynamics (PSID) with few observables (Albanesi and Olivetti, 2009; McGee *et al.*, 2015; Heywood and Parent, 2017).

and sales executives are both in the same sales-related occupation, the latter is two standard deviations more reliant on variable pay (according to our index) than the former. We test this hypothesis studying jobseeker application behavior on Glassdoor. This approach allows us to isolate a precursor to female labor supply directly rather than extrapolating from employment outcomes. We find that female application rates for vacancies that are one-standard-deviation more variable-pay intensive are 0.05 percentage points below that for males — a disparity equivalent to 5 percent of the mean application rate. This finding complements that of Heywood and Parent (2017), who observe sorting out of performance pay jobs for high-skill mothers, but contrasts that of Manning and Saidi (2010), who find limited evidence for such sorting behavior using firm-level measures of variable pay incidence. In Section 2, we postulate why women may avoid variable-pay-intensive roles.

What aspects of variable-paying jobs help explain this within-occupation gender gap in application rates? We find it is partially explained by their more competitive nature, consistent with Flory et al. (2015) and Samek (2019) who show, through field experiments, women shy away from jobs in which compensation relies on individual or relative performance. Although we do not observe variation in hours within occupations, evidence between occupations suggests this channel of competition is distinct from such roles demanding long hours (Goldin and Katz, 2010; Goldin, 2014). That variable-paying jobs tend to be high paying contributes to the difference in application rates, consistent with Guvenen et al. (2020). However, even after accounting for these two features, variable-pay intensity remains an important predictor of gender disparities in application rates — suggesting it does not simply proxy for the two. Differences in preferences thus contribute to men sorting into roles that are more variable-pay intensive and women those that are less so. This finding stands in stark contrast to that of de la Rica et al. (2014), who conclude the variable pay gap in Spain cannot be explained by gender differences in attitudes toward competition and variable-paying roles. While de la Rica et al. (2014) treat selection as a confounding factor, we study sorting behavior directly and propose job amenities as a mechanism for the patterns we uncover.

If women experience a disparity in working conditions and amenities in variable-paying jobs, then we would anticipate women to experience heightened turnover in such roles (Akerlof *et al.*, 1988) and possibly sort on such differences (Maestas *et al.*, 2023; Hampole *et al.*, 2023). We test for such a disparity by evaluating employer reviews on Glassdoor. Compared with their male peers, women report lower job satisfaction in roles that are more reliant on variable pay, in particular ones in which sales commissions constitute a greater share of variable pay, i.e., are more competitive. Evaluating the text of these reviews reveals that the aspects of the workplace women find of lower quality in more commission-intensive roles, compared with men, relate to respect, culture, stress, and colleagues. Further, evaluating

workers' perceptions of their firms' fringe benefits on Glassdoor, we find women are less satisfied with paid family leave in roles that rely more on sales commissions — a female-friendly benefit women particularly value in the workplace (e.g., Hotz *et al.*, 2017; Liu *et al.*, 2022).

Reduced match quality from worse amenities is consistent with the job transitions we observe in workers' resumes. Among younger workers, we find that firm tenure for women is about 2 percent lower when the job is one standard deviation more intensive in variable pay. This mechanism is distinct from that of Heywood and Parent (2017), who emphasize selection by ability for which we can partially control, and Kulich *et al.* (2011), who find a higher sensitivity of male performance pay to firm outcomes in leadership roles. Although Heywood and Wei (2006) provide suggestive evidence pay methods induce gender differences in job satisfaction, we show this gender gap in satisfaction primarily reflects differences in the assessment of working conditions, particularly work-life balance. While Albanesi and Olivetti (2009) posit gender differences in incentives for home production, we emphasize gender attitudes toward variable-paying roles, particularly those that involve sales commissions.

In sum, this paper links the literature on gender gaps to the less-developed empirical literature on variable pay — introducing a granular measure of variable-pay intensity and relating it to gender gaps in pay, amenities, search, tenure, and employment.<sup>5</sup> Our measure incorporates both the extensive and intensive margins of variable pay — distinguishing it from incidence-only based measures frequent in other studies of variable pay (e.g., Lemieux *et al.*, 2009; Kruse *et al.*, 2010; Theodoropoulos *et al.*, 2022). Beyond corroborating the ubiquity and size of the variable pay gap<sup>6</sup>, we associate it with women sorting out of variable-paying jobs, in part because of the amenities attached to such roles.

#### 2 How a Variable Pay Gap Could Arise

Different jobs offer different compensation packages. One important difference is the split between base and variable pay. If workers are risk-averse, then those in jobs that rely more on variable pay will need to receive higher expected total pay to compensate for the induced uncertainty (Rosen, 1986). Firms may use variable pay more in some jobs compared to others

<sup>&</sup>lt;sup>5</sup>See Blau and Kahn (2017) for a review of the literature on gender pay gaps.

<sup>&</sup>lt;sup>6</sup>Within this literature, the magnitude of the residual variable pay gap conditional on receiving it ranges from 8 percent (Grund, 2015) to 30–45 percent (Chauvin and Ash, 1994; Kulich *et al.*, 2011; de la Rica *et al.*, 2014; Reuben *et al.*, 2024). For workers receiving or firms offering variable pay, the raw incidence gap is about 5 percentage points (Manning and Saidi, 2010; Grund, 2015) while the residual gap is 1.2–2.5 percentage points (Manning and Saidi, 2010; de la Rica *et al.*, 2014; McGee *et al.*, 2015). With regard to the overall gender pay gap, estimates for the contribution from variable pay range from 6–21 percent (Albanesi and Olivetti, 2009; McGee *et al.*, 2015) to 34 percent (Chauvin and Ash, 1994). We find relatively large residual gaps in these three measures of 22 percent, 4.8 percentage points, and 21 percent, respectively.

because those jobs have more severe principal-agent frictions, such as moral hazard (Holmstrom, 1982), higher labor turnover (Oyer and Schaefer, 2005), and/or require incentives to raise productivity (Lazear, 2000). We refer to such jobs as variable-pay intensive.

Women could receive less variable pay, in principle, for three reasons. First, women may be less likely to fulfill the conditions to receive high variable pay. This may occur, for instance, because they are less productive, experience discrimination, or face more severe time constraints that limit their ability to work longer hours. Second, the structure of compensation may be determined during the bargaining process. Women could receive less variable pay if they prefer a fixed wage, or if they are less willing to bargain over variable components.<sup>7</sup> Third, women may be less likely to work in jobs that extensively use variable pay, resulting in women less often receiving variable pay. Since not all jobs offer variable pay, a variable pay gap can materialize along both the extensive and intensive margins. Less female representation within such roles could reflect various underlying mechanisms, such as preferences for less variable-pay-intensive jobs or discrimination in hiring. While much of the literature emphasizes the first two explanations, we focus in this paper on this third.

There are many theories for why women would avoid variable-pay-intensive roles. One is that women are more risk-averse (Eckel and Grossman, 2008; Borghans et al., 2009), though the evidence on this is mixed (e.g., Adams and Funk, 2012). If this were the case, women would be less willing to bear the income risk of variable pay, which is more volatile than base pay (Lemieux et al., 2012) and may involve more negotiations over salary, which women tend to avoid (Leibbrandt and List, 2014). A second is women under-perform in competitive environments (Gneezy et al., 2003; Gneezy and Rustichini, 2004) or jobs with high earnings uncertainty (Lindenlaub and Prummer, 2016), which may contribute to them shying away from settings in which compensation is set competitively (Niederle and Vesterlund, 2007; Flory et al., 2015). A third is women avoid management or leadership roles (Haegele, 2022), possibly because of skepticism in being evaluated fairly (Sarsons et al., 2021) or promoted (Benson et al., 2021) since they may face discrimination (Egan et al., 2022). A fourth is women may prioritize job quality out of family considerations (Mincer and Polachek, 1974; Fortin, 2005; Herr and Wolfram, 2012; Bertrand et al., 2015). In turn, women may sort away from variable-paying positions because of concerns over temporal flexibility, commuting time, work-life balance, and workplace friendliness (Bertrand et al., 2010; Goldin and Katz, 2010; Goldin, 2014; Fluchtmann et al., 2024; Cook et al., 2020). Finally, because of gender norms, women may be less drawn to higher-paying jobs (Wiswall and Zafar, 2017).

To investigate whether these five channels can explain why women are less represented

<sup>&</sup>lt;sup>7</sup>This could reflect women initially asking for lower pay (Roussille, 2024) or women accepting offers considerably earlier than men (Cortés *et al.*, 2023).

in variable-paying roles, we construct empirical proxies at the industry-job title level. For higher pay and income risk, we calculate the mean and standard deviation of total pay. For competitiveness, we measure the fraction of variable pay derived from sales commissions, which McGee *et al.* (2015) argue is a more competitive form of variable pay because commissions are won from a fixed pot. For managerial roles, we construct an indicator for whether the job title conveys a manager. For job quality, we take the overall ratings from employer reviews. These characteristics all correlate strongly with our index of variable-pay intensity (detailed in Section 3), together explaining 46 percent of the variation across jobs (Table E1). Variable-pay intensive jobs are higher paying, more competitive, more satisfying, more managerial, and, conditional on average pay, exhibit less volatile earnings. Accounting for differences between occupations modestly increases the variation explained to 58 percent. We later relate these five empirical proxies to female representation and jobseeker behavior.

### 3 Glassdoor Pay Reports

Our data come from the online labor platform Glassdoor, on which users can search for jobs, review their employers, and report their wages. We restrict our focus to most major U.S. private-sector industries, where industries are assigned to workers based on their employers.<sup>8</sup>

Pay reports are submitted voluntarily and anonymously, and workers are incentivized to contribute through a "give-to-get" policy whereby workers gain access to the information provided by others in exchange for contributing themselves. A pay report contains the following information about a worker's employment: year, job title, employment status, pay frequency, base pay, variable pay, location, years of experience, firm, and gender. Regarding variable pay, workers can detail the amount and frequency of each type, including cash bonuses, stock bonuses, profit sharing, and sales commissions. Workers can also report tips and gratuities, though we exclude this category.<sup>9</sup> Glassdoor assigns two-digit standard occupational classification (SOC) occupations to job titles using a language processing algorithm, from which we keep only assignments made with a high degree of confidence. We restrict our sample to full-time, salaried (i.e., annual pay frequency) private-sector workers and inflation-adjust pay to 2018 dollars using the consumer price index (CPI).<sup>10</sup> To avoid

<sup>&</sup>lt;sup>8</sup>We exclude pay reports from industries in the public sector (aerospace, education, and government), with low coverage (agriculture and mining), and where tips and gratuities are non-trivial (consumer services and food services). We also exclude pay reports where the industry associated with the firm is unavailable.

 $<sup>{}^{9}</sup>$ Except for travel accommodation (1.4 percent) and arts and entertainment (1.3 percent), less than 0.5 percent of workers in each industry report receiving tips.

<sup>&</sup>lt;sup>10</sup>Excluded are pay reports from part-time employees, seasonal or temporary hires, freelancers, interns, contractors, the self-employed, and workers paid monthly, hourly, or daily. In focusing on full-time, salaried workers, our results are not driven by gender differences in hourly labor supply or work intensity that might

ambiguity in units, account for outliers, and control for misreporting, we exclude the bottom and top 1 percent of total pay earners (effective lower and upper bounds of \$24,000 and \$296,655, respectively) along with observations where workers report earning less than \$200 in any of the variable-pay categories.<sup>11</sup> Last, because we incorporate representative weights by industry, occupation, metropolitan area, and sex from the American Community Survey (ACS), we drop the 4 percent of pay reports from outside the 252 metropolitan areas represented in both Glassdoor and the ACS.

The final sample consists of 2.62 million pay reports that span the years 2009–2021 and cover 101,000 employers.<sup>12</sup> For a subset of respondents, additional demographic information is available. For workers who also complete an employer review for their job, of which there are 236,000, we observe their years of tenure with the firm. For workers who have a registered profile with supplementary demographic information available, of which there are 897,000, we observe their age. Based on the worker's industry and job title, we develop a novel, continuous index to capture the extent to which a job relies on variable pay. We construct this index as the principal component of two measures for each industry-job title. The first, meant to capture the extensive margin, is the share of workers that receive variable pay. This dimension is observed in some datasets other than Glassdoor, such as the PSID, though not by job title. The second, meant to capture the intensive margin, is the average fraction of total pay attributable to variable pay. Other than Glassdoor, this margin is available in particularly few datasets, such as ADP payroll data studied in Grigsby et al. (2021). The first principal component captures 97 percent of the variation in these two measures. Presumably, the more a job relies on variable pay, the more likely workers are to expect to receive variable pay in that role.<sup>13</sup> We use this measure to study the relation between variable-pay intensity and wages, amenities, firm tenure, and labor market sorting.

Table 1 provides summary statistics for our dataset. About two-fifths of the workers in our sample are women, and the distribution across demographics for men and women is relatively similar. Despite the similarities in demographics, women are 10 percentage points less likely to receive variable pay compared with their male counterparts, and among those who receive variable pay, men receive on average \$6,000 more than women. Because men

relate to preferences for part-time work.

<sup>&</sup>lt;sup>11</sup>Such values could reasonably correspond to, for instance, percentage points, dollars, thousands of dollars, or tens of thousands of dollars. Incorporating such observations for analyses involving the incidence of variable pay does not alter the results.

<sup>&</sup>lt;sup>12</sup>Pay reports are more concentrated in later years, with about 72 percent of observations corresponding to the last five years of the period.

 $<sup>^{13}</sup>$ Implicitly, we assume aggregating realized variable pay across workers in an industry-job title over time provides ex ante population measures of how often and how much variable pay workers in that role can expect to receive. We follow the literature (e.g., Lemieux *et al.*, 2009) and characterize variable-paying jobs based on outcomes rather than expectations.

have a greater standard deviation for variable pay than women, and both standard deviations are greater than the mean (panel (b) of Figure D1), the distribution of variable pay for men is more right-skewed. In turn, women receive about 3 percentage points less of their total income from variable pay. These gender gaps in variable pay are mirrored within each type of variable pay. Females less often receive cash, stock, profit sharing, and commissions; and when they do, they are rewarded with less on average than men.

To speak broadly about the U.S. labor market, Glassdoor data should reflect labor market patterns observed in other data sources. Because Glassdoor data are submitted voluntarily, there may be measurement error from misreporting; however, Oyer (2004) finds the average survey respondent overestimates their earnings by about 5 percent, with workers compensated annually (i.e., our sample) providing more precise responses. Although Glassdoor does over-sample workers who are male, college-educated, aged 25–39, and employed in manufacturing and professional services industries (Liu et al., 2022), Glassdoor earnings have been found to be more representative when dis-aggregated. show Glassdoor wages have been show to broadly capture trends between industries and metropolitan areas (Karabarbounis and Pinto, 2019), and between occupations (Gibson, 2021). Further, Martellini et al. (2024) demonstrate that, compared with administrative tax data, Glassdoor pay reports provide an unbiased sample of average earnings by college.<sup>14</sup> With regards to variable pay, Sockin and Sockin (2022) show that Glassdoor data align with ADP data in mirroring the variable pay share of total pay across the base pay distribution as presented in Grigsby et al. (2021). We offer further evidence for the U.S. labor market by comparing Glassdoor with the American Community Survey (ACS). Additional details are provided in Internet Appendix A.

The ACS is an annual survey comprised of a national random sample of 1-in-100 of the U.S. population, which we obtain from the Integrated Public Use Microdata Series for the years 2009 through 2021. The ACS includes sampling weights that allow for a nationally representative summary of the U.S. economy. We observe the total income (which includes based and variable pay) received from wages and salaries over the previous year, along with the worker's gender, industry, occupation, and metropolitan area. Base and variable pay are not reported separately. To mirror the Glassdoor sample, we restrict the ACS sample to full-time workers not in the public sector, exclude the top and bottom 1 percent of earners, and inflation-adjust income. Because total income is measured from the previous year, we restrict the sample further to workers employed 50–52 weeks the previous year. We then aggregate to the industry-occupation-gender level in each dataset, where industry corresponds to Glassdoor industry and occupation reflects two-digit SOC

<sup>&</sup>lt;sup>14</sup>Glassdoor also provides a reasonably unbiased sample by college for other advanced economies considered in our international pay reports sample, such as Ireland and the United Kingdom.

categories. Correlations of pay- and employment-based measures between the two datasets applying representative weights from the ACS are presented in Table 2.

Glassdoor appears to capture differences between industries and occupations well. Between the two datasets, the correlation for means of total earnings is 0.88–0.90 and standard deviations of total earnings is 0.88. Because our work focuses heavily on the difference in earnings between men and women, we also compare the gender gaps observed in each dataset. We observe a strongly positive though slightly weaker correlation of 0.64, indicating that industry-occupations that have wider gender gaps in the ACS also tend to have wider gaps in Glassdoor. Because our work speaks to the gender composition of jobs, we also assess whether Glassdoor data reasonably capture female employment shares; given a correlation of 0.95, it appears they do. We provide additional tests for selection into the Glassdoor sample in Internet Appendix A.

We recognize that the sample composition in Glassdoor differs from that observed for the U.S. labor force more broadly. Glassdoor over-samples from the information technology and business services industries while under-sampling from construction and health care (Figure A4: panel a). Moreover, it over-represents occupations related to financial operations and management while under-sampling from occupations related to production and food preparation (Figure A4: panel b). Consequently, despite broadly capturing differences between industries and occupations, Glassdoor data are less representative of the U.S. economy in aggregate. To account for these sampling imbalances and ensure the variable pay gaps reflect the U.S. economy as a whole, we apply representative weights from the ACS by industry, occupation, metro, and gender to our cross-sectional pay analyses.

We also consider the possibility that workers systematically over- or under-report pay on Glassdoor. If men tend to over-report variable pay, or women under-report it, or both, then our conclusions might reflect this bias rather than structural aspects of the U.S. labor market. To rule out this concern, we narrow in on workers whom we can reasonably believe report the truth. To identify this sub-sample, we look at workers who provide both a pay report and an employer review, and then isolate workers whose reviews use the most concrete language — channeling the conclusion of Hansen and Wänke (2010) that statements are considered more honest when written using language that is more concrete and less abstract. Additional details are provided in Appendix A. For this sub-sample of concrete-language-using workers, we observe similar gaps in base and variable pay compared with the full sample (Table A5), suggesting Glassdoor data do not exhibit systematic reporting issues with pay by gender.

#### 4 Gender Differences in Variable Pay

We first examine gender differences in variable pay and document their ubiquity across and within occupations, industries, and countries. The summary statistics in Table 1 show women receive, on average, \$14,970 in variable pay with an incidence of 32 percent, compared with \$20,780 and 42 percent for men in our sample. The raw gender gap of 39 percent in variable pay between men and women is larger than the 18 percent gap in base pay. Reuben *et al.* (2024) similarly document a larger gender gap in variable pay for a cohort of MBAs.<sup>15</sup> For empirical probability density functions by gender of base pay, variable pay, and each type of variable pay, see Figure D1.

Mincerian Analysis Although there appear to be meaningful gender gaps in the incidence and magnitude of variable pay, these differences could reflect differences in demographics and/or disparities in the occupations, industries, and employers into which men and women self-select.<sup>16</sup> To address these issues, we regress measures of worker pay on a female indicator variable and iteratively incorporate worker and job characteristics. We cluster all standard errors at the employer level and report the results in Table 3.

The first column displays effectively the raw estimate for the gender gap in our sample, accounting only for differences over time. This specification facilitates comparison with column 2, in which our estimates account only for differences in human capital (i.e., a quadratic in years of work experience) and location. The gender gap in percentages is largest for the magnitude of variable pay at 29 percent (-35 log points), indicating observable characteristics cannot explain the male premium in variable pay. While the gender gap in variable pay remains unchanged once human capital is included, that for base pay shrinks by 5 percent. This in part reflects how differences in human capital can explain at most 2 percentage points more of the variation in variable pay.

While accounting for differences across occupations reduces the gender gap in log base pay by 27 percent (column 3), it reduces the gender gap in log variable pay only 9 percent and the gender gap in the incidence of variable pay remains unchanged. Industries and occupations are evidently worse predictors of variable pay than they are of base pay. Accounting for differences across employers somewhat attenuates the gender gaps in the magnitude of variable pay and its incidence to 22 percent and 4.8 percentage points, respectively (column 4). Comparing the gender gap in base pay with that for total pay reveals variable pay

<sup>&</sup>lt;sup>15</sup>In the year after graduating, the gender gap in total pay was 25 percent while that for bonuses was 80 percent; Seven years later, the gap in base pay was 21 percent whereas that for bonuses was 123 percent.

<sup>&</sup>lt;sup>16</sup>Although all industries exhibit sizable variable pay gaps, there is variation between them (Table C2). For instance, while the gap in most industries reflects disparities in cash or sales commissions, it primarily reflects stock for biotechnology and information technology. The same is true for occupations (Table C3).

accounts for at least one-fifth of the residual pay gap within occupations.

While studies tend to stop at occupations, Glassdoor data allow us to control for more granular differences through job titles. When we incorporate job title fixed effects in lieu of those for occupations — which would be redundant since occupations are assigned to job titles — variable pay gaps remain substantial. Women receive 4.5 percent less total pay, the product of 3.2 percent less base pay, a 3.7 percentage points lower likelihood of receiving variable pay, and 14.4 percent less variable pay among those who receive it. In turn, variable pay accounts for about three-tenths of the residual pay gap within job titles.

The same job title, however, may still correspond to dissimilar tasks or skill requirements across employers or locations. To account for this, we compare earnings for workers with the same job title at the same firm in the same state and year. Under this finer comparison, large variable pay gaps persist, with variable pay accounting for about one-third of the residual pay gap (Table E2). Finally, one may be concerned that shorter, less descriptive titles, such as consultant or engineer, exhibit more dissimilar work between them than longer, more specific titles such as customer service representative or senior user experience designer. However, even within more granular (longer) job titles, variable pay gaps still exist (Table E3).

Variable-pay intensity To proxy for the variable-pay intensity of a job, we use our variable pay index, i.e., the first principal component of two measures at the industry–job title level, the incidence of variable pay and the fraction of total pay attributable to variable pay. We then estimate a Mincerian equation that includes our index and its interaction with a female indicator. Table E5 displays the results. Consistent with Lemieux *et al.* (2009), who focus on male heads of households, variable-pay-intensive jobs receive a substantial wage premium over less variable-pay-intensive ones. One standard deviation greater variable-pay intensity is associated with male employees receiving 10.5 percent greater base earnings and 16.3 percent greater total earnings, highlighting that about one-third of the income premium for variable-pay-intensive roles stems from variable pay.

Although women also enjoy a pay premium from working in a variable-pay-intensive role, the gain is slightly lower: One standard deviation greater variable-pay intensity corresponds to a 15.8 percent increase in total pay for female employees, 0.5 percentage points below that for men. Partitioning total pay into base and variable pay, we observe that for base pay, the gender gap narrows with variable-pay intensity. However, this masks a widening gender disparity in the receipt of variable pay. A one standard deviation increase in the variable-pay intensity of a job is associated with a 2.0 percentage points lower likelihood of women receiving variable pay.<sup>17</sup> Relative to the gender gaps we observe within positions

<sup>&</sup>lt;sup>17</sup>While variable pay may incentivize males to be more productive, growth rates of base and variable pay

with average variable-pay intensity (row 1), this translates into a 58-percent widening of the gap. The conclusions are similar if we look within job titles instead of occupations, though variable pay now explains three-quarters of the total pay gap widening with variable-pay intensity rather than all of it (Table E7).

In sum, how much a role relies on variable pay explains a lot of the variable pay gender gap. This motivates us to examine in the sequel how attitudes toward variable-pay intensive roles differ by gender, and how this translates into selection into and out of such jobs.

**Country-level analysis** As an online platform with an international presence, Glassdoor data include pay reports from outside the United States. International pay reports have the same worker and firm information that U.S. data contain, along with the currency of the pay. Although we do not have external data on variable pay to compare Glassdoor with for each country, we show in Appendix A that Glassdoor appears to offer an unbiased snapshot for large U.K. firms; further, firms which disclose larger gaps in variable and total pay to the U.K. government exhibit larger gaps in Glassdoor. Looking over 2009–2021, we restrict attention to the 14 countries in our sample that have at least 500 male and 500 female full-time, salaried, private-sector workers who receive variable pay.<sup>18</sup> We implement a Mincerian regression on the magnitude and incidence of variable pay separately for each country controlling for years of experience, job title, and firm. The results are recorded in Table E6. Each country exhibits a gap in the incidence of variable pay (2.4–5.6 percentage points), and all but two exhibit gaps in the magnitude of variable pay of at least 20 percent. A variable pay gender gap thus appears to constitute a broad international phenomenon.

Additional analyses In Appendix B, we document the ubiquity and robustness of the U.S. variable pay gap. We consider each component of variable pay, typical determinants of the overall gender pay gap, such as human capital and firm tenure, worker productivity that we proxy for with educational background, and signing bonuses.

differ little by gender (Table E4) and the impact on effort is likely more muted for rank-and-file jobs than roles where variable pay is a large part of total pay, e.g., gig workers (Cook *et al.*, 2020) or C-suite executives.

<sup>&</sup>lt;sup>18</sup>Imposing these restrictions, our international sample of pay reports includes: Australia, Canada, France, Germany, India, Ireland, Italy, the Netherlands, New Zealand, Singapore, Spain, Switzerland, the United Kingdom, and the United States. Descriptive statistics for each country's sample is available in Table C4. For the international comparison, we restrict our observables to information obtained directly through the pay report survey: gender, job title, firm, and years of experience. We leave pay in local currencies and exclude pay reports not reported in the country's primary currency (less than 0.01 percent of the sample).

### 5 Gender Representation in Variable-Pay Jobs

We next ask whether variable pay can help inform our understanding of how men and women sort throughout roles within firms. Using Glassdoor pay reports, we first document women are less represented in jobs that rely more on variable pay. Then, using workers' job histories, we show this disparity in representation within variable-pay jobs widens over the life cycle.

**Representation in Pay Reports** Comparing the share of female employment with our measure for variable-pay intensity reveals that women are, for the most part, monotonically less employed in roles that rely more on variable pay (Figure 2).<sup>19</sup> Jobs that are the most reliant on variable pay exhibit female employment shares around 30 percent whereas those that utilize variable pay the least exhibit female employment shares around 55 percent. Put differently, in the most variable-pay-intensive jobs, men outnumber women more than two-to-one. We observe this pattern not just for the United States but other large economies as well, such as Australia, Canada, and the United Kingdom (Figure D2).

To understand how the gender composition of jobs varies with variable-pay intensity, we relate the female employment share within an industry-job title to our variable-pay intensity index and the five aforementioned characteristics associated with it. To account for variation across and possible sample selection related to employers, locations, and time, we first residualize female employment share and each covariate by firm, state, and year fixed effects, and then average the residuals by industry-job title. The results are recorded in Table 4. Our sample includes 14,247 industry-job titles with observation counts above the sample average.

On its own, our index for variable-pay intensity can explain 4 percent of the residual variation in the gender composition between jobs. As one would expect, selection into different occupations helps explain a significant portion of the remaining variation, raising the share of the variation explained to 55 percent. However, and more surprisingly, accounting for occupation does not reduce the economically and statistically significant coefficient attached to the variable-pay index. A one standard deviation increase in variable-pay intensity corresponds to a 4.3 percentage points lower female employment share. Since female employment share reflects the ratio of female employees to the total, this decline translates to a 8.6-percentage-points widening in the share of employment attributable to men and women.

When we include the set of attributes that may explain the aversion of females to variablepaying roles, the coefficient on variable-pay intensity diminishes by nearly one-half. This reflects less female representation among roles that are more competitive (i.e., a greater

<sup>&</sup>lt;sup>19</sup>It is worth highlighting this relation is not mechanical because there is a gender gap and we construct variable-pay intensity using male and female pay reports. The results would change little if we were to construct variable-pay-intensity using only male observations.

share of variable pay derived from sales commissions), more managerial, higher paid, and have greater pay variance. However, even after accounting for these characteristics, a onestandard-deviation increase in variable-pay intensity corresponds to a decline of 2.4 percentage points in female employment share. This suggests a phenomenon unexplained by industries, occupations, or these five covariates. This unexplained component could reflect supply-side factors (e.g., preferences for scheduling flexibility, hours, or gender-balanced workplaces), demand-side factors (e.g., offers, promotions, or separations), or both.

**Representation in Workers' Resumes** While the cross-section of workers' pay reports demonstrates that women represent a smaller fraction of employees in more variable-payintensive jobs, it remains to be seen how the gap in representation within such roles evolves for a fixed set of workers over the life cycle. To that end, we turn to the resumes workers provide to Glassdoor for facilitating job search on the platform.<sup>20</sup> Not all workers provide a resume, but about one-fourth do. A worker's resume details the history of jobs the worker has held in the past. For each job on their resume, the worker provides the following: the employer, the job title, the location, the date the job started, and the date the job ended (if not still employed in the role). Given our interest in the panel nature of resumes, we exclude the 27 percent of resumes that list only one job. We also exclude any resumes for which an entry was missing a job title or had an impossible tenure length. Finally, to study how variable-pay intensity evolves over the life cycle for men and women, we merge our variable pay index to each job on a worker's resume. (This necessarily excludes industry-job title pairs on resumes that are not observed in Glassdoor pay reports). Our final sample consists of 1.3 million resumes, for which the average number of jobs in total is 5.4, and the average number for which we can assign variable pay intensity is 2.1.

To uncover whether and to what extent workers are more levered on variable pay over the life cycle, we investigate variable pay intensity by the position of each job on a worker's resume. Intuitively, jobs later on in a worker's resume reflect jobs taken later in life.<sup>21</sup> To capture an overall life-cycle pattern and potential gender divide, we estimate

$$VPI_{i,P} = \sum_{p=1}^{10} (\beta_p + \gamma_p F_i) \times 1\{P = p\} + \lambda_{g(j(i,P)),\iota(k(i,P))} + \lambda_{t(i,P)} + \varepsilon_{i,P}, \tag{1}$$

where  $VPI_{i,P}$  is our variable pay index assigned to job number P on worker i's resume,  $F_i$ 

 $<sup>^{20}</sup>$ Glassdoor resumes have also been used in other context, e.g., documenting whether a worker has ever been a chief executive or entrepreneur (Martellini *et al.*, 2024).

<sup>&</sup>lt;sup>21</sup>Indeed, we would draw the same conclusion over the life cycle if we were to use, instead of the job number on the resume, the age of the worker (Figure D3).

is a female indicator,  $\lambda_{g(j(i,P)),\iota(k(i,P))}$  are fixed effects for the occupation associated with job title j(i, P) and industry associated with firm k(i, P) pair, and  $\lambda_{t(i,P)}$  are, to account for cohort-specific dynamics, fixed effects for the year that worker *i* began job *P*. For ease of exposition, the variable pay index is standardized to have standard deviation one.

The coefficients are plotted in Figure 3, with  $\beta_p$  and  $\gamma_p$  in panels (a) and (b), respectively. The omitted coefficient is  $\beta_1$ , such that  $\beta_p$  for p > 1 can be interpreted as the difference in variable-pay intensity between job p and the first job on a male worker's resume. The coefficients  $\gamma_p$  for  $p \ge 1$  can be interpreted as the difference in variable-pay intensity between men and women for job number p on their resumes. Three key takeaways emerge.

First, narrowing in on the first job, we observe that women, even within the same industries and occupations, start their careers at jobs that are on average 0.1 standard deviations less variable-pay intensive than men. This estimate,  $\gamma_1$ , is negative and highly significant. Second, the difference in variable-pay intensity between men and women widens over the life cycle. With each subsequent job,  $\gamma_p$  becomes more negative until it levels off at about 0.2 standard deviations around the eighth job. Thus, over the life cycle, men sort into more variable-pay intensive roles than women. And third, as workers transition jobs, on average they sort into more variable-pay intensive roles. For men, up until the eighth job on their resumes, their jobs increasingly become more variable-pay intensive—flattening out at roughly 0.3 standard deviation above their first job. For women, their jobs also become more variable-pay intensive on average over the life cycle ( $\beta_p + \gamma_p > \gamma_1, \forall p$ ), similarly flattening out around the eighth job; however, it is not to the same degree as men.

Because variable pay is persistent (Table E4) and workers in variable-pay-intensive jobs both, receive variable pay more often and receive larger premiums when they do (Table E5), women accumulate less in variable pay over time.<sup>22</sup> From Table E5, one standard deviation greater variable-pay intensity within an occupation is associated with 16 percent greater total pay. A back-of-the-envelope calculation suggests that, with a gender gap of 0.1 standard deviation in the first job, differences in the variable-pay intensity of men's and women's jobs can rationalize about 1.6 percentage points of the within-occupation gender pay gap early in the life cycle. As the gap widens to 0.2 standard deviations as men and women progress through their careers, variable-pay intensity can rationalize about 3 percentage points of the within-occupation gender pay gap later in the life cycle.

 $<sup>^{22}</sup>$ We test for the persistence of variable pay by estimating an autoregressive (AR1) process for variable pay using the panel of workers with multiple pay reports. The logarithm of variable pay exhibits similar persistence across men and women with AR1 coefficients of 0.57 and 0.55, respectively. Variable pay is less persistent than base pay, for which the corresponding AR1 coefficients are 0.73 and 0.74, respectively.

# 6 Why Less Representation in Variable-Paying Jobs?

#### 6.1 Gender Differences in Job Search

Since the representation of women in variable-paying positions is an equilibrium outcome, we turn to analyzing jobseeker application behavior on Glassdoor, since the online platform also acts as a job board through which workers can search through open vacancies and apply to jobs. Through studying job seeker behavior, we capture supply-side effects in the labor market that directly relate to worker preferences. Aggregating job listings from other online job boards, applicant tracking systems, and company websites, Glassdoor also effectively captures about four-fifths of total U.S. job openings as reported in the Job Openings and Labor Turnover Survey (Chamberlain and Zhao, 2019).

For each registered user on the website, we first record whether the individual (as tracked by an unique identifier) made an "impression" of a vacancy, i.e., the job listing is displayed on the user's active page of job search, with a page typically comprising 20 separate listings.<sup>23</sup> Next, we record whether the worker subsequently decided to "apply" to the listing, i.e., click on an "Apply Now" button embedded in each posting. For each job posting listed on Glassdoor from January 2017 through August 2019, we tabulate the total impressions and applies recorded by male and female jobseekers, restricting our attention to impressions and applies recorded within the first 72 hours from when a listing was posted.<sup>24</sup> Last, we restrict our sample to "active" postings, i.e., those that record at least 10 impressions for both male and female jobseekers, and to postings for which the industry-job title pair is represented in the Glassdoor pay data such that we can merge in our variable-pay index. For further description of Glassdoor job listings and jobseekers, see Marinescu *et al.* (2021b).

Summary statistics for our sample of 143,800 job listings, which cover 10,500 industry-job titles across 20,600 employers, are available in Panel B of Table C1. Job postings receive on average 84.0 impressions and 0.74 applies. Male jobseekers record on average 44.0 impressions and 0.41 applies, somewhat above the averages for female jobseekers of 42.0 impressions and 0.34 applies. Our principal measure of jobseeker application behavior is applies per 100 impressions, referred to hereafter as the application rate, as this measure reflects individual interest in a posting while accounting for differences in how frequently each posting populates jobseekers' displays. It averages 0.97 across our sample. Figure D4 shows how application

 $<sup>^{23}</sup>$ Job seekers frequently record multiple impressions for the same listing. We ignore these duplicate actions so that each individual contributes at most once to each posting.

<sup>&</sup>lt;sup>24</sup>Memory constraints induce a trade-off between the window over which data is collected and whether data extraction is successful. A 72-hour window is chosen for feasibility, and caused extraction to fail for about 17 percent of days. Because of limited access to new job search data, job postings extend only through mid-2019 while pay reports through 2021.

rates (panel a) and total applications (panel b) vary with the variable-pay intensity of the role for male and female jobseekers.<sup>25</sup> Although male and female jobseekers both avoid variable-pay-intensive roles, the effect is more pronounced for females.

To understand the specific attributes associated with variable-paying jobs that female jobseekers avoid, we calculate the difference in application rates between male and female jobseekers to the *exact same* job posting and relate these differences to our five variable-pay covariates. We incorporate industry-occupation, metro, and calendar-day fixed effects to isolate the relevance of variable pay from differential preferences for locations and occupations, as well as differences that might occur weekly, seasonally, or over time. To capture individual-level effects and limit measurement error (since the average impression count is below 45 and average application rate is about 1.0 by gender), we weight each posting by its impression count.<sup>26</sup> Table 5 reports the results.

The coefficient on our variable-pay intensity index is negative and statistically significant both across and within occupations. This suggests female jobseekers are more reluctant than men to apply to more variable-pay-intensive listings, and this aversion does not merely reflect occupational preferences because we observe this relation between jobs within occupations. A one-standard-deviation increase in the variable-pay intensity of a job is associated with a 0.05-percentage-points widening of the gap between female and male application rates (column 2). Adding in the characteristics related to variable-paying jobs reveals that the more-competitive nature of such roles explains part of the gender difference in application rates. When the share of variable pay attributable to sales commissions is incorporated, the relation with variable-pay intensity remains significant but shrinks by one-half. That competition, or job characteristics related to it, is associated with women less often applying to variable-paying jobs may help rationalize how differential preferences for competition explain 10 percent of the pay gap among high-ability MBA graduates (Reuben *et al.*, 2024).

What might explain why our variable-pay index remains an important predictor of a gender difference in application rates? One possible channel is that women may choose not to apply to variable-paying jobs because they are cognizant of the variable-pay gap and believe they will be underpaid in such positions. Especially if the receipt of variable pay is related to individual performance evaluation, women may sort out of such roles because they are concerned that they will not be given equal consideration (e.g., Sarsons *et al.*, 2021). Another is that although variable-paying roles tend to result in greater job satisfaction on average (Table E1), there could be a marked disparity in job quality between men and women

<sup>&</sup>lt;sup>25</sup>The distribution of postings by variable-pay intensity exhibits a long right tail (Figure D5).

<sup>&</sup>lt;sup>26</sup>Because we do not have data capturing individuals' impressions and their subsequent application decisions, we cannot control for current information about the worker that may affect search behavior, such as their employment status, wage, marital status, or location.

within more variable-pay-intensive roles, a possibility we explore in Section 7. A third is that women may avoid applying to such roles precisely because there are relatively few women in them, thereby perpetuating a self-fulfilling prophecy.

Our findings underscore that the under-subscription of women to variable-paying jobs at least in part reflects female jobseekers' preferences to avoid such roles. This pattern is largely related to these jobs being more competitive, consistent with the experimental evidence of Flory *et al.* (2015). Indeed, Leibbrandt and List (2014) provide evidence that women dislike jobs in which the rules of wages determination are more ambiguous. Other work suggests though that such aversion could, for instance, reflect gender differences in selfconfidence or beliefs over the likelihood of failure (Risse *et al.*, 2018), differential preferences for fixed-pay schemes that reflect broader preferences over risk (Dohmen and Falk, 2011), or concerns about possible discrimination on the job or in hiring decisions (Egan *et al.*, 2022). Whether it is variable pay itself, or the aspects of work associated with variable-pay schemes, heterogeneous preferences for variable-paying jobs are meaningful for labor supply decisions.

#### 6.2 Gender Differences in Job Tenure

If women are less likely to apply for more variable-pay intensive jobs, it seems natural to ask whether they are earlier to separate from such jobs when employed in them. It may precisely be poor experiences in variable-paying jobs that lead women to subsequently sort away from such roles. If this were the case, given the widening gender divergence in representation within variable-paying roles we observe over the life cycle, we anticipate tenure in these jobs to be shorter for women who are early in their careers. To test this postulation, we turn to workers' resumes, calculating the number of months spent in each job and relating it to our variable-pay intensity index. The results are presented in Table 6.

Although workers exhibit increasingly longer tenure in jobs that rely more on variable pay — perhaps not too surprising given the wage premium such roles offer (Table E5) — this relation is reduced by more than 10 percent for women (column 1). Indeed, even looking between jobs for the same worker, women exit the variable-pay intensive job earlier than men do (column 2). Partitioning the sample in half by age reveals that this pattern is driven largely by disparities between younger men and women. Tenure is about 2 percent lower per standard deviation increase in variable-pay intensity for women ages 18-26 compared with men ages 18-26 (column 3). This result attenuates but persists when comparing within the same job titles (column 4), and we would draw the same conclusion of shorter tenure among younger women if we were to consider the competitiveness of the role, as proxied for by the sales commission share of variable pay, in lieu of our variable-pay intensity index (Table 6).

This evidence suggests variable-paying and more competitive jobs tend to produce less stable matches for women than for men.

#### 7 Worse Satisfaction and Amenities as a Mechansim

Women might sort away and exit earlier from variable-paying jobs because they experience worse non-wage amenities in such roles. To explore this possibility, we turn to Glassdoor employer reviews, which are submitted voluntarily and anonymously. Workers are incentivized to contribute a review through the same "give-to-get" policy. After responding whether they are a current or former employee, workers rate their overall job satisfaction on a 1–5 stars Likert scale, with a greater number of stars indicating more satisfaction. Respondents are then prompted to provide similar star ratings for five sub-categories: career opportunities, compensation and benefits, culture and values, senior management, and work-life balance. Additionally, workers can detail their location of employment, job title, and tenure with the firm, though these fields are not mandatory.<sup>27</sup>

Summary statistics for the sample of 446,000 employer reviews are available in Panel A of Table C1. The average overall rating is 3.34 stars, with males reporting a modestly greater average of 3.38 compared with the 3.27 average for females. Men also report greater average ratings for each of the five sub-categories. The average worker is 35 years old and about three-fifths of the reviews are submitted by then still-currently-employed workers.

Regarding the external validity of these ratings, Sockin (2022) finds statistically significant correlations of about 0.5 between overall satisfaction ratings in Glassdoor and job satisfaction reported in the NLSY97 between industries and occupations. Further, Glassdoor ratings have been found to predict stock returns (Green *et al.*, 2019) and respond to unanticipated news of corporate misconduct (Gadgil and Sockin, 2020). The give-to-get policy under which Glassdoor reviews are largely submitted also helps to attenuate the selection bias present in online reviews (Marinescu *et al.*, 2021a).

The purpose of these employer reviews is two-fold. First, they are used to calculate the average job satisfaction rating by industry-job title pair, which is included as an explanatory variable for explaining gender representation across jobs (Section 5) and jobseeker behavior (Section 6.1). Second, we can directly speak to whether there are differences in perceptions of job quality by gender that relate to the variable-pay intensity of the job. If male and female workers experience disparate working conditions when they are employed in jobs that rely more heavily on variable pay, then we would expect a representation gap to develop within such roles—given that workers who are more satisfied with their jobs tend to exhibit

<sup>&</sup>lt;sup>27</sup>For a further description of Glassdoor reviews, see Sockin and Sojourner (2023).

longer employment spells (Freeman, 1978), especially when it pertains to non-wage attributes (Akerlof *et al.*, 1988; Sockin, 2022).

As with our analysis examining application rates for job postings, we assign to each review our index for variable pay intensity by industry-job title pair.<sup>28</sup> We then relate gender differences in satisfaction ratings to our variable-pay intensity index by estimating

$$R_{i,j,k,t} = \beta_1 F_i + (\beta_2 + \beta_3 F_i) \times VPI_{j,\iota(k)} + \rho X_{i,t} + \lambda_t + \lambda_{g(j),\iota(k)} + \lambda_k + \epsilon_{i,j,k,t}, \qquad (2)$$

where  $R_{i,j,k,t}$  is the star rating for firm k submitted in year-month t by worker i with job title j. We include industry-occupation fixed effects  $\lambda_{g(j),\iota(k)}$  to isolate variation within occupations along with firm fixed effects. The vector of worker observables  $X_{i,t}$  includes an indicator for whether the worker is a current employee at the time of the review and age fixed effects. The resulting coefficients of interest are reported in panel A of Table 7.

We observe that, even within the same occupations, gender differences in perceptions of job quality exist, consistent with Clark (1997). The disagreement in job quality though is significantly wider within variable-paying jobs. A one standard deviation increase in the variable pay intensity of a role is associated with a 50 percent larger gender gap in overall job satisfaction. Utilizing the sub-ratings that workers report reveals that the widening gender gap in overall satisfaction reflects differences in job quality. Within jobs that depend more on variable pay, women report worse career opportunities, compensation and benefits, culture, management, and work-life balance. While the disparities are broad-based, the largest gaps are observed for career opportunities and work-life balance. Thus, although jobs that increasingly rely on variable pay exhibit improved job satisfaction overall and across each sub-category, that growth is less steep for female employees. When it comes to work-life balance — a non-wage aspect of jobs that women particularly value (Goldin and Katz, 2010; Goldin, 2014; Wiswall and Zafar, 2017) — there is seemingly no boon for women whereas there is for men. These findings would be consistent, for instance, with women perceiving a "glass ceiling" within such roles (de la Rica et al., 2014), witnessing a male-centered work culture (Levanon et al., 2009), or preferring more flexible work schedules because of family considerations (Bertrand *et al.*, 2015).

Given that variable-pay intensive roles are associated with improved job quality and greater pay, it is perhaps not surprising that workers' roles become more variable-pay intensive over their careers (Figure 3). However, we have documented that women are relatively

<sup>&</sup>lt;sup>28</sup>Our sample is restricted to reviews for which a job title is available. Workers, however, may hide their title to reduce the likelihood of retaliation from employers (Sockin and Sojourner, 2023). Because females are more likely to conceal their job titles when providing negative reviews (results available upon request), our estimates are likely biased down, although how this pattern relates to variable-pay intensity is not obvious.

averse to variable-paying roles and that this aversion can in part be explained by the competitiveness of the role, i.e., its reliance on sales commissions (Tables 4 and 5). If job quality is indeed a mechanism by which we believe women are sorting out of variable-pay intensive roles, then we would anticipate gender differences in job quality to materialize within roles where sales commissions constitute a greater share of variable pay. To this end, we re-estimate equation (2), substituting in the sales commission share of variable pay for our variable pay index. The results are reported in panel B of Table 7.

Looking first at the overall relation, captured by  $\beta_2$ , while we observe greater satisfaction with compensation in jobs that rely more on sales commissions, we observe reduced satisfaction with work-life balance. Given the emphasis women place on work-life balance (Goldin and Katz, 2010; Goldin, 2014) and the import men place on compensation (Wiswall and Zafar, 2017), this divide alone would suggest differential sorting by gender. When we consider the differences in perceived job quality by gender, captured by  $\beta_3$ , we observe women on average report lower levels of satisfaction overall and for each sub-category.

Looking at the text of workers' Glassdoor reviews, we find a similar though more nuanced conclusion. Borrowing the text-based amenities of Sockin (2022), who implements a semisupervised topic modeling algorithm on the pros and cons sections of Glassdoor reviews, we re-estimate equation (2) using these amenities as our outcomes of interest. Each amenity ranges from -1 to 1, with a positive measure reflecting discussion in the pros section of the review, a negative measure in the cons section, and zero if it was mentioned in neither. Figure D6 reports  $\beta_3$  for each amenity when considering the sales commission share of variable pay. Two takeaways emerge. First, there is no workplace amenity, except possibly the sales commissions themselves, that women report greater satisfaction with than men. Second, there are a handful of non-wage amenities that women perceive more negatively than men, in particular respect/abuse, stress, culture, teams, coworkers, leadership, and office politics. Given the import of non-wage aspects of work for turnover (Akerlof *et al.*, 1988), this gender divide in perceptions of job quality is consistent with women sorting out of jobs that are more competitive for relying increasingly on sales commissions.

While the gender pay gap has been linked to the temporal inflexibility of jobs whereby individuals are rewarded for working long hours (Goldin and Katz, 2010; Goldin, 2014), the role of amenities and competitiveness appears to be a distinct channel. While we do not observe weekly hours in Glassdoor data to compare job titles within occupations, we do observe workers' hours and occupations in the CPS. Looking across occupations, we observe that indeed industry-occupation pairs in which full-time employees tend to work longer hours have less female representation and receive a greater fraction of their compensation from variable pay (Table E9). However, an occupation exhibiting longer work hours on average is neither associated with commissions representing a greater fraction of variable pay (i.e., being more competitive) nor reduced sentiment toward work-life balance. This would suggest the aversion to more competitive variable-paying jobs is not merely a reflection of hours.

One job attribute in particular the literature has found women value in a workplace is female-friendliness (Hotz *et al.*, 2017; Fluchtmann *et al.*, 2024; Liu *et al.*, 2022; Adrjan *et al.*, 2023). We can test whether women face a potential trade-off between female-friendliness and the variable-pay intensity or competitiveness of a job by looking at a separate Glassdoor dataset, workers' ratings of employers' fringe benefits.<sup>29</sup> Similar to pay reports and employer reviews, providing a fringe benefit review satisfies the give-to-get mechanism for visitors to the website. Motivated by Liu *et al.* (2022), we narrow in on workers' ratings of "Maternity & Paternity Leave" to capture a female-friendly benefit. We observe about 17,000 such ratings for full-time, private-sector employees with industry-job title pairs for which we can assign our measures of variable-pay intensity and competitiveness from Glassdoor pay reports.<sup>30</sup> The mean rating is 3.93 (out of 5) while the standard deviation is 1.22.

If there is a trade-off women face between variable pay and female-friendliness, we would anticipate ratings for this female-friendly benefit to be greater in jobs that are less reliant on variable-pay or sales commissions. To this end, we re-estimate a version of equation 2 with, given the thin sample size, less saturated fixed effects. The results are recorded in Table 8. When we consider the relation between our variable-pay intensity index and paid family leave rating, we find a strongly positive relation (column 1) — consistent with higherpaying jobs experiencing improved fringe benefits (e.g., Ouimet and Tate, 2023). However, we find no discrepancy between ratings for men and women (column 2). When we instead consider the competitiveness of the job, i.e., the degree to which variable pay is comprised of commissions, we observe that women, even conditional on the industry and occupation, rate paid family leave lower in jobs that rely more heavily on sales commissions (column 4). One standard deviation greater competitiveness (0.30) is associated with 2.5 percent of a standard deviation lower ratings. This evidence is consistent with more-competitive roles being less female friendly — which may help rationalize the aversion to more commission-intensive roles we observe among female job seekers.

### 8 Concluding Remarks

Our work suggests that the variable pay gender gap may be a structural component of the overall pay gap that is not easily remedied because it is, in part, related to women selecting

<sup>&</sup>lt;sup>29</sup>For further details about this dataset, see for instance, Liu *et al.* (2022) or Gadgil and Sockin (2020).

<sup>&</sup>lt;sup>30</sup>The sample is evenly split by gender and about 70 percent are written by current employees.

out of variable-paying roles. The aversion that women exhibit toward such jobs in their job search, coupled with — and possibly reflecting — disparate experiences with the quality of such jobs, contributes to women sorting out of variable-pay-intensive roles. In turn, as shown in workers' resumes, the gender gap in representation within variable-paying jobs widens over the life cycle. Since firms use bonuses to alleviate agency frictions and retain talent, the aversion of female job seekers to variable-paying jobs may hinder employers from providing such incentives to female employees.

In addition, our results highlight how any policy intervention aimed at closing the variable pay gender gap would also have to address the gap in representation by, for instance, encouraging women to apply to such roles and employers to hire women into them. We caution, however, that such policies need not be welfare-enhancing. If women sidestep variable-paying roles for amenities that other jobs provide, e.g., improved work-life balance, such policies might make women worse off despite harmonizing wages with men (Morchio and Moser, 2024). If, however, an increase in female representation within more competitive roles worked to improve non-wage aspects of work, such as respect, culture, and teamwork, such policies may be welfare enhancing. If other factors, such as asymmetric information in bargaining, influence the variable pay gap, then policies that address informational frictions may narrow pay gaps without such trade-offs (Roussille, 2024).

As new legislation is introduced, e.g., pay transparency policies that mandate job postings include details on compensation, assessing how such legislation pertains to variable pay will be critical. Although pay transparency initiatives have broadly led to reductions in gender pay gaps (Cullen, 2024) with seemingly limited impact on firm performance (Bennedsen *et al.*, 2022), whether such policies narrow the gender gap in variable pay, or the gender gap in representation within variable-paying jobs, is not yet clear. Further, determining whether there are differences in outcomes across the varied ways in which variable pay has been addressed in pay transparency legislation would be of interest. Given the ubiquity of variable pay gaps, even arising within the same firms and job titles, such policies could go a long way toward narrowing the overall gender pay gap.

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Figure 1: Female Representation and Bonus Intensity Across Large U.K. Firms



Notes: This figure relates, among 10,143 U.K. firms that must disclose pay statistics to the U.K. government for 2017-2018, the female share of employees within each firm (y-axis) to the fraction of the firm's employees who receive a bonus (x-axis). The fraction of employees who receive a bonus is rounded to the nearest two-hundredths, and dots are scaled by the number of firms in each bin. U.K. firms are required to disclose such statistics if they have 250 or more employees. Data are publicly available at https://gender-pay-gap.service.gov.uk/.

Figure 2: Female Representation Across Job Titles by Variable-Pay Intensity



Notes: This figure relates the female share of employees with the variable pay intensity of each job. Variable pay intensity is calculated by industry-job title and defined as the principal component of: the variable pay share of total pay and the share of workers that receive variable pay. Each dot reflects the average with the same variable-pay intensity rounded to the nearest hundredth. Black dashed line corresponds to a quadratic fit through these averages. Sample is weighted to match the American Community Survey by industry, occupation, metropolitan area, and sex.



Figure 3: Variable Pay Intensity over the Life Cycle According to Resumes

Notes: This figure plots the resulting coefficients from estimating equation (1) with workers' resumes from Glassdoor,  $\beta_p$  in panel (a) and  $\gamma_p$  in panel (b). Regression includes employer, industry-occupation, calendar year-month the job began, and age fixed effects. Standard errors are clustered by firm. Red vertical bars indicate 95% confidence intervals around each point estimate.

		Overall			Males			Females	
Measure	Ν	mean	sd	N	mean	sd	N	mean	sd
		Panel	A. Com	pensation	n				
Total pay	2.615	86.33	44.90	1.508	93.41	47.56	1.107	76.69	39.00
Base pay	2.615	79.26	36.82	1.508	84.62	38.52	1.107	71.96	33.00
VP share of total pay	2.615	0.06	0.11	1.508	0.07	0.12	1.107	0.04	0.09
Receives variable pay	2.615	0.38	0.49	1.508	0.42	0.49	1.107	0.32	0.47
Receives cash bonus	2.615	0.30	0.46	1.508	0.33	0.47	1.107	0.26	0.44
Receives stock bonus	2.615	0.05	0.21	1.508	0.06	0.24	1.107	0.03	0.16
Receives profit sharing	2.615	0.03	0.16	1.508	0.03	0.18	1.107	0.02	0.14
Receives sales commission	2.615	0.06	0.25	1.508	0.08	0.27	1.107	0.05	0.22
Variable pay	0.987	18.73	24.35	0.638	20.78	25.85	0.349	14.97	20.83
Cash bonus	0.785	11.97	14.34	0.500	13.04	15.12	0.286	10.09	12.67
Stock bonus	0.122	20.01	22.29	0.092	20.63	22.79	0.030	18.11	20.56
Profit sharing	0.070	7.62	9.70	0.050	8.03	10.18	0.021	6.62	8.33
Sales commission	0.169	36.09	33.87	0.114	38.91	34.94	0.055	30.24	30.72
	Par	nel B. Ob	oservable	characte	eristics				
Years of experience	2.615	6.56	6.63	1.508	6.76	6.79	1.107	6.29	6.38
Average years of experience	2.615	5.22	3.56	1.508	5.44	3.75	1.107	4.92	3.26
Managerial job title	2.615	0.24	0.43	1.508	0.24	0.42	1.107	0.24	0.43
VP intensity index	2.615	0.08	0.23	1.508	0.11	0.22	1.107	0.04	0.23
Age	0.897	33.21	8.74	0.527	33.38	8.64	0.370	32.97	8.87
Tenure at least three years	0.236	0.49	0.50	0.146	0.50	0.50	0.089	0.48	0.50
STEM major	0.334	0.35	0.48	0.196	0.43	0.50	0.138	0.22	0.41

Table 1: Summary Statistics for Glassdoor Pay Reports

Notes: This table presents the sample size (N), mean, and standard deviation (sd) for compensation (panel a) and observable characteristics (panel b) for the full sample of pay reports, for male workers, and for female workers. The sample spans 2009–2021 and is restricted to full-time, salaried, private-sector employees. Employee tenure available only for those employees who also complete an employer review and undergraduate major available only for those who also upload a resume. Sample sizes are in millions. Pay is inflation-adjusted using U.S. CPI and reported in thousands of 2018 dollars.

	Me total	ean l pay	Stan devia total	dard ation   pay	Gender rap in	Female	
	М	F	М	F	total pay	share	
Correlation	0.90	0.88	0.88	0.88	0.64	0.95	
Industry-occupations	318	318	318	318	318	318	
ACS weight (in millions)	26.3	20.3	26.3	20.3	46.5	46.5	

Table 2: Comparing Glassdoor and American Community Survey (ACS)

Notes: This table displays correlations between Glassdoor and ACS data from 2009–2021 across Glassdoor industry x two-digit SOC occupations. Correlations are weighted by annual average ACS weight. ACS sample restricted to workers who are in the private or non-profit sector, usually work 35+ hours per week, are at work, worked 50–52 weeks last year, and are in a metro area. Total pay reflects 2018 dollars.

			Within	Within occupation	Within job title
	Raw	Observables	occupation	and firm	and firm
Log total pay	-0.120***	-0.115***	-0.090***	-0.084***	-0.046***
	(0.005)	(0.004)	(0.003)	(0.002)	(0.001)
$\mathbb{R}^2$	0.02	0.14	0.38	0.57	0.77
Ν	$2,\!615,\!379$	$2,\!615,\!379$	$2,\!615,\!379$	$2,\!615,\!379$	$2,\!615,\!379$
Log base pay	-0.099***	-0.094***	-0.068***	-0.066***	-0.032***
	(0.004)	(0.004)	(0.003)	(0.002)	(0.001)
$\mathrm{R}^2$	0.02	0.15	0.39	0.57	0.78
Ν	$2,\!615,\!379$	$2,\!615,\!379$	$2,\!615,\!379$	$2,\!615,\!379$	$2,\!615,\!379$
1(Receives variable pay)	-0.055***	$-0.054^{***}$	$-0.054^{***}$	-0.048***	-0.037***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
$\mathbb{R}^2$	0.01	0.02	0.11	0.29	0.39
Ν	$2,\!615,\!379$	$2,\!615,\!379$	$2,\!615,\!379$	$2,\!615,\!379$	$2,\!615,\!379$
Log variable pay	-0.346***	-0.347***	-0.312***	-0.248***	-0.155***
	(0.030)	(0.030)	(0.016)	(0.011)	(0.009)
$\mathbb{R}^2$	0.02	0.04	0.26	0.56	0.72
Ν	$931,\!802$	931,802	$931,\!802$	$931,\!802$	$931,\!802$
Worker observables		$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Industry–occupation FE			$\checkmark$	$\checkmark$	
Firm FE				$\checkmark$	$\checkmark$
Industry–job title FE					$\checkmark$

Table 3: Gender Pay Gap in Base, Variable, and Total Pay

Notes: This table presents the coefficients on a female indicator, run separately for log total pay, log base pay, an indicator for the receipt of variable pay, and log variable pay. Worker observables include a quadratic in years of experience along with state and year fixed effects. Sample is weighted to match the American Community Survey by industry, occupation, metropolitan area, and sex. Standard errors are clustered by firm. Significance levels: \* 10%, \*\* 5%, \*\*\* 1%.

(Residual) Variable of interest	(Resid	(Residual) Female employment share					
VP intensity index	$-0.227^{***}$ (0.034)	$-0.255^{***}$ (0.025)		$-0.139^{***}$ (0.027)			
Average job satisfaction rating			$0.070^{***}$ (0.020)	$\begin{array}{c} 0.074^{***} \\ (0.020) \end{array}$			
Managerial job title			$-0.030^{**}$ (0.012)	$-0.024^{*}$ (0.012)			
Standard deviation of log pay			$-0.124^{**}$ (0.049)	$-0.150^{***}$ (0.049)			
Average of log pay			$-0.144^{***}$ (0.025)	$-0.110^{***}$ (0.025)			
Sales commission share of VP			$-0.166^{***}$ (0.034)	$-0.115^{***}$ (0.032)			
Industry–occupation FE		$\checkmark$	$\checkmark$	$\checkmark$			
VP intensity index std. dev.	0.17	0.17	0.17	0.17			
Ν	$14,\!247$	$14,\!247$	$14,\!247$	$14,\!247$			
Adjusted R <sup>2</sup>	0.04	0.55	0.57	0.58			

Table 4: Female Employment Share and Variable Pay Intensity

Notes: This table displays the association between the female employment share and our measure for variable pay intensity incorporating five covariates. Each observation is an industry-job title. The principal component of variable pay and each covariate are first demeaned by year, state, and employer. Sample is restricted to industry-job titles with sample size above the average (at least 8 observations). Sample is weighted to match the American Community Survey by industry, occupation, metropolitan area, and sex. Standard errors are clustered by industry-occupation. Significance levels: \* 10%, \*\* 5%, \*\*\* 1%.

	Difference in apply rate (female - male)						
VP intensity index	$-0.325^{***}$ (0.037)	$-0.258^{***}$ (0.047)	$-0.231^{***}$ (0.048)	$-0.117^{**}$ (0.056)			
Average job satisfaction rating			$0.026 \\ (0.016)$	$0.027 \\ (0.016)$			
Managerial job title			$\begin{array}{c} 0.023 \\ (0.021) \end{array}$	$0.016 \\ (0.021)$			
Standard deviation of log pay			$\begin{array}{c} 0.145 \\ (0.091) \end{array}$	$\begin{array}{c} 0.291^{***} \\ (0.095) \end{array}$			
Average of log pay			$-0.055^{*}$ (0.031)	$-0.118^{***}$ (0.035)			
Sales commission share of VP				$-0.205^{***}$ (0.041)			
Industry-occupation FE		$\checkmark$	$\checkmark$	$\checkmark$			
Mean apply rate	0.97	0.97	0.97	0.97			
VP intensity index std. dev. N	$0.20 \\ 143817$	$0.20 \\ 143817$	$0.20 \\ 143817$	$\begin{array}{c} 0.20\\ 143817\end{array}$			

Table 5: Gender Differences in Search Activity and Variable Pay Intensity

Notes: This table displays the association between variable-pay intensity (based on the advertised job title) and the gender difference in application rates. Each regression includes calendar day and metro fixed effects. Standard errors are clustered by firm. Significance levels: \* 10%, \*\* 5%, \*\*\* 1%.

Table 6: Tenure from	Workers'	Resumes	and	Variable Pay Intensity	

		Logarithm of firm tenure					
	All w	orkers	Ages	18-26	Ages 27–65		
VP intensity index	$0.336^{***} \\ (0.014)$	$\begin{array}{c} 0.322^{***} \\ (0.016) \end{array}$	$0.445^{***} \\ (0.024)$		$0.261^{***} \\ (0.014)$		
Female x VP intensity index	$-0.039^{***}$ (0.013)	$-0.054^{***}$ (0.020)	$-0.084^{***}$ (0.021)	$-0.053^{**}$ (0.025)	-0.008 (0.017)		
Female	$0.015^{***}$ (0.003)		$0.019^{***}$ (0.005)	$0.025^{***}$ (0.006)	$0.005 \\ (0.005)$		
Std. dev. VP intensity index Observations Adjusted R <sup>2</sup> Industry–occupation FE Worker FE	0.25 396319 0.25 $\checkmark$	0.25 396319 0.37	0.24 174876 0.28 $\checkmark$	$0.22 \\ 156210 \\ 0.34$	$0.26 \\ 204277 \\ 0.24 \\ \checkmark$		
Industry–job title FE		V		$\checkmark$			

Notes: This table relates the logarithm of firm tenure on workers' resumes to the variable pay intensity of their jobs. Each specification includes fixed effects for the firm, the worker's age, and the calendar month the job began. Standard errors are clustered by firm. Significance levels: \*10%, \*\*5%, \*\*\*1%.

	Overall	Career opportunities	Compensation and benefits	Culture and values	Senior management	Work-life balance			
	Panel A. VP intensity index								
Female	-0.031***	-0.017***	0.015***	-0.038***	-0.048***	-0.076***			
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)			
VP intensity index	0.302***	0.384***	0.339***	0 284***	0.287***	0 157***			
	(0.020)	(0.022)	(0.022)	(0.021)	(0.021)	(0.026)			
Female v VP intensity index	-0 125***	-0 133***	-0.053**	-0 106***	-0 088***	-0.141***			
Tenhate x VI moensity matex	(0.022)	(0.022)	(0.022)	(0.024)	(0.024)	(0.023)			
Ν	446193	446193	446193	446193	446193	446193			
Adjusted R <sup>2</sup>	0.25	0.22	0.21	0.24	0.24	0.22			
	Panel B. S	Sales commissio	n share of VP						
Female	-0.026***	-0.022***	0.017***	-0.034***	-0.042***	-0.069***			
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)			
Sales commission share of VP	-0.026	-0.012	0.078***	0.003	0.011	-0.086***			
	(0.017)	(0.016)	(0.016)	(0.018)	(0.018)	(0.030)			
Female x Sales commission share of VP	-0.060***	-0.030*	-0.051***	-0.052***	-0.064***	-0.058***			
	(0.016)	(0.016)	(0.015)	(0.017)	(0.017)	(0.017)			
Ν	419592	419592	419592	419592	419592	419592			
Adjusted R <sup>2</sup>	0.25	0.22	0.21	0.24	0.24	0.22			

#### Table 7: Ratings of Job Satisfaction and Variable Pay Intensity

Notes: This table displays how worker satisfaction relates to the intensity with which their jobs rely on variable pay (panel A) or rely on sales commissions for variable pay (panel B) and differs by gender. Sample is restricted to full-time workers who report their job titles and for whom ages are available. Each specification includes a dummy for the worker is a current employee and firm, industry-occupation, age, and year-month fixed effects. Standard errors are clustered by firm. Significance levels: \* 10%, \*\* 5%, \*\*\* 1%.

Table 8: Ratings of Paid Family Leave Benefit and Variable Pay Intensity

	Rating: Paternity & Maternity Leave				
Female	-0.069***	-0.044*	-0.047*		
	(0.021)	(0.025)	(0.024)		
VP intensity index	0.297**		0.306**		
	(0.121)		(0.118)		
Female x VP intensity index	0.078		0.059		
	(0.094)		(0.087)		
Sales commission share of VP		0.076	0.036		
		(0.054)	(0.047)		
Female x Sales commission share of VP		-0 101**	-0.091*		
Temate x bares commission share of VI		(0.049)	(0.047)		
N	17076	17076	17076		
Adjusted R <sup>2</sup>	0.07	0.07	0.07		

Notes: This table displays how workers' satisfaction with paid family leave relates to the intensity with which their jobs rely on variable pay or sales commissions. Sample is restricted to full-time workers for whom we can assign variable-pay intensity according to the industry and job title. Each specification includes a dummy variable for the worker is a current employee along with year-month and industry-occupation fixed effects. Standard errors are clustered by industry-occupation. Significance levels: \* 10%, \*\* 5%, \*\*\* 1%.

# INTERNET APPENDIX

### A Representativeness of Glassdoor Data

In this appendix, we present evidence that Glassdoor pay data have external validity by considering representative microdata from the American Community Survey (ACS) through IPUMS USA (Flood *et al.*, 2020). We make comparisons at the industry-occupation level based on two-digit standard occupational classification (SOC) occupations. For industries, we map the 1990 Census Bureau classifications in the ACS to Glassdoor industries. There are 18 Glassdoor industries we can crosswalk with the ACS using the following mapping: Accounting & Legal (841, 890); Arts, Entertainment & Recreation (800–810, 872); Biotech & Pharmaceuticals (891); Business Services (721–731, 740–741, 882, 891–893); Construction, Repair & Maintenance (60, 751–760); Finance (700–710); Health Care (812–840, 861–870); Information Technology (732); Insurance (711); Manufacturing (100–392); Media (440); Non-Profit (880–881); Oil, Gas, Energy & Utilities (450–472); Real Estate (712); Retail (580–640, 642–691); Telecommunications (441–442); Transportation & Logistics (400–432); and Travel & Tourism (762–770).

First, we examine to what extent there may be selection into the Glassdoor sample by considering how the distribution of earnings differs between Glassdoor and the ACS. We look first at the gender gap in total earnings. Although the differences between the two samples are normally distributed, Glassdoor underestimates the gender gap by on average 8.6 log points (Figure A1: panel a), indicating that our sample either positively selects on females or negatively selects on males. Comparing male and female earnings in the two samples reveals that it is the former. While there is almost no selection for males into Glassdoor, with a mean difference of 0.4 log points (Figure A1: panel b), females positively select into Glassdoor by an average of 9.1 log points (Figure A1: panel c). This selection on highwage females could reflect a number of factors, some that are observable (e.g., over-sampling from higher-paying firms) and some that are not (e.g., over-sampling greater motivation). One we can empirically rule out, which could contribute to gender disparities in variable pay, is differences in pay satisfaction. If women are more likely to submit Glassdoor pay reports when they are less satisfied with their compensation, perhaps because they did not receive a bonus, then our estimated variable pay gaps would likely be biased upward. From our sample of employer reviews, we observe workers' satisfaction with compensation and benefits. Because each worker has an unique identifier, we can track whether the worker also provides a pay report for that job and whether that decision relates to their own satisfaction with compensation. We show, in Table A1, that although workers who are more satisfied

with pay are more likely to submit a pay report, that relation does not differ by gender.

That Glassdoor selects on comparatively high-earning females, if anything, runs counter to us finding a gender pay gap. As such, our estimates may even *understate* variable pay gaps in the U.S. economy, though we do not find evidence this selection is related to variable pay. In Table A2, we relate the difference in the gender gap between the ACS and Glassdoor to the variable-pay intensity of jobs in each industry-occupation and find no significant relation. Moreover, the gender gaps in variable pay persist when we consider only industry-occupations with similar gender gaps in the two samples (Tables A3). We conclude the gender pay gap is not an artifact of studying Glassdoor data, but rather reflects structural labor market forces.

We also consider female employment shares across industry-occupations between the two datasets. The distribution of differences between Glassdoor and the ACS is normally distributed and, with a mean of 2.1 percentage points, is centered near zero (Figure A2). Thus, while Glassdoor selects more males overall, it does not select more males conditional on the job, and if anything, appears to select slightly fewer males. Reassuringly, although the distribution is somewhat diffuse, our findings regarding female representation in variable-paying jobs persist if we were to restrict the sample to only industry-occupations with similar female employment shares between the Glassdoor and ACS data (Table A4). We conclude the gender gap in representation in variable-paying jobs also does not appear to be an artifact of studying Glassdoor data but rather a broad feature of the U.S. labor market.

We also consider the possibility that workers systematically disingenuously report their earnings on Glassdoor, possibly inflating or deflating their earnings. Our findings, for instance, could reflect a propensity among men for over-reporting variable pay and women for under-reporting variable pay. To mitigate this concern, we narrow in on a subset of workers for whom we can reasonably assume report the truth. To identify such workers, we rely on the notion that statements are considered to be more honest or truthful when they are written using language that is concrete, as opposed to language that is abstract (Hansen and Wänke, 2010). Although pay reports do not have written statements with which we can determine the concreteness with which each worker speaks, employer reviews do. For those workers who also provide an employer review, we assign the text of each review a degree of concreteness using the mapping of words to concreteness scores produced by Brysbaert et al. (2014). For each review, we take the mean score across words that could be successfully mapped to this list. We then consider a review to use comparatively concrete language if its score is in the top 10 percent of the sample. We then estimate in Table A5 gender gaps in base and variable pay for this subset of workers whom we observe speak concretely. The gender gaps in this sub-sample are similar to the gaps observed among the full sample of pay reports. Thus, it does not appear the Glassdoor sample is subject to disingenuous overor under-reporting that would distort our conclusions about the variable pay gap.

We also examine whether Glassdoor data can speak to international pay dynamics by considering the United Kingdom. We compare the gender gaps in variable pay and total pay disclosed to the U.K. government by each firm for the 2017–2018 period to that observed in Glassdoor. Looking at the distribution of the differences in the gender gaps between the two datasets for the receipt of variable pay, the magnitude of variable pay, and total pay (Figure A3) reveals normal, albeit diffuse, distributions centered near zero — suggesting no clear selection bias by gender in the firms represented in Glassdoor. Further, we investigate whether firms that disclosed larger gender gaps have wider gender gaps in Glassdoor. For each of the three measures, we estimate a 1-percentage-point larger reported gap is associated with one-sixth to one-quarter of a percentage point wider gap in Glassdoor (Table A6). While these relations are not particularly strong, we take assurance in knowing that each is positive and statistically significant, and caveat that firms' reported statistics include employees that are not full-time, are not disaggregated by occupation, and may be fraudulent.<sup>31</sup>

Figure A1: Comparison of Average Total Pay Between Glassdoor and ACS



Notes: This figure plots the distribution, across Glassdoor industry x two-digit SOC occupation pairs, of the log difference between the gender gap in total pay (panel a), total pay for males (panel b), and total pay for females (panel c) between Glassdoor and the American Community Survey. The dashed blue line reflects the mean difference and the short-dashed black line reflects when the mean is the same in the two datasets.

<sup>&</sup>lt;sup>31</sup>For instance, Cox (2019) describes how some law firms argue their high-earning (largely male) partners should be excluded from the statistics because they are owners, not employees. Further, Ehrenberg-Shannon *et al.* (2017) conclude that one-in-twenty firms initially reported statistically improbable gender gaps.

Figure A2: Comparison of Gender Representation Gaps for Glassdoor and the ACS



Notes: This figure plots the distribution, across Glassdoor industry x two-digit SOC occupation pairs, of the difference in female employment share between Glassdoor and the American Community Survey. The dashed blue line reflects the mean difference and the short-dashed black line reflects when the mean is the same in the two datasets.

Figure A3: Comparison of Gender Gap in Total Pay, Variable Pay Incidence, and Variable Pay Magnitude for Glassdoor and Reported Statistics to the U.K. Government in 2017–2018



Notes: This figure plots the distribution across firms of the gender gap in total pay (panel a), the receipt of variable pay (panel b), and the magnitude of variable pay among employees who receive it (panel c) between Glassdoor and the disclosed pay statistics reported to the U.K. government in 2017–2018. The Glassdoor sample is restricted to U.K. pay reports submitted in 2017 and 2018. We restrict the sample to firms with at least 5 male and female 2017–2018 U.K. pay reports in Glassdoor. For the incidence of variable pay, excluded are firms that disclose gaps above 30 percentage points. For the magnitude of variable pay, excluded are firms that disclose gaps above 500 percent. The dashed blue line reflects the mean difference and the short-dashed black line reflects when the mean is the same in the two datasets.



#### Figure A4: Comparison of Sample Composition Between the ACS and Glassdoor





(b) Occupations

Notes: Industry corresponds to Glassdoor industries (panel a) and occupation (panel b) corresponds to twodigit SOC occupations.

	Whether also submits a pay report					
Compensation and benefits satisfaction rating	$     0.065^{***} \\     (0.003) $	$0.061^{***}$ (0.004)	$0.050^{***}$ (0.003)	$0.038^{***}$ (0.003)		
Female		$-0.192^{***}$ (0.018)	$-0.128^{***}$ (0.017)	$-0.047^{***}$ (0.016)		
Female <b>x</b> compensation and benefits satisfaction rating		0.003 (0.004)	-0.000 (0.004)	-0.005 $(0.004)$		
Pseudo R <sup>2</sup>	0.01	0.01	0.06	0.11		
Ν	365755	365755	365755	365755		
Worker observables	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$		
Firm FE			$\checkmark$	$\checkmark$		
Industry–job title FE				$\checkmark$		

Table A1: Pay Satisfaction	and Whether Workers	Provide a Pay Report
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Notes: This table displays how the coefficients from a Poisson regression between a worker's satisfaction with compensation and benefits from their employer review and whether they choose to also provide a pay report for that employer that year. Compensation and benefits ratings are on a 1–5 stars Likert scale. Regressions are estimated using the two-way high-dimensional fixed effects logit model of Correia (2016). Sample is restricted to full-time workers who report their job titles and for whom age is available. Worker observables include an indicator for is current employee along with age and year-month fixed effects. Standard errors are clustered by firm.

	VP intensity index			
Glassdoor log gender gap - ACS log gender gap	-0.052 (0.034)	0.004 (0.201)	-0.037 (0.189)	
Average DV	-0.058	-0.038	0.072	
Standard deviation DV	0.146	0.158	0.140	
Weighted by ACS weights		$\checkmark$		
Weighted by Glassdoor sample size			$\checkmark$	
Industry–occupation pairs	318	318	318	

Table A2: Variable Pay Measures Across Industry-occupations and Differences in the Gender Gap Between ACS and Glassdoor

Notes: This table reports the relation, across Glassdoor industry x two-digit SOC occupation pairs, between the difference in the gender gaps from Glassdoor and the American Community Survey and the variable-pay intensity of an industry-occupation, where variable-pay intensity for an industry-occupation is measured as the average of its industry-job titles' variable-pay intensities. Standard errors are Huber-White robust.

Table A3: Gender Pay Gap in Base, Variable, and Total Pay, Only Industry-Occupations With Similar Total Gaps in the ACS

			Within	Within occupation	Within job title
	Raw	OLS	occupation	and firm	and firm
Log total pay	$-0.321^{***}$	-0.300***	-0.089***	-0.085***	$-0.042^{***}$
	(0.008)	(0.007)	(0.004)	(0.003)	(0.002)
$\mathbb{R}^2$	0.11	0.25	0.50	0.66	0.83
Ν	$725,\!393$	$725,\!393$	$725,\!393$	$725,\!393$	725,393
Log base pay	-0.292***	-0.273***	-0.072***	-0.070***	-0.033***
	(0.007)	(0.006)	(0.004)	(0.003)	(0.002)
$\mathbf{R}^2$	0.10	0.25	0.50	0.66	0.83
Ν	725,393	$725,\!393$	$725,\!393$	$725,\!393$	725,393
1(Receives variable pay)	-0.121***	-0.116***	-0.053***	-0.048***	-0.035***
	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)
$\mathbb{R}^2$	0.03	0.04	0.10	0.31	0.42
Ν	$725,\!393$	$725,\!393$	$725,\!393$	$725,\!393$	$725,\!393$
Log variable pay	-0.772***	-0.731***	-0.304***	-0.213***	$-0.127^{***}$
	(0.038)	(0.038)	(0.025)	(0.020)	(0.017)
$\mathbf{R}^2$	0.09	0.13	0.29	0.60	0.75
Ν	272,910	$272,\!910$	$272,\!910$	$272,\!910$	272,910
Worker observables		$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Industry–occupation FE			$\checkmark$	$\checkmark$	
Firm FE				$\checkmark$	$\checkmark$
Industry–job title FE					$\checkmark$

Notes: This table presents the coefficients on a female indicator, run separately for log total pay, log base pay, the incidence of variable pay, and log variable pay. Worker observables include a quadratic in years of experience along with state and year fixed effects. Sample is restricted to industry-occupation pairs with gender gaps in total pay that are within 5 log points of the gender gaps in total earnings observed in the ACS. Sample is weighted to match the American Community Survey by industry, occupation, metropolitan area, and sex. Standard errors are clustered by firm.

(Residual) Variable of interest	(Resid	lual) Female	employment	share
VP intensity index	-0.183***	-0.218***		-0.110**
U U	(0.057)	(0.038)		(0.047)
Average job satisfaction rating			0.063	0.066
			(0.042)	(0.042)
Managerial job title			0.003	0.011
			(0.018)	(0.016)
Standard deviation of log pay			-0.127	-0.138
			(0.098)	(0.098)
Average of log pay			-0.134***	-0.111***
			(0.041)	(0.039)
Sales commission share of VP			-0.100**	-0.065*
			(0.040)	(0.035)
Industry–occupation FE		$\checkmark$	$\checkmark$	$\checkmark$
VP intensity index std. dev.	0.17	0.17	0.17	0.17
Ν	$5,\!462$	$5,\!462$	$5,\!462$	5,462
Adjusted $\mathbb{R}^2$	0.03	0.56	0.58	0.58

Table A4: Predicting Female Employment Share, Only Industry-Occupations With Similar Female Employment Shares in the ACS

Notes: This table displays the association between the female representation within a job and our measure for the variable pay intensity of the job, incorporating five covariates that pertain to earnings variance, competition for sales commissions, managerial responsibilities, job quality, and average earnings. Sample is restricted to industry-occupation pairs with female employment shares that are within 5 percentage points of the female employment shares observed in the ACS. Each observation reflects an industry-job title. The principal component of variable pay and each of the five covariates of interest are first demeaned by year, state, and employer. The average of log pay, standard deviation of log pay, and sales commission share of variable pay are calculated by industry-job title pair using Glassdoor earnings data. Average job satisfaction rating reflects the mean overall rating by year-industry-job title triple among Glassdoor employer reviews. Sample is restricted to industry-job titles with sample size above the average (at least 8 observations). Sample is weighted to match the American Community Survey by industry, occupation, metropolitan area, and sex. Standard errors are clustered by industry-occupation.

	Log ba	ise pay	1(Recei	ves VP)	Log vari	able pay
Female	$\begin{array}{c} -0.066^{***} & -0.066^{***} \\ (0.001) & (0.004) \end{array}$		$-0.238^{***}$ (0.004)	$-0.256^{***}$ (0.023)	$-0.061^{***}$ (0.001)	$-0.055^{***}$ (0.006)
Uses concrete language		$\checkmark$		$\checkmark$		$\checkmark$
Ν	2,615,379 34,46		964, 132	$13,\!893$	$2,\!615,\!379$	34,464
$\mathbb{R}^2$	0.58	0.64	0.46	0.53	0.23	0.33

Table A5: Gender Pay Gaps for Workers Who Use Comparatively Concrete Language

Notes: This table presents the coefficients on a female indicator, run separately for log base pay, an indicator for the receipt of variable pay, and log variable pay for the full sample and for workers who provide an employer review that uses relatively concrete language. To determine a review's concreteness, we assign each word the concreteness score from the list of Brysbaert *et al.* (2014). For each review, we take the mean score across matched words. We consider a review to use concrete language if its mean score is in the top 10 percent of the sample. Worker observables include a quadratic in years of experience along with state, year, industry-occupation, and firm fixed effects. Regressions are unweighted. Standard errors are clustered by firm. Significance levels: \*10%, \*\*5%, \*\*\*1%.

Table A6: Predicting Firm-Specific Gender Gaps Disclosed in the 2017–2018 U.K. Reported Statistics using Glassdoor Data

		DV: Glassdoor gender gap 2017–2018											
	Share re	eceives	Magni	tude of	Magnitude of								
	bonus	s pay	bonu	is pay	total pay								
Disclosed gender gap 2017–2018	$0.279^{***}$	$0.170^{*}$	$0.155^{*}$	$0.230^{**}$	$0.203^{**}$	$0.219^{**}$							
	(0.093)	(0.090)	(0.092)	(0.111)	(0.079)	(0.086)							
Minimum observations in Glassdoor Number of U.K. firms	5 733	$\begin{array}{c} 10\\ 431 \end{array}$	$5\\269$	$\begin{array}{c} 10 \\ 155 \end{array}$	$5 \\ 621$	$\begin{array}{c} 10\\ 369 \end{array}$							

Notes: This table reports the relation across firms between the difference in the gender gap in the receipt of variable pay, the magnitude of variable pay among those who receive it, and total pay, between Glassdoor and U.K. reported statistics. The Glassdoor sample is restricted to U.K. pay reports submitted in 2017 and 2018. The gender gap in the receipt of variable pay is measured as fraction of men that receive variable pay minus the fraction of women that receive variable pay. The gender gap in the magnitude of variable pay is measured as the difference in the median variable pay received between men and women, conditional on receiving variable pay, as a fraction of the median for men. The gender gap in total pay is measured as the difference in the median total pay received between men and women as a fraction of the median for men. To account for outliers, excluded are firms that disclose gender gaps with magnitudes not within: 25 percentage points for the receipt of variable pay, 500 percent for the magnitude of variable pay, and 30 percent for total pay. Minimum observations in Glassdoor reflects the number of male and female 2017–2018 U.K. pay reports required to be included. Standard errors are bootstrapped.

### **B** Additional Dimensions of the Variable Pay Gap

We first briefly describe the additional observables we see in the Glassdoor data. For workers who provide their resumes on Glassdoor when creating a profile, of which there are 334,000, we observe their universities attended, degrees attained, and majors studied. We view these education-related characteristics as proxies for an employee's latent ability and social network.<sup>32</sup> We construct a measure for job seniority by calculating the median years of experience within an industry-job title pair.<sup>33</sup> For whether the pay report is for a managerial role, in the spirit of Gornall *et al.* (2021), we create an indicator for the job title includes a managerial identifier, such as chief, director, manager, supervisor, principal, or president, making sure to exclude instances where the role is considerably junior, e.g., assistant manager, or task-specific, e.g., account manager, office manager, or product manager.

Components of variable pay Looking at the raw distribution of each variable pay type by gender (Figure D1) reveals that, conditional on their receipt, women receive on average less of each type. These gaps cannot be explained by observable characteristics, e.g., human capital, job title, or employer (Table B1). Although the gender gap is present in all four types, it narrows monotonically as we control for differences across occupations, firms, and job titles. In our most conservative regressions looking within the same industry-job title pairs, the gender gap is largest in magnitude for cash bonuses and sales commissions (each 11–12 percent), followed by stock (9 percent) and profit sharing (7 percent).

With respect to the incidence of variable-pay, a gender gap is present in all four types. Under our most conservative specification, the gender gap in incidence is largest for cash bonuses (3.3 percentage points), followed by stock (1.4 p.p.), sales commissions (1.2 p.p.), and profit sharing (0.8 p.p.).<sup>34</sup> Under our most conservative approach, women also experience a 2.9-percentage-points lower probability of receiving a second type of variable pay conditional on receiving at least one. Even when they are compensated with variable pay, women systematically receive less by receiving fewer types.

**Typical determinants of the gender pay gap** Next, we explore whether known determinants of the gender pay gap can help explain the variable pay gap. We identify three

 $<sup>^{32}</sup>$ Altonji *et al.* (2016) describes college major as both pre-college ability and coursework.

 $<sup>^{33}</sup>$ Sockin and Sockin (2019) show that years of experience is a reasonable proxy for job hierarchy by analyzing the minimum required years of experience listed in job advertisements.

<sup>&</sup>lt;sup>34</sup>Our estimates are comparable with McGee *et al.* (2015), who estimate women are 1.6 percentage points less likely to receive commissions and 1.8 percentage points less likely to receive all other bonuses. In our most comparable approach, we find a smaller gap for stock (0.9 percentage points), a slightly larger gap for commissions (2.0 percentage points), and a noticeably larger gap for cash (3.3 percentage points).

worker characteristics that command large premia in pay and that the literature has documented strongly correlates with the gender pay gap: work experience, firm tenure, and job hierarchy.<sup>3536</sup> We also consider two occupation characteristics based on the literature. The first is the degree to which a job relies on science, technology, engineering and math (STEM) skills.<sup>37</sup> We label an occupation STEM-intensive if the occupation's fraction of workers (based on their resumes) who studied STEM is above the sample median. Second, because occupations with greater female employment shares tend to pay less (Levanon *et al.*, 2009), we label an occupation as male-dominated if its female employment share is below the sample median. Allowing for differential pay premia by gender, we estimate our Mincerian regression along each of these five partitions and record the results for the receipt of variable pay and log variable pay in panels A and B of Table B2, respectively. For incidence, the gender gap is universal at at least 4 percentage points, with even starker gaps in high-experience and high-seniority jobs. For the magnitude of variable pay, while the gaps are 7–10 percentage points greater in jobs that are high-experience, less-STEM-intensive, or more male-dominated, there is a gap of at least 15 percent in every partition.

Worker ability For the subset of workers for whom we observe their educational histories, since choice of major is correlated with gender (Zafar, 2013), we investigate the extent to which the variable pay gap reflects differences in unobserved ability and sorting across majors.<sup>38</sup> To this end, we re-examine our Mincerian analysis within this sub-sample but now accounting for differences across workers in the undergraduate university they attended, their major of study, and graduate degree attained (if any). Again, observable differences cannot account for the sizable gaps we observe in variable pay (Table B3). Although accounting for these additional factors closes the gender gap in base pay by a substantive 14 percent, the gap in the receipt of variable pay fails to attenuate at all while that for the magnitude of variable pay attenuates only 4 percent. As such, collegiate background, our proxy for ability and perhaps social network, cannot explain gender differences in variable pay.

**Signing bonuses** Although we do not observe workers' contracts, and cannot distinguish whether variable pay is a reward for performance or promised compensation, there is one contracting dimension related to variable pay for which we can proxy: signing bonuses. To

<sup>&</sup>lt;sup>35</sup>Grund (2015), for instance, shows the pay gap widens as men and women progress through their careers. <sup>36</sup>High experience, high tenure, or high seniority reflect the years of experience, years with the firm, or

industry-job title's median years experience being above the sample averages of 7, 2, and 6 years, respectively. <sup>37</sup>Beede *et al.* (2011), for instance, find the gender gap is noticeably narrower within STEM fields and

that women account for only about one-quarter of STEM jobs.

<sup>&</sup>lt;sup>38</sup>Paglin and Rufolo (1990), Brown and Corcoran (1997), and McDonald and Thornton (2007) link the gender gap in total pay among recent college graduates to differences in fields of study of highest degree.

do this, we narrow our sample to workers for whom we also observe their tenure with the firm (because they also provided an employer review), and then split the sample into those with less than one year of tenure, i.e., a new hire, and those with longer tenure. We focus on cash bonuses because such pay will likely have already been dispensed and conceivably reflects onboard incentives rather than performance. We find the gender gap in signing bonuses is largely comparable to that observed for cash bonuses more broadly (Table B4). Among those who receive a cash bonus, the gender gap for new hires is 25 log points, similar in magnitude to the 24 log points in one-off bonuses (which includes relocation, tuition, and retention at year-end bonuses in addition to a signing bonus) observed among graduating MBA students (Reuben *et al.*, 2024). In terms of receiving a signing bonus, women are 3 percentage points less likely. Disparities in variable pay thus arise even before a job begins, and not just for business school graduates, but more broadly throughout the U.S. labor market.

				Within	Within
			Within	occupation	job title
	Raw	OLS	occupation	and firm	and firm
1(Beceives cash bonus)	-0 033***	-0 032***	-0 033***	-0 032***	-0 025***
r(necerves cash bonus)	(0.002)	(0.002)	(0.000)	(0.002)	(0.020)
D <sup>2</sup>	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
R-	0.01	0.01	0.08	0.27	0.30
N	2,615,379	2,615,379	2,615,379	2,615,379	2,615,379
1(Beceives stock bonus)	-0.012***	-0.012***	-0 009***	-0.008***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.000)	(0,000)
$\mathbf{D}^2$	(0.001)	(0.001)	(0.001)	0.20	(0.000)
N	2.615.370	2.615.370	2.615.270	2.615.270	2.615.270
	2,015,579	2,015,579	2,015,579	2,015,579	2,015,579
1(Receives profit sharing)	-0.012***	-0.012***	-0.008***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\mathbb{R}^2$	0.00	0.01	0.02	0.23	0.30
N	2.615.379	2.615.379	2.615.379	2.615.379	2.615.379
	_,010,010	_,010,010	=,010,010	_,010,010	2,010,010
1(Receives sales commissions)	$-0.016^{***}$	$-0.017^{***}$	-0.020***	-0.016***	-0.011***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
$\mathbb{R}^2$	0.01	0.01	0.13	0.31	0.46
Ν	2,615,379	2,615,379	2,615,379	2,615,379	2,615,379
	, ,	, ,	, ,	, ,	, ,
$1(\text{Receives multiple types} \mid \text{receives VP})$	-0.044***	-0.043***	-0.027***	$-0.024^{***}$	$-0.019^{***}$
	(0.007)	(0.006)	(0.003)	(0.003)	(0.003)
$\mathbb{R}^2$	0.01	0.01	0.04	0.31	0.42
Ν	$931,\!802$	$931,\!802$	$931,\!802$	$931,\!802$	$931,\!802$
	0.004***	0.004***	0.000***	0.005***	0 105***
Log cash bonus	-0.204	-0.264	-0.233	-0.205	-0.125
<b>D</b> <sup>2</sup>	(0.028)	(0.027)	(0.015)	(0.010)	(0.009)
R <sup>2</sup>	0.01	0.06	0.25	0.53	0.70
N	$730,\!128$	730,128	730,128	$730,\!128$	$730,\!128$
Log stock bonus	-0.348***	-0.347***	-0 112***	-0 142***	-0 114***
hog stook sonas	(0.086)	(0.072)	(0.038)	(0.034)	(0.032)
B <sup>2</sup>	0.05	(0.072)	0.28	0.50	0.69
N	105 024	105 024	105.024	105 024	105 024
IN	105,024	105,024	105,024	105,024	105,024
Log profit sharing	$-0.217^{***}$	-0.236***	-0.185***	$-0.107^{***}$	$-0.074^{***}$
	(0.060)	(0.057)	(0.053)	(0.033)	(0.018)
$\mathbb{R}^2$	0.03	0.08	0.18	0.62	0.76
N	50.074	50.074	50.074	50.074	50.074
	00,011	00,011	00,011	00,011	00,011
Log sales commissions	-0.390***	$-0.381^{***}$	$-0.282^{***}$	$-0.188^{***}$	$-0.139^{***}$
	(0.038)	(0.037)	(0.028)	(0.021)	(0.019)
$\mathbb{R}^2$	0.03	0.06	0.20	0.56	0.69
Ν	$148,\!571$	$148,\!571$	148,571	148,571	$148,\!571$
		/	/	/	/
Worker observables		$\checkmark$	$\checkmark$	√	$\checkmark$
Industry–occupation FE			$\checkmark$	$\checkmark$	
Firm FE				$\checkmark$	$\checkmark$
Industry–job title FE					$\checkmark$

#### Table B1: Gender Gap in Magnitude and Incidence of Each Variable Pay Type

Notes: This table presents the coefficients on a female indicator, run separately for the magnitude and incidence of each variable pay type, along with an indicator for receiving two or more types conditional on receiving at least one. Worker observables include a quadratic in years of experience along with state and year fixed effects. Sample is weighted to match the American Community Survey by industry, occupation, metropolitan area, and sex. Standard errors are clustered by firm.

	High experience	High tenure	High seniority	STEM- intensive occupation	Male- dominated occupation
	Panel A.	1(Receives	variable pay)		
Female	$-0.043^{***}$ (0.002)	$-0.061^{***}$ (0.007)	$-0.043^{***}$ (0.002)	$-0.050^{***}$ (0.002)	$-0.047^{***}$ (0.004)
Standalone indicator	$0.055^{***}$ $(0.003)$	$0.066^{***}$ (0.008)	$0.059^{***}$ (0.004)		
Female x indicator	$-0.015^{***}$ (0.004)	$0.003 \\ (0.009)$	$-0.022^{***}$ (0.004)	$0.006 \\ (0.005)$	-0.002 (0.004)
Ν	2615379	213791	2615379	2615379	2615379
	Pane	el B. Log var	iable pay		
Female	$-0.218^{***}$ (0.013)	$-0.257^{***}$ (0.034)	$-0.243^{***}$ (0.012)	$-0.283^{***}$ (0.013)	$-0.210^{***}$ (0.019)
Standalone indicator	$0.407^{***}$ (0.014)	$0.175^{***}$ (0.025)	$0.275^{***}$ (0.020)		
Female x indicator	$-0.081^{***}$ (0.020)	$0.003 \\ (0.043)$	-0.005 (0.025)	$0.108^{***}$ (0.022)	$-0.074^{***}$ (0.021)
Ν	964132	88668	964132	964132	964132

Table B2: Typical Determinants of the Gender Pay Gap

Notes: This table displays the gender gaps in the incidence (panel a) and magnitude (panel b) of variable pay between sub-populations of workers. High experience reflects above-average (7+) years of experience. High tenure reflects above-average (3+) years of employment with the firm. High seniority reflects industry-job title pairings for which the median years of experience is more than 6 years. A STEM-intensive occupation reflects an industry-occupation pair with an above-average share of college graduates with STEM degrees. Based on the National Survey of Student Engagement, we partition majors into four STEM (Biological Sciences, Engineering, Physical Sciences, and Technology) and seven non-STEM (Arts and Humanities, Business, Communication, Education, Health Service, Social Sciences, and Social Service) categories. A male-dominated occupation reflects an industry-occupation pair with an above-average share of male workers. The standalone indicator is equal to one if the worker belongs to the category listed in each column and zero otherwise. Regressions include a quadratic in years of experience (except for the high experience specification), along with firm, industry-occupation, state, and year fixed effects. Sample is weighted to match the American Community Survey by industry, occupation, metropolitan area, and sex. Standard errors are clustered by firm. Significance levels: \* 10%, \*\* 5%, \*\*\* 1%.

	Log ba	ase pay	1(Recei	ves VP)	Log variable pay		
Female	$-0.050^{***}$ (0.004)	$-0.043^{***}$ (0.003)	$-0.049^{***}$ (0.005)	$-0.050^{***}$ (0.004)	-0.201*** (0.020)	$-0.192^{***}$ (0.014)	
Worker observables	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	
Industry–occupation FE	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	
Firm FE	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	
University-major, graduate degree FE		$\checkmark$		$\checkmark$		$\checkmark$	
N: universities	3,136	$3,\!136$	3,136	3,136	2,192	2,192	
N: salaries	302,090	302,090	302,090	302,090	106,596	106,596	
$\mathbb{R}^2$	0.66	0.73	0.38	0.47	0.59	0.71	

Table B3: Variable-Pay Gap Incorporating Alma Mater and Major of Study

Notes: This table presents the coefficients on a female indicator, run separately for base pay, variable pay, and the incidence of variable pay. Each specification includes a quadratic in years of experience and fixed effects for year, state, industry-occupation, and employer. Sample is restricted to workers with a Bachelor's degree for whom an undergraduate university and major of study are available from their resume, for workers who submit a resume on the website. The set of universities included is restricted to those that can be successfully matched to one of the names included in the exhaustive list of universities available through the Integrated Postsecondary Education Data System (IPEDS). The second column under each heading includes fixed effects for university-major pair and if any, graduate degree attained (Postgraduate, Master's, JD, MBA, or PhD). Major of study reflects the ten "Major Field Categories" detailed by the National Survey of Student Engagement along with an added "Technology" major. Workers for whom the major of study does not fall into any of these eleven categories are excluded. Sample is weighted to match the American Community Survey by industry, occupation, metropolitan area, and sex. Standard errors are clustered by firm.

	Log c	ash bonus	1(Receives cash bonu				
	New hire	Not new hire	New hire	Not new hire			
Female	$-0.248^{***}$ (0.056)	$-0.221^{***}$ (0.027)	-0.029*** (0.008)	$-0.039^{***}$ (0.005)			
$\mathbb{R}^2$	0.65	0.59	0.46	0.38			
Ν	6,012	$58,\!667$	$32,\!578$	$171,\!388$			
Worker observables	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$			
Industry–occupation FE	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$			
Firm FE	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$			

Table B4: The Gender Gap in Cash Bonuses Among New Hires

Notes: This table presents the coefficients on a female indicator, run separately for log cash bonus and an indicator for receives a cash bonus. A new hire reflects workers with less than one year of firm tenure, Worker observables include a quadratic in years of experience along with state and year fixed effects. Sample is weighted to match the American Community Survey by industry, occupation, metropolitan area, and sex. Significance levels: \* 10%, \*\* 5%, \*\*\* 1%.

# C Additional Summary Statistics

		Overall			Males		Females			
Measure	N	mean	sd	N	mean	sd	N	mean	sd	
Panel A. Employer reviews										
Overall rating	446.2	3.34	1.41	252.6	3.38	1.41	193.6	3.27	1.42	
Career opportunities rating	446.2	3.24	1.43	252.6	3.28	1.42	193.6	3.19	1.45	
Compensation and benefits rating	446.2	3.37	1.31	252.6	3.40	1.29	193.6	3.32	1.34	
Culture and values rating	446.2	3.35	1.51	252.6	3.39	1.49	193.6	3.30	1.54	
Senior management rating	446.2	3.01	1.52	252.6	3.06	1.50	193.6	2.95	1.53	
Work-life balance rating	446.2	3.25	1.44	252.6	3.30	1.41	193.6	3.17	1.46	
Current employee	446.2	0.59	0.49	252.6	0.61	0.49	193.6	0.57	0.50	
Age	446.2	35.06	9.94	252.6	35.02	9.72	193.6	35.12	10.23	
VP intensity index	446.2	0.00	0.21	252.6	0.03	0.21	193.6	-0.04	0.21	
	Panel	B. Jobse	eeker sea	rch activ	vity					
Impressions	143.8	83.92	94.20	143.8	44.06	50.87	143.8	41.96	48.81	
Applies	143.8	0.74	1.58	143.8	0.41	1.05	143.8	0.34	0.82	
Applies per 100 impressions	143.8	0.97	1.81	143.8	0.98	2.31	143.8	0.91	2.29	
VP intensity index	143.8	0.26	0.44	143.8	0.26	0.44	143.8	0.26	0.44	
Standard deviation of log pay	143.8	0.29	0.08	143.8	0.29	0.08	143.8	0.29	0.08	
Sales commission share of VP	143.8	0.10	0.22	143.8	0.10	0.22	143.8	0.10	0.22	
Managerial job title	143.8	0.26	0.44	143.8	0.26	0.44	143.8	0.26	0.44	
Average job satisfaction rating	143.8	3.69	0.48	143.8	3.69	0.48	143.8	3.69	0.48	
Average years of experience	143.8	5.18	3.53	143.8	5.18	3.53	143.8	5.18	3.53	
Average of log pay	143.8	11.22	0.36	143.8	11.22	0.36	143.8	11.22	0.36	

Table C1: Summary Statistics for Employer Reviews and Jobseeker Search Activity

Notes: This table presents the sample size (N), mean, and standard deviation (sd) for the employer reviews (panel a) and job search data (panel b) for the full sample, for male workers, and for female workers. Employer reviews span 2012–2021 and are restricted to full-time, private-sector employees for which variable-pay intensity could be assigned based on industry-job title. Glassdoor ratings are recorded on 1–5 stars Likert scale. Sample of job listings for jobseeker search activity spans January 2017 to August 2019. Impressions and applies are totaled for each job listing within the first three calendar days from the hour in which the job was posted. Each jobseeker contributes at most once to each posting's impression and apply totals. An "impression" is defined as the job listing being displayed on the user's current page of their job search (which typically will consists of 20 listings). An "apply" is defined as starting an application by clicking on the "Apply Now" button of a job listing. Sample sizes are in thousands.

	Samp (10	ole size 00s)	Rec VP	Receive VP (%)		n VP 000s)	Gende in V	r gap /P	Share of gender gap attributable to VP type (%)				
Industry	М	F	 M	F	М	F	\$1000s	%	cash bonus	stock bonus	profit sharing	sales commissions	
Accounting & Legal	49	48	40	32	9.6	7.4	-2.2	-22.8	87	0	1	12	
Arts, Entertainment & Recreation	11	10	31	21	14.2	11.5	-2.7	-19.1	70	12	11	8	
Biotech & Pharmaceuticals	39	37	53	46	20.8	17.9	-2.9	-14.1	41	41	4	14	
Business Services	233	203	38	29	16.0	12.5	-3.5	-22.0	54	6	9	31	
Construction, Repair & Maintenance	29	12	39	31	15.9	12.9	-2.9	-18.6	83	10	17	-10	
Finance	150	98	54	45	21.4	15.7	-5.7	-26.8	56	6	3	36	
Health Care	73	125	25	16	14.4	10.0	-4.4	-30.3	49	13	4	35	
Information Technology	401	178	45	38	30.0	24.4	-5.6	-18.7	22	41	3	35	
Insurance	51	54	46	36	14.0	9.6	-4.4	-31.4	45	4	6	45	
Manufacturing	175	90	43	35	15.6	12.8	-2.7	-17.7	26	23	14	38	
Media	33	35	33	25	19.2	14.8	-4.4	-22.8	69	29	15	-13	
Non-Profit	16	40	8	6	6.6	4.5	-2.1	-31.9	44	9	6	41	
Oil, Gas, Energy & Utilities	39	17	47	41	17.7	13.9	-3.8	-21.3	51	16	5	28	
Real Estate	19	25	42	37	18.9	12.7	-6.3	-33.2	43	16	3	39	
Retail	92	88	41	30	16.4	11.1	-5.3	-32.4	41	17	5	38	
Telecommunications	42	17	55	48	22.2	18.0	-4.2	-19.1	12	12	3	73	
Transportation & Logistics	39	16	32	27	15.4	11.7	-3.8	-24.3	17	11	2	71	
Travel & Tourism	25	23	30	25	16.4	11.8	-4.6	-28.3	31	6	15	47	

Table C2: Summary of Gender Gap in Variable Pay Within Industries

Notes: This table presents summary statistics for the earnings of male and female workers by industry. "M" and "F" refer to male and female workers, respectively. The following Glassdoor industries were excluded from the analysis: Aerospace & Defense, Agriculture & Forestry, Education, Government, Mining & Metals, and Restaurants, Bars & Food Services.

	$\begin{array}{c} \text{Sample size} \\ (1000s) \end{array}$		Rec VP	eive (%)	Mear (\$10	n VP 00s)	Gende in V	r gap /P	Share of gender gap attributable to VP type (%)			
Industry	М	M F		F	М	F	\$1000s	%	cash bonus	stock bonus	profit sharing	sales commissions
Architecture and Engineering	134	37	39	35	14.4	11.6	-2.7	-18.9	54	32	12	2
Arts, Design, Entertainment, Sports, and Media	40	58	26	20	14.4	8.5	-5.9	-40.9	42	40	6	12
Building and Grounds Cleaning and Maintenance	1	1	10	8	15.3	7.6	-7.7	-50.5	51	28	9	13
Business and Financial Operations	281	256	43	33	15.0	11.3	-3.7	-24.6	52	6	4	38
Community and Social Service	5	21	11	9	13.8	5.5	-8.4	-60.5	38	4	13	44
Computer and Mathematical	330	88	38	32	19.0	15.2	-3.8	-19.9	39	55	5	1
Construction and Extraction	1	0	12	11	11.2	12.9	1.7	14.9	-78	22	158	-1
Education, Training, and Library	3	4	19	15	11.1	8.8	-2.3	-20.3	26	72	10	-9
Food Preparation and Serving Related	2	1	18	13	10.9	7.5	-3.4	-31.3	52	9	0	40
Healthcare Practitioners and Technical	21	42	20	13	12.7	8.7	-4.0	-31.7	34	18	9	38
Healthcare Support	0	2	18	9	9.6	5.0	-4.6	-47.6	56	19	5	20
Installation, Maintenance, and Repair	10	1	21	23	9.2	9.6	0.4	4.1	-202	-53	-2	357
Legal	8	14	35	28	19.0	10.6	-8.4	-44.3	56	7	2	35
Life, Physical, and Social Science	29	26	34	27	14.8	10.0	-4.8	-32.3	55	40	5	0
Management	416	346	49	37	23.5	17.2	-6.3	-26.9	35	14	4	46
Office and Administrative Support	55	109	30	22	9.9	6.8	-3.1	-31.4	23	4	4	70
Personal Care and Service	1	2	22	16	14.9	8.7	-6.1	-41.2	39	0	2	59
Production	5	3	21	16	8.7	5.0	-3.7	-42.5	74	18	10	-1
Protective Service	4	2	28	25	13.8	12.3	-1.5	-10.7	77	54	1	-32
Sales and Related	150	94	56	43	34.1	26.3	-7.8	-22.8	8	4	2	87
Transportation and Material Moving	11	2	16	15	8.8	9.1	0.2	2.8	186	173	-100	-159

Table C3: Summary of Gender Gap in Variable Pay Within Occupations

Notes: This table presents summary statistics for the earnings of male and female workers by two-digit SOC occupation. "M" and "F" refer to male and female workers, respectively.

			Job	Sample size $(1000s)$		Mear expe	Mean years experience		Receive VP (%)		Mean base pay $($1000s)$		n VP 00s)
Country	Currency	Firms	titles	М	F	М	F	M	F	М	F	Μ	F
Australia	AUD	4773	4598	57	32	6.4	5.5	34.2	27.5	115	104	21	16
Canada	CAD	10815	9984	132	80	5.8	5.3	41.5	34.5	80	71	13	9
France	EUR	4981	5624	63	30	5.5	4.9	33.6	31.3	50	46	8	6
Germany	EUR	4947	4083	53	17	6.3	5.1	28.3	21.8	69	61	11	8
India	INR	18726	17188	632	168	4.9	4.3	21.8	18.6	1186	1008	175	134
Ireland	EUR	1908	3248	29	16	4.9	4.2	39.6	33.1	50	47	11	9
Italy	EUR	1360	1529	16	4	5.3	4.8	31.1	24.8	44	41	7	6
Netherlands	EUR	1326	1444	11	4	7.2	5.5	37.2	29.2	71	64	16	10
Singapore	$\operatorname{SGD}$	1262	1154	10	5	7.4	6.3	45.2	38.9	117	98	27	22
Spain	EUR	2246	2614	23	9	5.5	5.0	26.1	22.8	44	39	9	7
Switzerland	$\operatorname{CHF}$	996	1549	11	4	7.4	6.8	42.3	32.3	127	120	19	16
United Kingdom	GBP	21155	20526	339	218	6.1	5.2	35.5	27.4	51	45	11	7
United States	USD	117264	77364	1847	1355	7.0	6.5	43.8	33.9	93	84	20	14

Table C4: Summary of International Pay Data within Countries

Notes: This table presents summary statistics for male and female workers in each country's sample. "M" and "F" refer to male and female workers, respectively. Samples span 2009–2021 and are restricted to full-time, salaried, private-sector employees. We exclude the top and bottom 1 percent of earners for each country's sample. Workers who report income in a currency different from the country's primary currency are excluded. The sample of countries is restricted to those that represent at least 500 male and 500 female workers who receive variable pay. Pay is reported in local currencies and in nominal terms.

# **D** Additional Figures



Figure D1: PDFs of Base and Variable Pay by Gender

Notes: This figure displays kernel density estimates for base pay, variable pay, and each type of variable pay for male and female workers separately. Distribution for variable pay restricted to workers who receive it. Sample spans 2009–2021 and is restricted to full-time, salaried, private-sector employees. Pay is inflationadjusted using U.S. CPI to 2018 dollars. Sample is weighted to match the American Community Survey by industry, occupation, metropolitan area, and sex.

Figure D2: Female Representation and Variable-Pay Intensity, Other Advanced Economies



Notes: This figure relates the female share of employees with the variable pay intensity of each job separately for Australia, Canada, and the United Kingdom. Variable pay intensity is calculated by industry-job title and defined as the principal component of: the variable pay share of total pay and the share of workers that receive variable pay. Each dot reflects the average with the same variable-pay intensity rounded to the nearest hundredth. Black dashed line corresponds to a quadratic fit through these averages.

Figure D3: Gender Gap in Variable Pay Intensity of the Job over the Life Cycle According to Resumes, Using Age Rather than Job Number



Notes: This figure plots the resulting coefficients from estimating a version of equation (1) with workers' resumes from Glassdoor, substituting job number on the resume with the bins for the worker's age. We plot the coefficients  $\gamma_p$ . Regression includes employer, industry-occupation, calendar year-month the job began, and age fixed effects. With age fixed effects,  $\beta_p$  are redundant. Standard errors are clustered by firm. Red vertical bars indicate 95% confidence intervals around each point estimate.





Notes: This figure presents a quadratic fit of the relation between the variable pay intensity of a job posting and male and female jobseekers' application rates in panel (a) and the logarithm of their total applications in panel (b). Variable pay intensity is calculated by industry-job title and defined as the principal component of: the variable pay share of total pay and the share of workers that receive variable pay. Each job listing is weighted by its impression count and dashed lines represent 95% prediction intervals.

Figure D5: Distribution of Job Postings by Variable-Pay Intensity



Notes: This figure presents the distribution of job postings by variable pay intensity.

Figure D6: Differential Relation by Gender between Job Amenities of Glassdoor Reviews and Sales Commission Share of Variable Pay



Notes: This figure displays how satisfaction with the 48 specific workplace amenities of Sockin (2022) relates to the intensity with which their jobs rely on sales commissions for variable pay differs by gender. Sample is restricted to full-time workers for whom their job titles can be assigned a sales commission share of variable pay. Each specification includes a dummy variable for the worker is a current employee along with firm, industry-occupation, age, and year-month fixed effects. Standard errors are clustered by firm. Blue diamonds indicate point estimates and horizontal intervals around each one represents 95 percent confidence intervals.

# E Additional Tables

(Residual) Variable of interest	(Residual)	VP intensity index
Average job satisfaction rating	$0.054^{***}$	0.027***
	(0.008)	(0.007)
Managerial job title	0.083***	0.045***
Tranagoria, jos crore	(0.011)	(0.012)
Standard deviation of log pay	0.012	-0 189***
Standard deviation of log pay	(0.042)	(0.049)
Average of log pay	0 204***	$0.247^{***}$
	(0.037)	(0.030)
Sales commission share of VP	0 421***	0.364***
Sales commission share of vi	(0.028)	(0.032)
Industry-occupation FE		✓
N	14,247	$14,\!247$
Adjusted $\mathbb{R}^2$	0.46	0.58

Table E1: Characteristics of Variable-Paying Jobs

Notes: This table relays the extent to which our measure for the variable pay intensity of a job can be explained by five covariates that pertain to earnings variance, competition for sales commissions, managerial responsibilities, job quality, job seniority, and average earnings. Each observation reflects an industry-job title. The principal component of variable pay and each of the five covariates of interest are first demeaned by year, state, and employer. Sample is restricted to industry-job titles with sample size above the average (at least 8 observations). Sample is weighted to match the American Community Survey by industry, occupation, metropolitan area, and sex. Standard errors are clustered by industry-occupation.

	Dom	OLS	Within job title	Within	Within job title x firm	Within job title x firm
	Raw	OLS	and nrm	JOD TITLE X IITM	x state	x state x year
Log total pay	$-0.117^{***}$	$-0.124^{***}$	-0.033***	-0.033***	-0.033***	-0.032***
0	(0.011)	(0.010)	(0.004)	(0.004)	(0.005)	(0.005)
$\mathbb{R}^2$	0.02	0.16	0.81	0.81	0.87	0.89
Ν	706,260	706,260	706,260	706,260	706,260	706,260
Log base pay	-0.090***	-0.096***	-0.022***	-0.022***	-0.022***	-0.021***
	(0.010)	(0.009)	(0.004)	(0.004)	(0.005)	(0.006)
$\mathbb{R}^2$	0.02	0.17	0.83	0.83	0.89	0.91
Ν	706,260	706,260	706,260	706,260	706,260	706,260
1(Receives variable pay)	-0.074***	-0.075***	-0.031***	-0.031***	-0.027***	-0.025**
	(0.010)	(0.009)	(0.009)	(0.009)	(0.010)	(0.012)
$\mathbb{R}^2$	0.02	0.03	0.42	0.42	0.55	0.63
Ν	706,260	706,260	706,260	706,260	706,260	706,260
Log variable pay	-0.443***	-0.444***	-0.119***	-0.119***	-0.121***	-0.113***
	(0.040)	(0.039)	(0.020)	(0.020)	(0.022)	(0.023)
$\mathbb{R}^2$	0.03	0.07	0.73	0.73	0.81	0.84
Ν	$235,\!265$	235,265	235,265	235,265	235,265	235,265
Worker observables		$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Firm FE			$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Industry–job title FE			$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Firm–job title FE				$\checkmark$		
Firm–job title–state FE					$\checkmark$	
Firm–job title–state–year FE						$\checkmark$

#### Table E2: Gender Pay Gaps Within Finer Peer Comparisons

Notes: This table presents the coefficients on a female indicator, run separately for base pay, variable pay, total pay, and the incidence of variable pay. Worker observables include a quadratic in years of experience along with state and year fixed effects. Sample is weighted to match the American Community Survey by industry, occupation, metropolitan area, and sex. Standard errors are clustered by firm.

		Length of job title					
	One word	Two words	Three words	Four or more words			
Log total pay	-0.052***	-0.045***	-0.043***	-0.031***			
	(0.003)	(0.002)	(0.002)	(0.004)			
$\mathbb{R}^2$	0.76	0.76	0.84	0.89			
Ν	267488	1322344	781663	153731			
Log base pay	-0.042***	-0.032***	-0.029***	-0.017***			
	(0.003)	(0.002)	(0.002)	(0.004)			
$\mathbb{R}^2$	0.77	0.77	0.85	0.90			
Ν	267488	1322344	781663	153731			
1(Receives variable pay)	-0.034***	-0.035***	-0.043***	-0.047***			
	(0.004)	(0.002)	(0.003)	(0.006)			
$\mathbb{R}^2$	0.42	0.38	0.47	0.56			
Ν	267488	1322344	781663	153731			
Log variable pay	-0.151***	-0.158***	-0.132***	-0.083***			
	(0.020)	(0.011)	(0.016)	(0.028)			
$\mathrm{R}^2$	0.75	0.70	0.75	0.81			
N	76649	440588	310465	66343			
Worker observables	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$			
Firm FE	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$			
Industry–job title FE	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$			

Table E3: Gender Pay Gaps Within Job Titles by Word Length of Job Title

Notes: This table presents the coefficients on a female indicator, run separately for base pay, variable pay, total pay, and the incidence of variable pay. Worker observables include a quadratic in years of experience along with state and year fixed effects. Sample is weighted to match the American Community Survey by industry, occupation, metropolitan area, and sex. Standard errors are clustered by firm.

	Ba	se pay	Vari	able pay
	Log	Dollars	Log	Dollars
Female	$-0.131^{***}$ (0.041)	$\begin{array}{c} -3176.218^{***} \\ (372.226) \end{array}$	$-0.093^{*}$ (0.054)	$\begin{array}{c} -2198.065^{***} \\ (135.825) \end{array}$
Previous pay: male	$0.730^{***}$ (0.006)	$0.840^{***}$ (0.008)	$\begin{array}{c} 0.557^{***} \\ (0.007) \end{array}$	$0.601^{***}$ (0.010)
Previous pay: female	$0.740^{***}$ (0.006)	$\begin{array}{c} 0.853^{***} \\ (0.007) \end{array}$	$0.553^{***}$ (0.009)	$0.535^{***}$ (0.011)
$\mathbf{N}$ Adjusted $\mathbf{R}^2$	$307053 \\ 0.65$	$307053 \\ 0.67$	$90265 \\ 0.43$	$307053 \\ 0.29$

Table E4: Persistence in Workers' Base and Variable Earnings

Notes: This table presents the coefficients from regressing current earnings on those from the previous job in our sample, run separately for base pay and variable pay. For variable pay, log specifications exclude 0s whereas dollar specifications include 0s. Each specification includes a quadratic in years of experience for the previous job, along with fixed effects for previous state, previous industry-occupation, and previous and current year. Standard errors are clustered by previous industry-occupation.

	Log total pay	Log base pay	1(Receives VP)	$\log VP$
Female	-0.071***	-0.057***	-0.032***	-0.215***
	(0.002)	(0.002)	(0.002)	(0.012)
VP intensity index	0 657***	0 432***	0 842***	1 603***
vi meenorey maan	(0.010)	(0.012)	(0.007)	(0.046)
Female x VP intensity index	-0.018**	0.053***	-0.088***	-0.022
	(0.009)	(0.009)	(0.006)	(0.048)
$R^2$	0.61	0.59	0.36	0.59
Ν	$2,\!615,\!379$	$2,\!615,\!379$	$2,\!615,\!379$	964, 132
Worker observables	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Industry–occupation FE	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Firm FE	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$

Table E5: Gender Pay Gap and Variable Pay Intensity of the Job

Notes: This table reports how gender gaps in log total pay, log base pay, the incidence of variable pay, and log variable pay vary with variable pay intensity. Worker observables include a quadratic in years of experience along with state and year fixed effects. Sample is weighted to match the American Community Survey by industry, occupation, metropolitan area, and sex. Standard errors are clustered by firm.

	1(	(Receives va	riable pa	y)	Log variable pay			
Country	Point estimate	Standard error	Ν	$\begin{array}{c} \text{Adjusted} \\ R^2 \end{array}$	Point estimate	Standard error	Ν	$\begin{array}{c} \text{Adjusted} \\ R^2 \end{array}$
Australia	-0.033***	(0.003)	88809	0.27	-0.209***	(0.037)	24531	0.18
Canada	-0.036***	(0.003)	212236	0.25	-0.269***	(0.023)	74655	0.16
France	-0.025***	(0.004)	93206	0.17	-0.350***	(0.037)	25733	0.19
Germany	-0.048***	(0.006)	69971	0.20	-0.457***	(0.070)	15071	0.14
Ireland	-0.024***	(0.005)	45476	0.27	-0.224***	(0.040)	15138	0.21
India	-0.028***	(0.003)	799399	0.18	-0.315***	(0.027)	155565	0.09
Italy	-0.033***	(0.009)	20127	0.23	-0.326***	(0.094)	4833	0.15
The Netherlands	-0.041***	(0.010)	15017	0.21	-0.599***	(0.149)	4089	0.16
Singapore	-0.036***	(0.010)	14941	0.13	-0.031	(0.113)	5437	0.21
Spain	-0.050***	(0.007)	31966	0.28	-0.234***	(0.084)	6101	0.14
Switzerland	-0.056***	(0.011)	14420	0.21	-0.136	(0.116)	4609	0.15
United Kingdom	-0.037***	(0.001)	556477	0.25	-0.266***	(0.015)	163672	0.23
United States	-0.043***	(0.001)	3201030	0.24	-0.284***	(0.006)	1198970	0.20

Table E6: International Gender Gaps in Variable-Pay

Notes: This table presents the coefficients of a female indicator on the magnitude and incidence of variable pay, run separately on each country's pay reports. Each specification includes a quadratic in years of experience along with year, industry-job title, and firm fixed effects. Sample of countries is restricted to those that represent at least 500 male and 500 female workers who receive variable pay. Countries are listed in alphabetical order. Standard errors are clustered by firm. Significance levels: \* 10%, \*\* 5%, \*\*\* 1%.

	Log total pay	Log base pay	1(Receives VP)	$\log VP$
Female	-0.046***	-0.032***	-0.037***	-0.150***
	(0.001)	(0.001)	(0.002)	(0.012)
Female x VP intensity index	$-0.049^{***}$ (0.005)	$0.010^{*}$ (0.005)	$-0.097^{***}$ (0.006)	-0.037 $(0.043)$
$\mathbb{R}^2$	0.77	0.78	0.39	0.72
N	2,615,379	2,615,379	2,615,379	931,802
Worker observables	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Industry–job title FE	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Firm FE	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$

Table E7: Gender Pay Gap and Variable Pay Intensity of the Job, Fixed Effects for Industry-Job Title Instead of Industry-Occupation

Notes: This table reports how the gender gaps vary with the variable pay intensity of the job when industryjob title fixed effects are included in lieu of industry-occupation. Sample is weighted to match the American Community Survey by industry, occupation, metropolitan area, and sex. Standard errors are clustered by firm. Significance levels: \* 10%, \*\* 5%, \*\*\* 1%.

Tuble Lo, Tollare Holl Workers Tuble and Daile Commission Diale of Variable Table	Table 1	E8:	Tenure from	Workers'	Resumes	and	Sales	Commission	Share	of V	'ariable	Pav
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	Logarithm of firm tenure						
	All w	All workers		Ages 18–26			
Sales commission share of VP	$0.021 \\ (0.015)$	$-0.044^{***}$ (0.017)	$0.055^{**}$ (0.025)		-0.008 (0.014)		
Female x Sales commission share of VP	$-0.038^{***}$ (0.011)	0.001 (0.020)	$-0.061^{***}$ (0.019)	$-0.064^{***}$ (0.019)	-0.009 (0.016)		
Female	$0.007^{*}$ (0.004)		$0.017^{***}$ (0.006)	$0.031^{***}$ (0.006)	-0.004 (0.005)		
Std. dev. Sales commission share of VP Observations Adjusted R <sup>2</sup>	$0.29 \\ 325812 \\ 0.25$	$0.29 \\ 325812 \\ 0.36$	$0.30 \\ 140178 \\ 0.27$	$0.30 \\ 129259 \\ 0.33$	$0.28 \\ 171214 \\ 0.23 $		
Industry–occupation FE Worker FE Industry–job title FE	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$		

Notes: This table relates the logarithm of firm tenure on workers' resumes to the variable pay intensity of their jobs. Each specification includes fixed effects for the firm, the worker's age, and the calendar month the job began. Standard errors are clustered by firm. Significance levels: \*10%, \*\*5%, \*\*\*1%.

	1(Female)	VP share of total pay	Sales commission share of VP	Work-life balance
Average full-time weekly hours	-0.038***	0.008***	0.008	0.001
	(0.014)	(0.002)	(0.007)	(0.019)
Mean weekly hours	43.70	43.70	43.70	43.71
Ν	305	305	304	260
Adjusted $\mathbb{R}^2$	0.08	0.16	0.00	-0.00

Table E9: Variable Pay Compensation and Weekly Full-Time Hours from the ACS

Notes: This table regresses average hours among full-time workers within an industry-occupation pair in the ACS with average variable-pay-reltaed measures and ratings from Glassdoor. Industry-occupation pairs are Glassdoor industries x two-digit SOC occupations. Regressions are weighted by annual average ACS weight. ACS sample is restricted to workers who are in the private or non-profit sector, usually work 35+ hours per week, are at work, worked 50–52 weeks last year, and are in a metro area. Sample restricted to industry-occupation pairs with at least 50 Glassdoor pay reports for columns (1)-(3) and 50 Glassdoor reviews in column (4).

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