

Please do not cite without permission.

**Gender Pay Equity Analytics:
A Case Study of a Large Multinational Company**

Linda Barrington
Executive Director
Institute for Compensation Studies
Associate Dean for External Relations
Cornell SC Johnson College of Business
Cornell University

Kevin F. Hallock
Director
Institute for Compensation Studies
Dean
Cornell SC Johnson College of Business
Cornell University

December 2, 2019

We gratefully acknowledge the executives and technical staff at the Company studied for sharing their time, data and invaluable insights regarding the compensation system in their organization. We also thank Nichole Szembrot for her excellent research assistance on this project. Helpful comments were provided by participants of the Cornell University Conference: “Increasing Inclusion/Reducing Discrimination: What Works?”. The data used in this project are proprietary and cannot be shared with other researchers without the permission of the firm.

Please do not cite without permission.

**Gender Pay Equity Analytics:
A Case Study of a Large Multinational Company**

Abstract

Compensation inequity is a key metric of workplace inequality. But there is scant documentation of internal company practices regarding gender pay equity and analytics. We present a rare case study of one company's internal pay equity analytics. Using (anonymized) microdata from a single firm with more than 10,000 employees within ten selected countries, we estimated within-firm gender pay gaps, controlling for a host of measurable employee characteristics. We supplement these quantitative findings with some qualitative information about the organization's associated HR practices for hiring and performance review as they relate to compensation. We also discuss the control variables chosen for this within-company gender pay gap analysis vis-à-vis explanatory variables commonly seen in the academic literature.

Linda Barrington
Cornell SC Johnson College of Business
Cornell University
Tata Innovation Center
New York, NY 10016
linda.barrington@cornell.edu

Kevin F. Hallock
Cornell SC Johnson College of Business
Cornell University
174 Statler Hall
Ithaca, NY 14853

Please do not cite without permission.

hallock@cornell.edu

The gender pay gap is a key metric of workplace inequity. There is a large and growing literature on the gender pay gap, particularly in the U.S., however there is scant documentation of internal company practices regarding gender pay equity and company-specific estimates of gender pay ratios. (For notable exceptions, see Castilla, 2008 and 2015). Empirical research estimating gender pay gaps must typically rely instead on national survey data. While these data are rich in individual-level demographic data including educational attainment or family composition, they do not include many important explanatory factors of pay such as direct measures of performance at work. Standard economic analysis of pay gaps using national survey data must instead rely on proxies of on-the-job performance or individual productivity, such as educational attainment, years in the labor market or sometimes seniority.

We present a rare case study of one company's internal pay equity analytics and a point-in-time estimate of the organization's gender pay ratio. Using (anonymized) microdata from a single firm (within the last five years) with more than 10,000 employees within ten selected countries, we estimated within-firm gender pay gaps, controlling for a host of measurable employee characteristics. We supplement these quantitative findings with some qualitative information about the organization's associated HR practices for hiring and performance review as they relate to compensation.¹ We also discuss the control variables chosen for this within-company gender pay gap analysis vis-à-vis explanatory variables commonly seen in the academic literature.

¹ It should be noted that we do not address in this paper any purposeful employer practices addressing diversity and inclusion, such as employee affinity groups, diversity training or work in support of a culture of diversity. Nor do we directly address recruitment, selection or promotion practices. Our focus is limited to compensation.

Please do not cite without permission.

Access to employee microdata of a single employer allowed us to use control variables that more directly measure the explanatory factors of job rank, experience in the company, and employee performance than those typically available in national survey data. In addition, we were able to place this company's internal gender equity analysis process within the context of its broader HR practices. This case study serves as a launching point to consider differences in the framing of the gender pay gap analysis from the academic and employer perspectives and identify opportunities for future research that could aid in bridging existing gender pay gap literature and equity analysis of single-company employee compensation data.

Case study of “the Company”

The subject of this study is a global organization with more than 30,000 employees in at least 10 countries.² We undertook this study to answer the question: “Is the gender pay equity analysis used by the Company in line with academic standards for accurately estimating a gender pay gap?” Internally, we refer to this as considering whether the company had pay practices that were “gender neutral.”

Employee-level data from ten countries were provided by the Company for the analysis presented in this paper. Some of these countries were locations where the Company employed larger numbers of employees. Six of these countries are members of the OECD,³ four are located in Asia or Africa. All personal identifiers were removed before the data were securely transferred from the Company to the authors. The Company data are rich, containing information on individual employees such as their gender, age in cohorts, years with the company, ex-Pat status,

² Our agreement with the Company included our ability to publish academic articles from our findings, but stipulated that we protect the organization's anonymity. To this end, we will refer to the organization as “the Company” throughout this paper. The data used in this project are proprietary and cannot be shared with other researchers without the permission of the Company.

³ The U.S. is not one of the countries included in this analysis.

Please do not cite without permission.

full-time or part-time status, level in the organization, and importantly, a measure of performance. Many of these variables are not available in national survey datasets.

The authors and representatives from the Company met more than a dozen times in person or by telephone throughout the project. Representatives of the Company were very supportive, answering questions regarding base and variable pay policies, construction of specific variables in the dataset, data cleaning routines, and Human Resource (HR) practices that may be related to pay.

With a goal of gender-neutral pay practices, the Company took a proactive approach to its HR policies, in particular its gender pay equity analysis but also through other broader and complementary policies. In whole, there was a four-pronged continuum of practices that we believed could directly impact gender pay equity within the Company. These practices came into play at (i) the point of hire, (ii) in the performance review process, (iii) with the annual pay increase, and (iv) in the analysis of existing pay outcomes. (See Figure 1.) While it is the fourth prong that was the focus of our study, considering the Company's broader context of policies and practices was critical to understanding their workplace approach and interpreting the results of the gender equity analysis.⁴

First, and at the start of employment, the company had a strong practice of not negotiating starting salary offers. As it was explained, the hiring offer was made and if the candidate was not satisfied with the offer, the policy was that no negotiation takes place. The candidate could always choose not to take the offer and look for employment elsewhere. Starting offers were based on objective job criteria which should alleviate the introduction of a gender pay gap at hire.

⁴ Of course, other HR practices can impact this analysis. For example, if there is inequity by gender in promotion, then controlling for job rank in an analysis of pay can lead to misinterpretation of the gender pay gap. We discuss this in more detail below.

Please do not cite without permission.

Next, as employment continues, employees' performance was reviewed. As we understood it, the Company also performed a gender equity analysis of performance review scores. If disparities by gender were found in scores awarded by a given manager, "further explanation" was sought. The Company believed this process reduced the risk of gender bias in performance scores.

Performance scores were then translated through a formula into pay increases. There was no manager discretion on pay increases (once performance scores were set), limiting any "performance-reward bias" (Castilla, 2008). Once an employee was informed of her performance score, she should have been able to plug that score into the Company's pay increase formula and precisely compute her annual pay increase.

Finally, to look for gender pay inequity across its workforce, the Company conducted a two-step analysis. Within each country in which it operates, the Company first computed the raw gender pay gap (average female wage divided by the average male wage). If the gap between the two averages was less than three percent the analysis stopped. (We note below that this practice may mask important issues). If a gap over 3 percent was found, the Company then conducted a more robust econometric analysis on the data for that country. If a gap over a certain threshold remained after controlling for a set of characteristics, a lump sum was transferred to the operations in that country to correct the differences in pay.

It is important to note that sincere interest was shown by executives of the Company in our pursuing this study. Such interest may suggest that the Company was not representative of general practices regarding workplace equity analysis and was likely a "leading edge" employer.⁵ While we would caution against generalizing any specific point estimates reported in

⁵ This assessment of the uniqueness of the Company is based on the authors' own judgment as objective and thorough inventories do not exist of how widespread and robust employer practices are surrounding gender pay gap analysis.

Please do not cite without permission.

this article, we believe our study provides value in allowing consideration of the impact that using more direct measures of the explanatory factors of pay can have in estimating (perhaps less noisy) gender wage gaps, and in bettering the understanding of one employer's framework for analyzing gender pay equity.

Discrimination in the labor market

Economists view gender discrimination in the labor market as occurring when “two equally qualified individuals are treated differently solely on the basis of their gender” (Blau, Ferber and Winkler, 2010, p 193). Gary Becker won the 1992 Nobel Prize in economics in part for work on human capital theory and in part for his work on the economics of discrimination (1964, 1971). Becker argued that a set of types of discrimination could be based on what he called “taste,” where one group may not want to associate or work with another group based on some demographic characteristic (e.g. gender, age, or race).⁶ Customer, employee and employer discrimination can all be considered taste-based in that one group effectively pays a higher price for something due to a “distaste” for or association with a particular group. For example, in the past it might have been common for customers to have preferred that flight attendants be female and stock brokers be male. As a result, employers would want to pay male flight attendants and female stock brokers less (if hired at all) since presumably customers would demand to pay less if served by these groups. Or, if in a particular occupation, men preferred to not work with women, the market outcome would be either lower wages for women or occupational segregation where men would work in one area and women another, or some blend of both. In the case where taste-based discrimination is perpetuated by employers, female employees would essentially impose an additional “cost” on the employer equal to the level of the employers’

⁶ Parts of this section are based on the straightforward description of labor market discrimination offered by Blau, Ferber and Winkler (2010).

Please do not cite without permission.

distaste. By paying female workers less than male workers, the employer would “offset” this cost. An interesting point made by Becker (1971) is that in perfectly competitive labor markets, taste-based discrimination on behalf of employers would have to disappear under competitive pressure for profits.

An additional form of discrimination (not taste based) discussed in Phelps (1972) and Aigner and Cain (1977) is that of statistical discrimination where beliefs (correct or not) about the typical member of a group are applied to the entire group. For example, if an employer believes that the average female employee is less productive, less attached to the labor force or less hard working than the average male employee, and cannot easily evaluate the productivity of individuals, she may generalize her belief about the average female employee to all women. This would constitute statistical discrimination against women. In today’s parlance, we might call this gender profiling.

Human capital theory, individual pay and productivity

Human capital theory underpins the economist’s competitive market framing of why individuals earn what they do. Individuals bring to the labor market a bundle of human capital that includes their educational attainment, experience, innate abilities, etc. (Becker, 1964). Some employees have more human capital than others. In a competitive market, where employees are paid equal to the value they provide to their employers, it follows that those with more human capital will receive higher wages.

Within this framework, discrimination exists if a pay gap exists between two otherwise equally productive individuals. However, in attempting to measure such discriminatory pay gaps, individual productivity is rarely known with accuracy. Human capital theory identifies characteristics that, if measurable, can be used as proxies for individual productivity. In other

Please do not cite without permission.

words, if education, ability and experience determine an individual's productivity, knowing these human capital characteristics allows one to estimate her productivity.

In modelling determinants of income, it is recognized that the translation of human capital through productivity into earnings occurs within a labor market that is subject to the forces of supply and demand. Workplace characteristics affecting the relative bargaining power of employees and employers, such as the existence and strength of unions, can also impact the level of pay. The combining of these market place filters (industry, occupation, union status, etc.) with human capital determined productivity frames the structure of the standard empirical analysis of gender pay gaps that is found in the economics literature.

Raw versus adjusted pay gaps

It is reasonable to begin considering the size of the gender pay gap by calculating the difference in typical (median) earnings of men and women. (See Cain, 1986, or Blau, Ferber and Winkler, 2010, for examples). As of the third quarter of 2019, the median usual weekly earnings of full-time female workers (16 years and over) in the U.S. was 82.3 percent of that earned by full-time male workers (16 years and over), implying a gap of 17.7 percent⁷ (United States Department of Labor, "Usual Weekly Earnings," 2019). This is termed the raw or unadjusted gap, as it does not recognize any differences in the distribution of human capital characteristics or market filters that may affect pay, as discussed previously.

Human capital theory would dictate, however, that this raw gap cannot be interpreted solely as discrimination due to gender. For example, one reason women may have lower average earnings than men is that, as workers, they are younger on average and there is a well-

⁷ In the U.S., women's-to-men's earnings ratio also varies by race and ethnicity. In the third quarter of 2019, for fulltime workers 16 years and over, white women's median weekly earnings were 82.2 percent of white men's. The ratio for black women relative to black men was 88.9 percent. For Asians and Hispanics, women's-to-men's earnings ratio was 83.7 percent and 87.3 percent, respectively. United States Department of Labor, "Usual Weekly Earnings," released October 16, 2019.

Please do not cite without permission.

documented age-earnings profile (Ehrenberg and Smith, 2012). Women are also overrepresented in lower paying occupations and industries, more likely to work part-time and less likely to be in unionized jobs. Any differences in average male and female productivity levels and representation across the market filters of industry, occupation, union status, etc., would need to be factored out in order to isolate that part of the pay gap left unexplained *except* for gender. The objective of the statistical regression analysis is to remove the effects of explanatory variables other than gender and create a statistical comparison of peer men and women who are otherwise comparable, on average, in all relevant market filters and productivity (human capital) characteristics. The statistically adjusted gender pay gap that results from regression analysis (and is regularly smaller than the raw gap) is formally called the “unexplained wage gap.”

A classic study of the impact that various human capital and market filter factors have on the gender pay gap is Blau and Kahn (2006). They compute a raw gender pay gap (“wage differential”) of 20.3 percent and then control for several explanatory factors of pay. (See Figure 2.) After adjusting for these control variables, 59 percent of the raw gap is “explained,” leaving 41 percent of the 20.3 percent raw pay gap unexplained – an adjusted gender pay gap of just over eight percent between men and women of these same characteristics. Note that some of this “unexplained” gap could be discrimination. At the same time, it may be that it is simply the case that other variables (e.g. “productivity”) were not measured in the data sources used.

Estimating adjusted gender pay gaps using national survey datasets

To estimate adjusted gender pay gaps, economists most often deploy national survey datasets, such as the American Community Survey (ACS), Current Population Survey (CPS), Survey of Income and Program Participation (SIPP), Health and Retirement Study (HRS),

Please do not cite without permission.

among others.⁸ The data accessible through these national survey datasets include detailed information on individuals and/or households and can allow for a long list of explanatory factors or control variables to be included in regression analysis of the gender pay gap. Controls for industry, occupation, union status, race, gender, age, family characteristics and education are typical in studies using these data.

There are limitations to these datasets, however, namely that there is often less information than desired about an individual's employer or job characteristics. And while there are datasets that contain survey responses from employers, such as the National Compensation Survey, the unit of observation in these surveys is typically the occupation, but not the individual employee. It should also be noted that national surveys differ in purpose, resulting in the sampling framework and number and definition of variables not being consistent across surveys.⁹ As a result, care must be taken in interpreting any point estimates of pay gaps, as these can vary notably across even the most commonly used national survey datasets (Hallock, Jin and Barrington, 2014).¹⁰

In terms of estimating gender pay gaps, perhaps the biggest omission from national survey datasets is a direct measure of individual-level productivity. Fortunately, human capital theory allows for exploitation of the existing and rich data on individuals and/or households to

⁸ The "Disability and Compensation Variables Catalog" provides a convenient overview of which variables related to work and employer characteristics, including compensation such as pay and benefits, are available in these and seven other major U.S. national survey datasets. It can be found at <http://www.disabilitystatistics.org/eprtc/codebook.cfm>.

⁹ For example, the Survey of Income and Program Participation (SIPP) over-samples participants in government supplementary income programs because the "main objective of SIPP is to provide accurate and comprehensive information about the income and program participation of individuals and households" (Fisher, accessed in 2015). See also United States Department of Commerce, <http://www.census.gov/programs-surveys/sipp/about/sipp-introduction-history.html>.

¹⁰ Hallock, Jin and Barrington's (2014) estimates of the unexplained pay gap between male employees with disabilities and their nondisabled peers range from a statistically significant 9.3% using the 2009 ACS to a statistically insignificant 3.9% using data from the 2010 CPS with "identical" control variables.

Please do not cite without permission.

proxy the unavailable individual level productivity. For example, since Mincer (1974), economists have sometimes controlled for experience, if work history is not known, by approximating an employee's years of work experience as something like $[(\text{age}) - (\text{years of education for highest degree attained}) - 6]$. Such a computation for a 30 year old college graduate would yield: $30 - 16 - 6 = 8$. This approximation approach produces a very accurate estimate for those who work continuously after (and not during) their years of education, so long as the individual is continually working and does not experience spells of non-employment.

Proxy measures of productivity and computing the unexplained wage gap

Once the effects of other explanatory variables of pay are controlled for, the residual variation in pay attributed to gender—the unexplained gender wage gap—is often attributed to discrimination. However, one should use caution in doing so, especially if proxy measures for pay determinants have been used in the regression analysis. Any error introduced by less than perfect proxies, if correlated with gender, can send a false signal. Consider the commonly used $[(\text{age}) - (\text{years of education for highest degree attained}) - 6]$ proxy for labor market experience. This is a good approximation for someone who has had a long-term commitment to the labor force and worked continuously after and not during school. To the extent that women, on average, are less strongly attached to the labor force over time, such a formulaic approach to estimating years of experience will relatively overestimate labor market experience for women. If it is the case that men have more labor market experience than women and labor market experience is correlated with compensation (both true in national survey data) then estimating experience in this form will lead to an overestimation of the unexplained gender wage gap.

Blau and Kahn (2013) provide an excellent related discussion. They find that including “data on actual work histories add considerable explanatory power to wage regressions for women, even if they control for potential experience (defined as age minus years of schooling

Please do not cite without permission.

minus 6, or roughly the number of years that have elapsed since leaving school) and current job tenure” (p S21). They write:

We find that having information on actual full-time and part-time work experience can reduce the unexplained gender gap by up to 48% in the PSID (data are for 1990) and 15% in the 2008 PDII. Moreover, inclusion of information on actual experience is helpful in understanding wage determination of women as well as for analyzing female wage inequality. Experience profiles for women are generally found to be much steeper when we use actual full-time and part-time experience rather than potential experience. Failure to include such data causes us to severely underestimate women’s on-the-job human capital accumulation. Moreover, using potential rather than actual experience causes us to overstate the increase in women’s residual wage inequality from 1980 to 1999 by about 20% (pp S26 – S27).

Through our study of the Company, we add to the existing literature by offering an empirical example that is free from reliance on some of the typical proxy variables employed (by necessity) in most research analyzing national survey data. Access to micro-level employee data of a single corporation allowed us to use control variables that more directly measure the explanatory factors of job rank, experience in the company, and employee performance, although we did not have all desirable explanatory variables (for example, work experience gained outside of the Company).

Determination of Company pay

The major differences in our case study of the Company from more typical pay gap analyses using national survey data are two-fold. First, the fact that we analyzed one employer, and to the extent that employees sort into firms based on quality (see the firm-size wage gap literature including Iddson and Oi,1999), differences in employee quality might have already

Please do not cite without permission.

been accounted for through self-selection.¹¹ Second, employee performance scores were available to us. Employee performance scores can replace human capital proxies often used as controls for productivity in the economics literature. The flow chart in Figure 3 illustrates, from an economist's perspective, a framing for the structure of pay determination within the Company, underpinning the gender pay gap analysis we present here.

At the Company, each employee's pay is determined by the combination of her individual productivity (measured through the performance review process) and market filters (benchmarks) integrated into the compensation structure. Using this framing, the Company's continuum of HR practices that supported gender pay equity as previously discussed (Figure 1) can be overlain to illustrate their impact along the flow of pay determination. (See Figure 4.)

Limiting salary negotiation at the point of hire, as the Company reported that they did, can have the effect of reducing discretionary and potentially gender-biased deviations from otherwise objective market-benchmarked pay levels and may eliminate (or certainly reduce) gender differences in interest in negotiating (Babcock and Lasever, 2003). Checking for gender bias in performance review scores could have contributed to these scores being an unbiased measure of productivity.¹² And setting annual pay increases formulaically in addition to conducting a gender equity analysis of existing pay outcomes addressed the effectiveness of the process meant to translate productivity into pay.

Gender pay gap estimates within the Company

Our study focused on assessing whether the gender pay equity analysis used by the Company was in line with academic standards for accurately estimating a gender pay gap. Using

¹¹ To impact the gender pay gap, however, the self-selection of workers may need to differ, on average, between men and women.

¹² Unless, of course, productivity objectively does differ by gender. The Company representatives with whom we spoke seemed clear that there were no such differences by gender. We see no reason to believe there should be any differences at the Company.

Please do not cite without permission.

the Company's rich dataset, the gender pay gap was estimated using an ordinary least squares regression on the log of salary controlling for job rank, time in position, tenure with the Company, whether the worker is working full time or part-time and measures of individual performance for the current year and two years prior, job rank, as well as demographic controls for gender, age, whether the employee is a national of the country in which he or she works, and a measure of nationality. The primary empirical specification was the following, estimated separately for each of the countries considered:¹³

$$\begin{aligned} \ln(\text{salary}_i) = & \alpha + \beta_1 \text{female}_i + \beta_2 \text{national}_i + \beta_3 \text{european}_i + \beta_4 \text{full time}_i + \\ & \beta_5 \text{performance}_{i,t} + \beta_6 \text{performance}_{i,t-1} + \beta_7 \text{performance}_{i,t-2} + \\ & \beta_8 \text{seniority}_i + \sum_{q=1}^8 \gamma_1^q (\text{birth cohort})_{iq} + \sum_{q=1}^8 \gamma_2^q (\text{start cohort})_{iq} + \\ & + \sum_{p=1}^{12} \gamma_3^p (\text{job rank})_{ip} \end{aligned}$$

where:

salary is the annualized salary of the individual employee *i*

female is an indicator variable equal to 1 if the employee *i* is female and 0 otherwise

national is an indicator equal to 1 if individual *i* is a national of the country being modeled and 0 otherwise

european is equal to 1 if employee *i* is a national of another European country than the country being modeled and is equal to 0 otherwise

full time is equal to 1 if individual *i* is working full time and equal to zero otherwise

performance is a linear term for performance of person *i*. It is included in the most recent year as well as the year prior and the year prior to that and is normalized to have a particular mean within workgroup

seniority is a linear term for the number of years since the last promotion

birth cohort represents a series of indicator variables equal to 1 for the cohort in which an individual is born and equal to zero otherwise

start cohort represents a series of indicator variables equal to 1 for the cohort in which an individual first began at The Company and zero otherwise

¹³ Regressions were also estimated interacting the control variables with gender and coefficients on *female* changed little. Results are not presented here, but are available upon request.

Please do not cite without permission.

job rank represents a set of twelve indicator variables for the job level or rank in the organization in which individual *i* works. If individual *i* works in level *p* then the work level *p* indicator takes a value of 1 and it takes values of 0 otherwise.

The regression coefficients on the variable *female* were estimated separately for each country. These estimates of the unexplained gender pay gap by country are summarized in Table 1. (See Appendix A for full regression results by country.)

In two of the six OECD countries analyzed, we estimated statistically significant negative coefficients on gender of 5.0 and 5.4 percent. In other words, there was a five and five-plus percent disparity in the average pay of male and female employees in these two countries after controlling for relevant explanatory factors, including performance. For one OECD country, a statistically significant positive coefficient was estimated, showing that, after controlling for the explanatory factors included in the model, there was an adjusted or conditional gender pay gap of 3.2 percent but in *favor* of female employees. In the remaining three OECD countries and three of the four non-OECD countries, the estimated coefficients on gender were not statistically significant, implying there was no estimated gender pay inequity among the Company's employees in these countries. In one country in Asia or Africa, an unexplained gender pay gap of 13 percent for the Company's Type X employees and 3 percent for its non-Type X employees was estimated. Both of these coefficients are statistically significant at the 1 percent level.

In line with academic standards? Some discussion

For the most part, the Company's gender equity analysis was rigorous and met "academic standards." As with empirical studies in general, some opportunities for possible strengthening of the model could be identified. For example, the Company included a 0 or 1 control variable to capture whether an employee was a full time worker or not. This means that employees working half-time and 80 percent time would be defined identically as "not full time." The Company's employee database did contain, however, information to define part-time status in finer

Please do not cite without permission.

gradations. As can be seen in Table 2 for operations of the Company in selected OECD countries, using a less restricted measure of part-time hours did generally increase the gender pay gap estimate due to the greater likelihood that women were part-time workers. We recommended continuing use of this measure as in general it is prudent to not put more structure on a variable than is necessary.¹⁴

The more interesting considerations involve inclusion of control variables that economists expect to see in pay gap regressions, in part due to the need to proxying of productivity. Here, we explicitly discuss education, lifetime labor market experience, and race, along with the performance measure. Our discussion with the Company over these explanatory variables proved illuminating of the different perspectives of and data available to academic economists and employers, and revealed some opportunities for future research.

Education

As noted in the earlier discussion of human capital, education is very highly correlated with labor market earnings. This has been documented across countries and over time (Becker, 1967, Mincer, 1974 and Card, 2001). The Company, however, did not control for education in any of its statistical analysis of gender neutrality in pay practices. This created a problem if the employees of the Company differed in their levels of education by gender and if compensation in the Company was also correlated with education distinct from its correlation with job rank or performance (which are controlled for). There is evidence in the academic literature and in practice that education matters for wages even within job categories. However, if this evidence is

¹⁴ Another example of an overly complicated specification being used by the company was found in the dependent pay variable. The Company had defined the left-hand variable in a manner that aligned with the Company's use of pay ranges in its compensation structure, but which introduced more structure into the measure of pay than was ideal. The measure was also less intuitive than the natural log of salary used throughout the analysis presented in this paper, making it more difficult to explain the equity analysis results to Company managers and executives outside the compensation function. Changing the definition of the dependent variable to the natural log of pay aligns better with standard academic practice and interpretation, and resulted in little change in the estimated gender coefficients.

Please do not cite without permission.

underpinned by analysis in which education is a proxy for performance, and if performance can be measured directly (and accurately), then omitting education as an explanatory variable should not present misspecification concerns. In other words, if the output of productivity can be measured directly, objectively and accurately then input measures to that productivity, such as education, are not necessary as a proxy.

We discussed with representatives from the Company the exclusion of education as a right-hand variable. The Company's explanation for why they did not include education as an explanatory factor was exactly this measuring-outputs logic, although their language was different. They stated that a certain level of education is required to be hired or promoted into a particular position in the Company. If one has achieved that level of education, she/he could be eligible for the job. Without the necessary level of education, the person could not be considered for the job. According to the Company, their practice was that education is only a requirement for access to a job, not a criterion considered in any pay decision. Pay increases were not made to reward an employee for completing additional education after hire. In other words, no compensation differentials were paid for additional education at the Company.¹⁵ Furthermore, the Company believed that actual productivity was captured by the performance metric included in the analysis and it was that performance measure that was directly translated into pay increases. If this were the case – that no direct reward was paid for additional education and performance scores captured true productivity, then the exclusion of education should not have introduced mismeasurement of the gender pay gap and education was not needed as a proxy for productivity. If education level of employees were added to the dataset then further empirical

¹⁵ This practice of the Company is in contrast to what is described as a “pay-for-knowledge” system in the literature (Milkovich, Newman and Gerhart, 2014). A pay-for-knowledge plan would “pay employees more for learning a variety of different jobs or skills” (p 527).

Please do not cite without permission.

analysis could test if including education as a control variable along with performance is indeed redundant. But note that the company was assuming that they measured productivity correctly.

Experience

Labor market experience is an important correlate of compensation. As referenced earlier, the literature includes discussion of measuring experience when precise measures are not available, as in large national survey datasets, and the resulting potential for measurement error. In the case of estimating the gender pay gap within the Company, the employee data used by the company included measures of experience within a particular job or position (*seniority* reports years since last promotion) and tenure at the Company (*start cohort* measures time since employee joined the Company). These measures are valuable measures of experience within the company itself, which could be considered company-specific human capital. They did not, however, capture total labor market experience, which would have included time worked outside of the present organization.

To what degree did controlling for within-Company experience create mismeasurement and could estimating total labor market experience with the common approximation of $[(age) - (years\ of\ education) - 6]$ have added explanatory power? It depends in part on the differences in experience gained by men and women respectively. For employees who took no break from work and joined the company directly after finishing their education, the in-Company experience measure we used and the common $[(age) - (years\ of\ education) - 6]$ proxy would have been identical. Also, if the length and type of work experience that men and women gained prior to joining the Company did not differ in the value it contributes to their current performance, there would have been no disadvantage in controlling for in-Company experience only. However, if women's pre-Company work experience were, for example, less relevant to (or correlated with)

Please do not cite without permission.

performance in their current job than it were for men (either because it was shorter or less directly applicable), then either measure could have mismeasured actual (relevant) experience, and the size of that relative mismeasurement would depend on how large the relevance gap of pre-Company experience was between male and female employees.

In either case, within the human capital framework, if performance were fully capturing productivity, experience would have been an unnecessary control variable. The significance of these variables in our Company regressions would suggest that pay was determined by some function of tenure, not performance scores alone.

Better testing of the effectiveness of experience vis-à-vis the performance score as measures of productivity and determinants of income, along with the value of including additional and common human capital characteristics, is worth exploring in future research.

Race and ethnicity

Race is correlated with compensation in the U.S. labor market, as has been carefully documented by a great deal of research (Cain, 1986). Additionally, due to regulatory requirements and cultural norms, many organizations in the U.S. are as concerned with race neutrality in compensation as they are with gender neutrality. For these reasons, controlling for race and ethnicity is expected in pay analyses on U.S. national data sources.

In countries where the Company operates, however, organizations may be barred from collecting information on the race of employees. Because of this, the company did not include race as a variable in its gender pay equity analysis and did not have that data compiled for these countries. The Company did, however, record employee nationality. There was concern on the part of the Company that bias in favor of Europeans and/or those working in their home countries could have created its own inequity in pay and therefore explanatory variables to identify this possible bias were also included in the pay equity regression.

Please do not cite without permission.

Performance measures of productivity

The assumption that individual performance scores accurately captured productivity underpins the Company's gender pay equity analysis and the empirical results presented in Table 1. To the extent that group, team or division performance contributed to productivity in a manner not captured by the individual performance measure (Alchian and Demsetz, 1972) and this missing measure was correlated with gender, mismeasurement of the true gender pay gap could have resulted. Ideally, further measures would be collected to capture productivity resulting from any joint-production factors.

Potential endogeneity presented another concern regarding the validity of the performance measure. Because Company managers understood that any merit or bonus pay increase was determined strictly by the performance score, a manager wishing to pay an employee more would know what performance score she needed give the employee to make this happen. If this scenario accurately represented a common behavior among managers, the desired pay increase would have become an explanatory factor of the performance score.¹⁶

As mentioned above, we were informed by the Company that a separate test for gender neutrality of performance scores was conducted. While the specifics of this test process were not made fully clear to us, our understanding was that performance scores awarded by all managers were reviewed for gender disparities. If such a disparity were identified in the scores of a particular manager, "further explanation" was requested. To the degree that this process did eliminate gender bias in performance scores, any endogeneity in performance scores that did

¹⁶ In his field study of a large private company, Castilla (2015) finds no significant shift in the distribution of performance ratings by demographic characteristics following the introduction of greater organizational accountability and transparency into the pay determination process.

Please do not cite without permission.

exist should not have a gender component. Future research could be conducted to test for such endogeneity, as well as to determine whether any gender disparities in performance scores exist.

An interesting variable that was collected by the Company but not used in the statistical analyses of pay neutrality is “potential score.” If this was a neutral and objective measure of potential, it could have provided a valuable additional measure in a study of gender pay neutrality. If one’s potential is high, additional pay may be warranted for retention purposes. If gender imbalance exists in the population of employees identified as high-potentials and retention bonuses are paid, this measure should be included in the equity analysis. If, however, being a high potential does not translate into pay increases beyond that determined by the current performance score, then this measure should not have any explanatory power in the gender pay gap regression. Additional analyses to investigate the explanatory power of this measure could be considered in future work.

Occupational segregation: beyond the pay gap analysis

A further observation from our case study related to the relationship between gender pay equity and overall workplace equality. Analyzing compensation for gender inequity per se doesn’t reflect or inform on overall equality in the workplace, specifically in terms of occupational representation. Gender pay equity means simply that employees get paid the same if they are doing the same job equally well, regardless of their gender. Overall *equality* means that there is no difference by gender in who is doing what jobs or the pay they are receiving. For the ten countries analyzed in this case study, notable clustering of women by job rank was observed in the data, consistent with labor market patterns at-large in countries across the globe.

The issue of the occupational or job rank distribution is very important in considering gender pay neutrality. The reason is plain to see: as mentioned earlier, if female employees are distributed in lower paying positions and an analysis “controls” for position held then gender differences in overall compensation equality could be masked. This is not to suggest that it is

Please do not cite without permission.

inappropriate to control for occupation. Rather, this is meant to highlight this incredibly important issue in any analysis of gender compensation neutrality.

Within the Company, the fraction of employees within each job rank that were female varied dramatically. For example, among employees in the lowest job rank, 68 percent were women in Country A, while roughly 10 percent of those in the highest rank were women. To summarize the distribution of female employees across job rank within country, an index of dissimilarity, or job rank segregation, was computed (see Table 3) using the following simple equation:

$$D = \frac{1}{2} \sum_1^k |x_i - y_i|$$

where

x_i is the percentage of all male employees in a given country employed in job rank i
 y_i is the percentage of all female employees in that country employed in job rank i .

This dissimilarity index is often referred to as the Duncan Index (Duncan and Duncan, 1955). It can be interpreted as the proportion of female employees in the country who would have to change job rank in order to spread the female representation evenly across all job ranks, or have the proportion of women in each job rank equal to the proportion of female employees in the country overall (p 211).

The index values computed ranged from a low of 5 within Country H for Type X employees to a high of 33 in Country F. This job rank segregation is important to note. We found that, controlling for a variety of factors including importantly job rank, there was little measured difference in the pay of men and women. But such controls can obviously mask bias or discrimination in promotion or hire.

There are many reasons why women may be more likely in some job ranks of an organization rather than another (or in some jobs such as Type X jobs). Among them could be

Please do not cite without permission.

societal reasons, taste differences or discrimination. Some have argued that there may be “feedback effects” (Blau, Ferber and Winkler, 2010), where if women feel that they may be discriminated against they may be less likely to invest in human capital in the first place. The level and variation of the dissimilarity indexes for the Company across the selected ten countries suggests that an important next step for the Company was to more carefully investigate the hiring and promotion practices within each country and across the organization to be sure that these practices were gender neutral as well. An organization cannot truly know about the gender neutrality of its pay practices in the absence of a holistic analysis of balanced treatment by gender throughout its human resource systems.

Conclusion

We conclude that the Company’s statistical analysis was on par with academic standards in most respects. As with any empirical analysis, there is always room for considering additional information, alternative modeling or future research; but, in general, the Company’s proactive efforts to test the gender neutrality of its pay practices should be considered a promising practice for others to emulate. In addition, what we understand of the Company’s broader HR practices that limited discretionary control of its hiring and supervising managers in determining pay suggests that having supporting structures in place across the organization that work toward gender equity in the workplace overall is important. In this regard, our results align with Castilla (2015), who concludes from his longitudinal case study analysis “that the introduction of certain organizational accountability and transparency procedures into pay decisions is associated with a reduction in the observed pay gap” (p 328).

Please do not cite without permission.

References

Aigner, Dennis J. and Glen G. Cain, 1977, "Statistical Theories of Discrimination in Labor Markets," *Industrial and Labor Relations Review*, 30, 175 – 187.

Alchian, Armen A. and Harold Demsetz, 1972, "Production, information costs, and economic organization," *American Economic Review* 62 (December), 777-795.

Babcock, Linda and Sara Laschever, 2003, *Women Don't Ask: Negotiation and the Gender Divide*, Princeton University Press.

Becker, Gary S., 1964, *Human Capital: A Theoretical and Empirical Analysis with Special Reference to Education* (also 1975 and 1993), University of Chicago Press.

Becker, Gary S., 1971, *The Economics of Discrimination*, University of Chicago Press, 2nd ed.

Blau, Francine, Marianne Ferber and Anne Winkler, 2010, *The Economics of Women, Men and Work*, Prentice-Hall, 6th Edition.

Blau, Francine D. and Lawrence M. Kahn, 2006, "The US Gender Pay Gap in the 1990s: Slowing Convergence," *Industrial and Labor Relations Review* 60, no. 1, 45-66.

Blau, Francine and Lawrence M. Kahn, 2013, "The Feasibility and Importance of Adding Measures of Actual Experience to Cross-Sectional Data Collection," *Journal of Labor Economics*, 31(2), s17-s58.

Cain, Glen G., 1986, "The Economic Analysis of Labor Market Discrimination: A Survey," in Orley Ashenfelter and Richard Layard, Editors, *The Handbook of Labor Economics*, Vol 1, North-Holland, 693 – 785.

Castilla, Emilio J., 2015, "Accounting for the Gap" *Organization Science* 26, no. 2, 311-333.

Please do not cite without permission.

Castilla, Emilio J., 2008, "Gender, Race and Meritocracy in Organizational Careers" *American Journal of Sociology* 116, no. 6, 1479-1526.

Duncan, Otis D., and Beverly Duncan. 1955. "A Methodological Analysis of Segregation Indices" *American Sociological Review* 20, 210-17.

Ehrenberg, Ronald G. and Robert S. Smith, 2012, *Modern Labor Economics: Theory and Public Policy*, Prentice Hall, 11th Edition.

Employment and Disability Institute, "The Disability and Compensation Variables Catalog," Cornell University. <http://www.disabilitystatistics.org/eprrtc/codebook.cfm>.

Fisher, Patricia J. "Assessing the Effect of Allocated Data on the Estimated Value of Total Household Income in the Survey of Income and Program Participation (SIPP), No. 244" U.S. Census Bureau United States Department of Commerce, US Census Bureau, <https://www.census.gov/sipp/workpapr/wp244.pdf>. Accessed May 1, 2015.

Hallock, Kevin F., Xin Jin, Linda Barrington, 2014, "Estimating Pay Gaps for Workers with Disabilities: Implications from Broadening Definitions and Data Sets," *Special Issue: Employer practices in improving employment outcomes for people with disabilities: A trans-disciplinary and employer-inclusive research approach; Rehabilitation Research, Policy and Education*, 28 no. 4, 264-290.

Mincer, Jacob, 1974, *Schooling, Experience and Earnings*, Columbia University Press.

Milkovich, George T., Jerry M. Newman and Barry Gerhart, 2014, *Compensation*, McGraw-Hill Irwin, 11th Edition.

Oi, Walter, and Todd Iddson, 1999, "Firm Size and Wages," in Orley Ashenfelter and David Card, Editors, *Handbook of Labor Economics*, volume 3B, Elsevier Science Publishers, 2165-2214.

Please do not cite without permission.

Phelps, Edmund, 1972, “The Statistical Theory of Racism and Sexism,” *The American Economic Review*, 62(4), September, 659 – 661.

United States Department of Commerce, US Census Bureau, Survey of Income and Program Participation, SIPP Introduction and History, <http://www.census.gov/programs-surveys/sipp/about/sipp-introduction-history.html>, Accessed May 1, 2015.

United States Department of Labor, US Bureau of Labor Statistics, “Employer Costs for Employee Compensation for December 2014,” released March 11, 2015, USDL-15-0386. <http://www.bls.gov/news.release/ecec.nr0.htm>. Retrieved April 30, 2015.

United States Department of Labor, US Bureau of Labor Statistics, “Usual Weekly Earnings of Wage and Salary Workers – Third Quarter 2019”, released October 16, 2019, USDL-19-1818. <https://www.bls.gov/news.release/pdf/wkyeng.pdf>. Accessed December 1, 2019.

Figure 1 The Company’s continuum of HR practices supporting gender pay equity

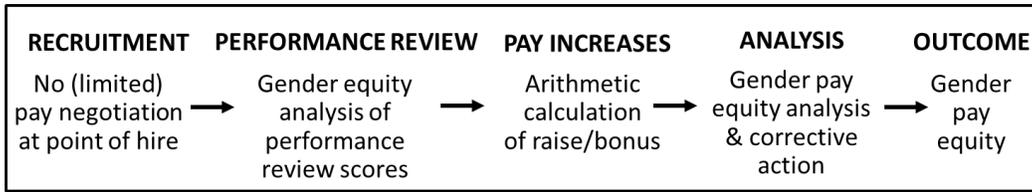


Figure 2 Contribution of Measured Characteristics in Explaining Gender Pay Gap

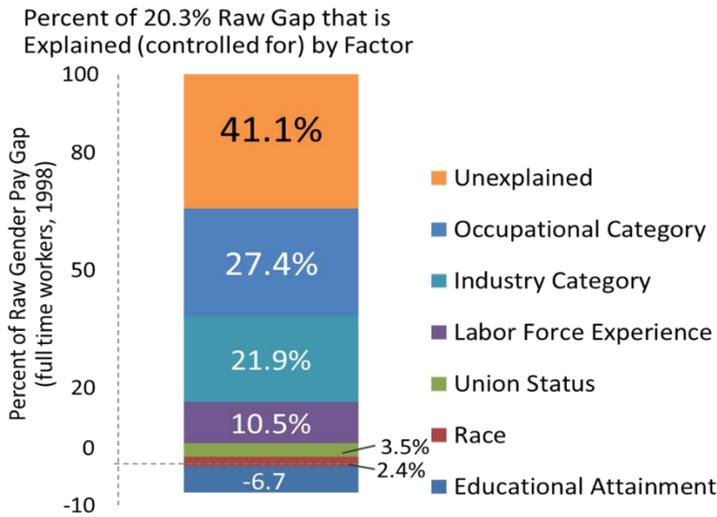


Chart constructed from Table 7-1 in Blau, Francine, Marianne Ferber and Anne Winkler, 2010, *The Economics of Women, Men and Work*, Prentice-Hall, 6th ed., page 196.

Figure 3 Framing of Pay Determination in the Company

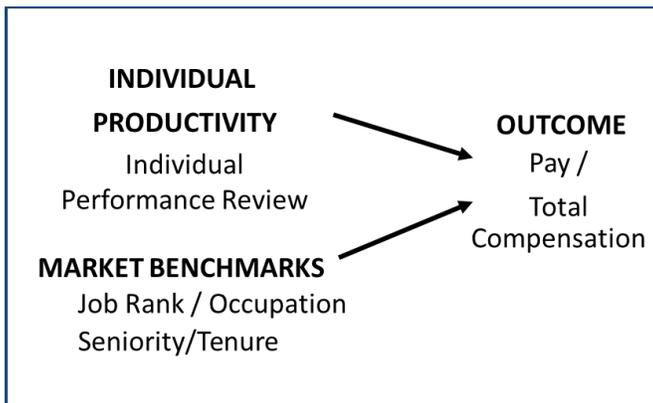


Figure 4 Junctures where company’s HR practices check pay determination

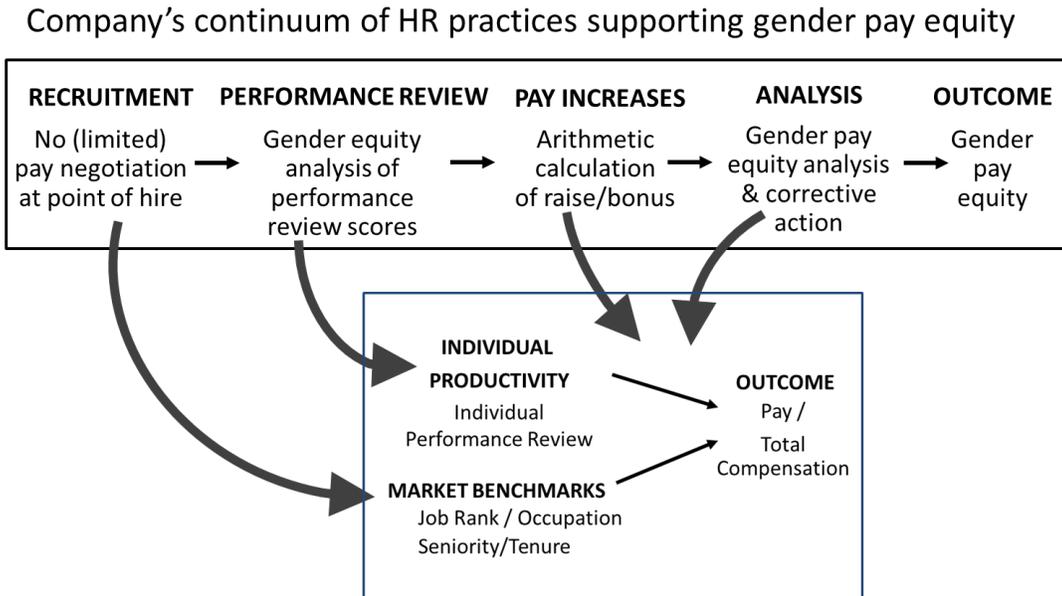


Table 1 Unexplained Gender Wage Gap Estimates.
Coefficient on (female) Across Countries

Countries in OECD	Coefficient on <i>female</i>	Countries in Asia or Africa	Coefficient on <i>female</i>
A	- 0.050*** (0.004)	G	- 0.002 (0.006)
B	0.032*** (0.007)	H (nonType X)	0.007 (0.009)
C	- 0.054*** (0.003)	H (Type X)	- 0.007 (0.011)
D	0.017 (0.021)	I (nonType X)	- 0.030*** (0.007)
E	- 0.006 (0.020)	I (Type X)	- 0.130*** (0.016)
F	- 0.005 (0.012)	J	- 0.0004 (0.003)

The coefficient estimates on the female indicator variable in log salary regressions are reported, controlling also for national, european, full time, performance, seniority, birth cohort, start cohort, job rank. Standard errors are in parentheses. *** denotes statistical significance at the 0.01 level.

Type X denotes specific sets of locations where employees are doing very similar work in a specific context. In countries H and I, the firm had these locations and felt it important to do the analysis separately in those locations. Regressions were also estimated with interaction terms. Little change occurred in the coefficient *female*. Results are not presented here, but are available.

Table 2 Gender Wage Gap Estimates with Alternative Measure of Part-time

Countries in OECD	Coefficient on <i>female</i>	
	Part-time VS Full time	Refined Part-time VS Full time (0-20%, 20-40%, ... 80-100%)
A	- 0.050*** (0.004)	- 0.060*** (0.004)
B	0.032*** (0.007)	- 0.006 (0.006)
C	- 0.054*** (0.003)	- 0.075*** (0.002)
D	0.017 (0.021)	-0.011 (0.019)
E	- 0.006 (0.020)	- 0.012 (0.013)
F	- 0.005 (0.012)	- 0.013 (0.012)

Column 2 reports the coefficient estimates on the female indicator variable in log salary regressions, controlling also for national, european, full time, performance, seniority, birth cohort, start cohort, job rank. Standard errors are in parentheses. *** denotes statistical significance at the 0.01 level.

Column 3 is created by using all the same control specifications as in earlier regressions but replacing the Part-time variable with five indicators to capture varying degrees of time worked 0-20%, 20-40%, 40-60%, 60-80%, and 80-100%.

Table 3 Index of Job Rank Segregation within Country

Countries in OECD	Index of Rank Segregation	Countries in Asia or Africa	Index of Rank Segregation
A	17	G	14
B	12	H (nonType X)	18
C	12	H (Type X)	5
D	23	I (nonType X)	16
E	18	I (Type X)	17
F	33	J	20

The indexes are computed for 12 job ranks, except for one, Country F, which uses more job ranks. Type X denotes specific locations where employees are doing very similar work in a specific context. In countries H and I, the firm had such operations and felt it important to do the analysis separately in those locations.

Please do not cite without permission.

Appendix A.

Basic Specifications: Dependent Variable = Natural Logarithm of Salary

Country A.					
	(1)	(2)	(3)	(4)	(5)
Female	-0.295*** (0.012)	-0.240*** (0.012)	-0.267*** (0.013)	-0.198*** (0.012)	-0.050*** (0.004)
National		-0.000 (0.026)	-0.039 (0.031)	-0.161*** (0.028)	-0.014 (0.009)
European		0.023 (0.036)	-0.006 (0.042)	-0.047 (0.038)	-0.028** (0.012)
Full time		0.341*** (0.024)	0.358*** (0.024)	0.390*** (0.022)	0.286*** (0.007)
Performance			0.069 (0.053)	0.208*** (0.048)	0.126*** (0.016)
Performance _{t-1}			0.065 (0.055)	0.139*** (0.050)	-0.011 (0.017)
Performance _{t-2}			0.507*** (0.048)	0.395*** (0.044)	0.076*** (0.016)
Seniority				-0.044** (0.019)	-0.045*** (0.006)
Birth Cohorts	No	No	No	Yes	Yes
Start Cohorts	No	No	No	Yes	Yes
Job ranks	No	No	No	No	Yes
Adjusted R ²	0.089	0.120	0.184	0.340	0.928

Notes: Standard errors are in parentheses. *, ** and *** indicated significant at 0.10, 0.05 and 0.01, respectively.

5000 < N < 10000 employees.

Country B.					
	(1)	(2)	(3)	(4)	(5)
Female	-0.150*** (0.016)	-0.045*** (0.014)	-0.043*** (0.014)	-0.006 (0.014)	0.032*** (0.007)
National		0.210*** (0.052)	0.146** (0.059)	0.082 (0.056)	0.065** (0.030)
European		0.159*** (0.060)	0.122* (0.067)	0.111* (0.063)	0.071** (0.034)
Full time		0.541*** (0.018)	0.548*** (0.017)	0.573*** (0.017)	0.548*** (0.009)
Performance			-0.008 (0.048)	0.043 (0.045)	0.044* (0.024)
Performance _{t-1}			0.031 (0.052)	0.109** (0.050)	0.039 (0.027)
Performance _{t-2}			0.306*** (0.044)	0.269*** (0.042)	0.126*** (0.022)
Seniority				-0.048** (0.014)	-0.047*** (0.007)
Birth Cohorts	No	No	No	Yes	Yes
Start Cohorts	No	No	No	Yes	Yes
Job ranks	No	No	No	No	Yes
Adjusted R ²	0.044	0.367	0.442	0.500	0.861

Notes: Standard errors are in parentheses. *, ** and *** indicated significant at 0.10, 0.05 and 0.01, respectively.

1000 < N < 2500 employees.

Country C.

	(1)	(2)	(3)	(4)	(5)
Female	-0.289*** (0.011)	-0.179*** (0.012)	-0.176*** (0.013)	-0.130*** (0.012)	-0.054*** (0.003)
National		0.074*** (0.026)	0.028 (0.030)	-0.076*** (0.029)	-0.016** (0.007)
European		0.021 (0.029)	0.026 (0.034)	-0.006 (0.033)	-0.002 (0.008)
Full time		0.296*** (0.015)	0.311*** (0.016)	0.323*** (0.015)	0.240*** (0.004)
Performance			0.034 (0.040)	0.113*** (0.038)	0.052*** (0.009)
Performance _{t-1}			0.024 (0.042)	0.062*** (0.040)	0.063*** (0.009)
Performance _{t-2}			0.290*** (0.038)	0.305*** (0.035)	0.036*** (0.009)
Seniority				-0.038** (0.009)	-0.026*** (0.002)
Birth Cohorts	No	No	No	Yes	Yes
Start Cohorts	No	No	No	Yes	Yes
Job ranks	No	No	No	No	Yes
Adjusted R ₂	0.079	0.119	0.139	0.241	0.954

Notes: Standard errors are in parentheses. *, ** and *** indicated significant at 0.10, 0.05 and 0.01, respectively.

5000 < N < 10000 employees.

Country D.

	(1)	(2)	(3)	(4)	(5)
Female	-0.235*** (0.035)	-0.133*** (0.037)	-0.137*** (0.039)	-0.087** (0.039)	0.017 (0.021)
National		-0.045 (0.052)	-0.065 (0.062)	-0.084 (0.060)	-0.001 (0.032)
European					
Full time		0.435*** (0.067)	0.434*** (0.070)	0.529*** (0.069)	0.442*** (0.036)
Performance			0.170 (0.121)	0.171 (0.117)	-0.045*** (0.062)
Performance _{t-1}			0.030 (0.124)	0.0004 (0.118)	0.123* (0.063)
Performance _{t-2}			0.178* (0.105)	0.249** (0.102)	0.080 (0.054)
Seniority				-0.023* (0.019)	-0.032*** (0.006)
Birth Cohorts	No	No	No	Yes	Yes
Start Cohorts	No	No	No	Yes	Yes
Job ranks	No	No	No	No	Yes
Adjusted R ²	0.102	0.189	0.229	0.312	0.814

Notes: Standard errors are in parentheses. *, ** and *** indicated significant at 0.10, 0.05 and 0.01, respectively.

100 < N < 500 employees.

Country E.

	(1)	(2)	(3)	(4)	(5)
Female	-0.166*** (0.040)	-0.120*** (0.038)	-0.119*** (0.041)	-0.096** (0.042)	-0.006 (0.020)
National		0.273 (0.306)	-0.329* (0.178)		
European		0.645* (0.354)		0.275 (0.174)	0.026 (0.083)
Full time		0.618*** (0.089)	0.640*** (0.096)	0.671*** (0.096)	0.543*** (0.044)
Performance			-0.078 (0.163)	0.051 (0.161)	0.036 (0.073)
Performance _{t-1}			0.085 (0.157)	0.129 (0.153)	0.025 (0.070)
Performance _{t-2}			0.274* (0.152)	0.243 (0.151)	0.201*** (0.069)
Seniority				-0.130*** (0.046)	-0.106*** (0.021)
Birth Cohorts	No	No	No	Yes	Yes
Start Cohorts	No	No	No	Yes	Yes
Job ranks	No	No	No	No	Yes
Adjusted R ²	0.054	0.200	0.254	0.314	0.859

Notes: Standard errors are in parentheses. *, ** and *** indicated significant at 0.10, 0.05 and 0.01, respectively.

European dropped due to collinearity in (3), “National” dropped due to collinearity in (4) and (5).

100 < N < 500 employees.

Country F.					
	(1)	(2)	(3)	(4)	(5)
Female	-0.205*** (0.044)	-0.197*** (0.044)	-0.195*** (0.046)	-0.151*** (0.046)	-0.005 (0.012)
National		0.179 (0.178)	-0.159 (0.193)	-0.011 (0.189)	0.024 (0.047)
European		0.098 (0.217)	0.097 (0.231)	-0.037 (0.226)	0.058 (0.056)
Full time		0.082 (0.105)	0.088 (0.118)	0.136 (0.114)	0.171*** (0.028)
Performance			0.218 (0.165)	0.293* (0.159)	0.051 (0.040)
Performance _{t-1}			-0.192 (0.186)	-0.060 (0.180)	0.035 (0.045)
Performance _{t-2}			0.331** (0.150)	0.355** (0.146)	0.015 (0.038)
Seniority				-0.078 (0.103)	0.060** (0.026)
Birth Cohorts	No	No	No	Yes	Yes
Start Cohorts	No	No	No	Yes	Yes
Job ranks	No	No	No	No	Yes
Adjusted R ²	0.048	0.046	0.063	0.143	0.949

Notes: Standard errors are in parentheses. *, ** and *** indicated significant at 0.10, 0.05 and 0.01, respectively.

100 < N < 500 employees.

Country G.

	(1)	(2)	(3)	(4)	(5)
Female	-0.086*** (0.023)	-0.085*** (0.023)	-0.039 (0.024)	0.020 (0.025)	-0.002 (0.006)
National		-0.015 (0.026)	-0.071** (0.028)	-0.087*** (0.028)	-0.0002 (0.007)
European					
Full time		0.037 (0.156)	-0.025 (0.167)	0.037 (0.159)	0.224*** (0.040)
Performance			-0.042 (0.093)	0.035 (0.090)	0.023 (0.022)
Performance _{t-1}			-0.006 (0.102)	0.139 (0.099)	0.033 (0.025)
Performance _{t-2}			0.372*** (0.098)	0.359*** (0.093)	0.047** (0.024)
Seniority				0.034*** (0.013)	-0.015*** (0.003)
Birth Cohorts	No	No	No	Yes	Yes
Start Cohorts	No	No	No	Yes	Yes
Job ranks	No	No	No	No	Yes
Adjusted R ²	0.009	0.008	0.016	0.109	0.945

Notes: Standard errors are in parentheses. *, ** and *** indicated significant at 0.10, 0.05 and 0.01, respectively.

1000 < N < 2500 employees.

Country H.

	(1)	(2)	(3)	(4)	(5)
Female	-0.574*** (0.028)	-0.574*** (0.028)	-0.753*** (0.039)	-0.247*** (0.032)	-0.092*** (0.017)
National		0.280 (0.206)	0.272 (0.319)	0.367 (0.232)	0.079 (0.122)
European					
Full time		-0.017 (0.524)			
Performance			-0.247 (0.153)	0.239** (0.112)	-0.062 (0.059)
Performance _{t-1}			0.043 (0.158)	0.353*** (0.115)	0.025 (0.061)
Performance _{t-2}			1.013*** (0.116)	0.695*** (0.084)	0.008 (0.046)
Seniority				0.010 (0.016)	-0.033*** (0.009)
Birth Cohorts	No	No	No	Yes	Yes
Start Cohorts	No	No	No	Yes	Yes
Job ranks	No	No	No	No	Yes
Adjusted R ²	0.123	0.123	0.254	0.610	0.892

Notes: Standard errors are in parentheses. *, ** and *** indicated significant at 0.10, 0.05 and 0.01, respectively.

Fulltime is dropped due to collinearity in specifications (3)-(5).

1000 < N < 3500 employees.

**Country H.
(Type X)**

	(1)	(2)	(3)	(4)	(5)
Female	-0.074*** (0.021)	-0.073*** (0.021)	-0.229*** (0.046)	-0.165*** (0.036)	-0.007 (0.011)
National		0.027 (0.131)	0.073 (0.260)	0.127 (0.200)	-0.027 (0.059)
European					
Fulltime		0.448 (0.451)			
Performance			-0.186 (0.157)	0.092 (0.122)	-0.011 (0.036)
Performance _{t-1}			0.162 (0.158)	0.259** (0.122)	0.009 (0.037)
Performance _{t-2}			0.777*** (0.112)	0.582*** (0.087)	0.046* (0.027)
Seniority				-0.221** (0.092)	0.924*** (0.155)
Birth Cohorts	No	No	No	Yes	Yes
Start Cohorts	No	No	No	Yes	Yes
Job ranks	No	No	No	No	Yes
Adjusted R ²	0.005	0.004	0.103	0.471	0.954

Notes: Standard errors are in parentheses. *, ** and *** indicated significant at 0.10, 0.05 and 0.01, respectively.

Full time omitted because of collinearity in (3)-(5).

500 < N < 2500 employees.

In this country, the firm had operations where the bulk of employees are doing very similar work in a specific context, denoted here as Type X employees. The Company felt it important to analyze separately Type X employees and non-Type X employees in these locations.

**Country H.
(non-Type X)**

	(1)	(2)	(3)	(4)	(5)
Female	-0.279*** (0.041)	-0.278*** (0.041)	-0.280*** (0.039)	-0.050 (0.035)	0.007 (0.009)
National		-0.468 (0.534)	-0.272 (0.465)	-0.322 (0.389)	-0.439*** (0.102)
European					
Full time		0.152 (0.534)			
Performance			0.060 (0.142)	0.322*** (0.118)	0.005 (0.031)
Performance _{t-1}			0.226 (0.149)	0.408*** (0.123)	0.086*** (0.033)
Performance _{t-2}			0.585*** (0.116)	0.550*** (0.095)	0.062** (0.026)
Seniority				-0.031** (0.012)	-0.042*** (0.003)
Birth Cohorts	No	No	No	Yes	Yes
Start Cohorts	No	No	No	Yes	Yes
Job ranks	No	No	No	No	Yes
Adjusted R ²	0.056	0.055	0.116	0.413	0.960

Notes: Standard errors are in parentheses. *, ** and *** indicated significant at 0.10, 0.05 and 0.01, respectively.

Full time omitted due to collinearity in (3)-(5).

500 < N < 1000 employees.

In this country, the firm had operations where the bulk of employees are doing very similar work in a specific context, denoted here as Type X employees. The Company felt it important to analyze separately Type X employees and non-Type X employees in these locations.

Country I.					
	(1)	(2)	(3)	(4)	(5)
Female	-0.478*** (0.018)	-0.454*** (0.018)	-0.385*** (0.018)	-0.230*** (0.017)	-0.088*** (0.008)
National		-0.587*** (0.044)	-0.394*** (0.047)	-0.349*** (0.042)	-0.285*** (0.019)
European					
Full time		-0.061 (0.423)	-0.070 (0.375)	-0.083 (0.328)	0.132 (0.150)
Performance			-0.081 (0.076)	0.135** (0.067)	-0.008 (0.031)
Performance _{t-1}			0.067 (0.081)	0.194*** (0.071)	0.063* (0.033)
Performance _{t-2}			0.472*** (0.071)	0.407*** (0.062)	0.079*** (0.029)
Seniority				-0.012 (0.007)	-0.041*** (0.003)
Birth Cohorts	No	No	No	Yes	Yes
Start Cohorts	No	No	No	Yes	Yes
Job ranks	No	No	No	No	Yes
Adjusted R ²	0.128	0.160	0.143	0.346	0.863

Notes: Standard errors are in parentheses. *, ** and *** indicated significant at 0.10, 0.05 and 0.01, respectively.

1000 < N < 5000 employees.

Country I.					
(Type X)					
	(1)	(2)	(3)	(4)	(5)
Female	-0.376*** (0.034)	-0.372*** (0.035)	-0.392*** (0.040)	-0.238*** (0.034)	-0.130*** (0.016)
National		-0.119 (0.090)	-0.157 (0.120)	-0.109 (0.100)	-0.150*** (0.047)
European					
Full time					
Performance			0.057 (0.158)	0.259** (0.131)	0.005 (0.062)
Performance _{t-1}			0.090 (0.165)	0.210 (0.137)	0.004 (0.064)
Performance _{t-2}			0.686*** (0.144)	0.689*** (0.119)	0.010 (0.057)
Seniority				-0.200*** (0.047)	-0.363*** (0.023)
Birth Cohorts	No	No	No	Yes	Yes
Start Cohorts	No	No	No	Yes	Yes
Job ranks	No	No	No	No	Yes
Adjusted R ²	0.080	0.080	0.123	0.404	0.869

Notes: Standard errors are in parentheses. *, ** and *** indicated significant at 0.10, 0.05 and 0.01, respectively.

Full time omitted because of collinearity in (2)-(5).

500 < N < 1500 employees.

In this country, the firm had operations where the bulk of employees are doing very similar work in a specific context, denoted here as Type X employees. The Company felt it important to analyze separately Type X employees and non-Type X employees in these locations.

**Country I.
(non-Type X)**

	(1)	(2)	(3)	(4)	(5)
Female	-0.286*** (0.020)	-0.250*** (0.020)	-0.238*** (0.020)	-0.135*** (0.018)	-0.030*** (0.007)
National		-0.766*** (0.043)	-0.435*** (0.046)	-0.366*** (0.042)	-0.314*** (0.016)
European					
Full time	0.317 (0.358)	0.172 (0.332)	0.136 (0.297)	0.227** (0.115)	
Performance		-0.075 (0.080)	0.104 (0.072)	-0.005 (0.028)	
Performance _{t-1}		-0.015 (0.086)	0.111 (0.077)	0.018 (0.030)	
Performance _{t-2}		0.361*** (0.075)	0.313*** (0.068)	0.065** (0.026)	
Seniority			-0.015** (0.007)	-0.036*** (0.003)	
Birth Cohorts	No	No	No	Yes	Yes
Start Cohorts	No	No	No	Yes	Yes
Job ranks	No	No	No	No	Yes
Adjusted R ²	0.057	0.140	0.093	0.276	0.892

Notes: Standard errors are in parentheses. *, ** and *** indicated significant at 0.10, 0.05 and 0.01, respectively.

1000 < N < 3500 employees.

In this country, the firm had operations where the bulk of employees are doing very similar work in a specific context, denoted here as Type X employees. The Company felt it important to analyze separately Type X employees and non-Type X employees in these locations.

Country J.

	(1)	(2)	(3)	(4)	(5)
Female	-0.197*** (0.018)	-0.201*** (0.018)	-0.190*** (0.019)	-0.101*** (0.015)	-0.0004 (0.003)
National		-0.344** (0.136)	-0.405** (0.165)	-0.516*** (0.135)	-0.136*** (0.026)
European					
Full time					
Performance			-0.185*** (0.065)	0.056 (0.054)	0.082*** (0.011)
Performance _{t-1}			0.206*** (0.060)	0.230 (0.048)	0.027 (0.009)
Performance _{t-2}			0.404*** (0.053)	0.340 (0.043)	0.017** (0.008)
Seniority				-0.039 (0.043)	-0.139*** (0.009)
Birth Cohorts	No	No	No	Yes	Yes
Start Cohorts	No	No	No	Yes	Yes
Job ranks	No	No	No	No	Yes
Adjusted R ²	0.029	0.030	0.055	0.372	0.976

Notes: Standard errors are in parentheses. *, ** and *** indicated significant at 0.10, 0.05 and 0.01, respectively.

Full time is omitted since perfectly collinear with other variables.

1000 < N < 5000 employees.