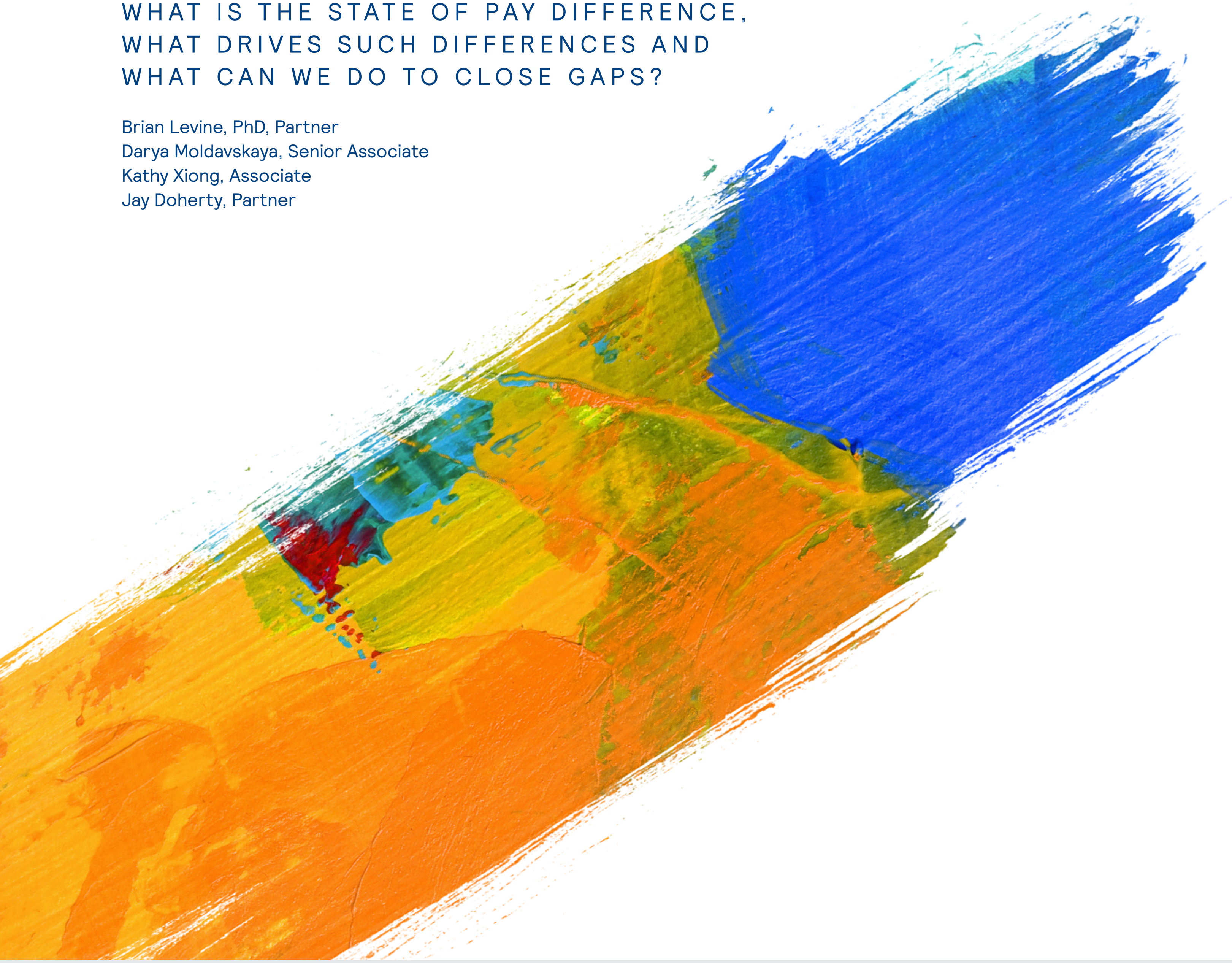
HEALTH WEALTH CAREER

GLOBAL GENDER PAY EQUITY
AN EXAMINATION OF GAPS OUTSIDE THE US

WHAT IS THE STATE OF PAY DIFFERENCE, WHAT DRIVES SUCH DIFFERENCES AND WHAT CAN WE DO TO CLOSE GAPS?

Brian Levine, PhD, Partner
Darya Moldavskaya, Senior Associate
Kathy Xiong, Associate
Jay Doherty, Partner



MAKE TOMORROW, TODAY

MERCER

ABSTRACT

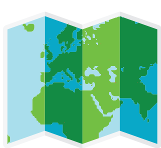
Leveraging data from Mercer's Total Remuneration Survey (TRS), we report on the state of pay equity from a sample of more than 2.5 million employees in 11 countries: Brazil, China, Finland, France, Germany, India, Italy, Japan, Sweden, Switzerland and the United Kingdom. Because the data contain information on employee role, experience and performance, as well as industry and company, we are able to go beyond "raw gaps" to represent pay differences between women and men after accounting for differences in their attributes. In fact, we are able to use sophisticated statistical techniques to parcel out the sources of these raw gaps, country by country. We also assess the impact of likely automation on the pay gap.

This research provides value to companies focused on improving their pay programs. It gives insight on the drivers of pay, generally, in each country, against which a company might consider its own practices; for example, such drivers would reveal the extent to which companies pay for "bought" vs. "built" talent and how pay varies with performance. Furthermore, it provides insight on specific actions companies can take to eliminate gender pay gaps and prevent them from reemerging.

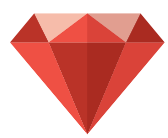
Key findings related to gender include: In most of the countries analyzed, 15%–40% of the pay gap appears to be driven by women and men occupying different career levels and 0%–30% of the gap appears to be driven by women being newer to the workforce (that is, they are younger); women appear to be rewarded better for each year of tenure with an organization, reflecting what might be a "loyalty bonus" (a reward based on a greater perceived ability to retain tenured women into the future); the pay gap is less substantial in jobs subject to automation risk. The last finding seems to stem from women being concentrated in administrative jobs, which are currently less impacted on pay than the manufacturing jobs men are more likely to occupy. Women, who are more concentrated generally in roles subject to automation risk, do face a significant threat of job loss and lower pay rates in those roles but are not facing a larger pay gap relative to men in such roles.

INTRODUCTION

In 2016, Mercer's *When Women Thrive, Businesses Thrive* survey showed that only 35% of organizations had robust, statistical processes for assessing pay equity and only 34% had formal remediation processes linked to such efforts (Mercer, 2016). In a little more than a year since the publication of those statistics, Mercer has seen a significant upsurge in client emphasis on this issue. The upsurge is driven by four factors:



1. **Increasing global regulation**, including a new requirement in the UK that companies publish in April 2018 data on the aggregate pay gap — that is, the total difference in average pay levels between their female and male workforces



2. **Investor proposals** demanding that employers share details on the state of pay equity in their organizations — such proposals have been, so far, focused on the technology, financial services, retail and telecommunications sectors

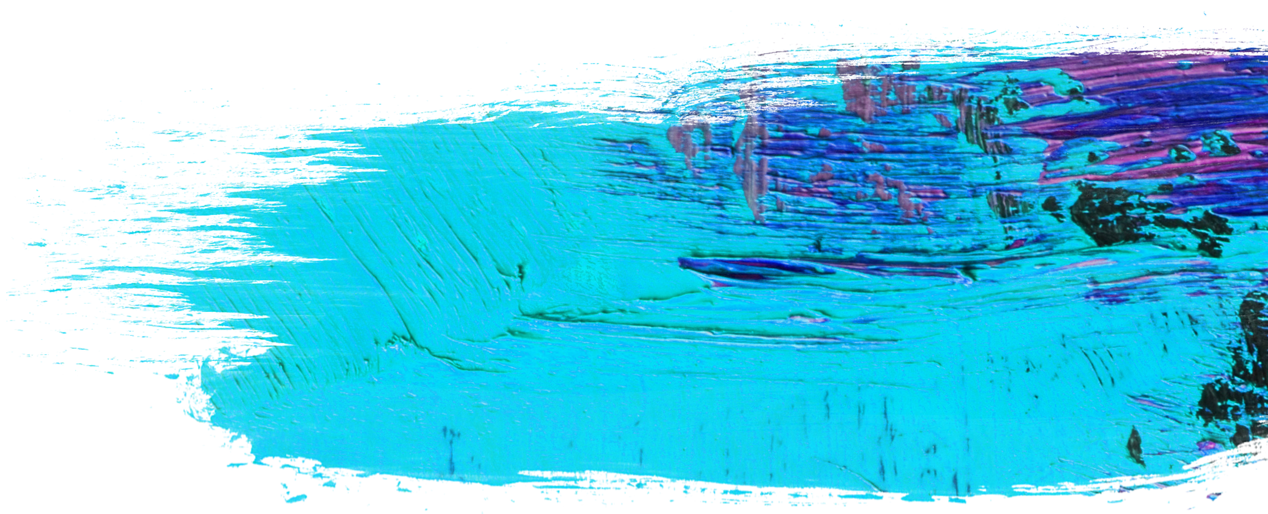
3. **The link between pay equity efforts and success on diversity efforts** — a relationship formalized in Mercer's *When Women Thrive* study

4. **A desire of companies to respond to all the above forces through proactive analysis** — understanding where gaps might exist; the reason for these gaps; the specific actions to effectively respond to the emergence of the gaps; remedial actions to eliminate the gaps; and, finally, how they might communicate their stories to different constituencies, including investors, current and prospective employees, and customers

Although Mercer has worked with companies to conduct such analyses for many years, we believe insights can be generated by looking across companies, both as a starting point for some to consider areas of focus and as a point of comparison for others. For that reason, we have leveraged data from Mercer's Total Remuneration Survey (TRS), which includes extensive employee-level data for companies across multiple countries. This research covers 2.5 million employees in 11 countries: Brazil, China, Finland, France, Germany, India, Italy, Japan, Sweden, Switzerland and the United Kingdom. Because the data contain information on company industry as well as employee role, experience and performance, we are able to go beyond "raw gaps" to represent pay differences between women and men, after accounting for differences in their attributes. In fact, we are able to use sophisticated statistical techniques to parcel out sources of these raw gaps, country by country. We are also able to assess the impact of likely automation on the pay gap.

This research provides value to companies focused on improving their pay practices. It gives insight on the drivers of pay for each country, against which a company might consider its own practices. Such drivers would, for example, reveal the extent to which companies pay for "bought" vs. "built" talent, reward above average performance and vary pay across levels of the hierarchy. Furthermore, it offers insight on specific actions companies can take to eliminate pay gaps and prevent them from reemerging. For example, because women are concentrated in lower-level jobs, companies would be well served by extending their emphasis on equity to cover advancement opportunities and reexamination of often outdated leadership competency models (that is, working to ensure that the strengths of women, also reflected in Mercer's *When Women Thrive* research, are represented and emphasized in these competencies); similarly, a review of differences in performance ratings and associated performance management may serve to accelerate progress.

Although we hope that the data provide helpful context for organizations focused on pay equity, we believe it is important for each organization to engage in a thorough analysis of its own gaps in pay and associated employment opportunities, as we have found that the realities vary significantly across companies — as do the most effective solutions.



METHODOLOGY

REGRESSION

Commonly cited pay equity statistics are calculated in the aggregate — examining how average or median pay differs between women and men. In the US, the Department of Labor calculates that women are paid 79.6% of what men are paid, based on 2015 US Census Bureau data (US Department of Labor, 2016). Although there is value in tracking such statistics, which we call "raw gaps," it is well known that they do not account for differences between women and men in the roles and industries they occupy and in their labor market experience. Methods to calculate "adjusted gaps" or "unexplained gaps" attempt to control for such relevant differences. In understanding the explanations for the parts of the gap, we can accelerate progress to achieve gender equity. Furthermore, in calculating unexplained gaps, we can, perhaps, more accurately reflect the scope of potential discrimination (differences in treatment between individuals who are alike except for their gender).[1]

In our analysis, we rely on multiple regression analysis, country by country. Regression is a statistical technique that estimates the relationship between an outcome variable and multiple predictor variables at once. Importantly, regression provides insight on how a predictor variable (gender) affects the outcome (pay) while holding constant all other predictor variables (which, in this case, would include employee role, experience, performance and organizational characteristics) — it provides an estimate of the aforementioned unexplained gap. The regression analysis sheds light not only on the impact of gender on pay, once the effect of various differences between women and men are taken into account, but also on the compensation strategies taken by organizations operating in each of these countries. Specifically, the analysis reveals:

1. Whether organizations are focused on buying or building talent: the extent to which organizations reward general experience (proxied by age) relative to firm-specific experience (represented by tenure at the organization) — labor economists theorize that firm-specific experience will be valued in organizations where deep knowledge of unique processes or products and/or internal networks are of high value; in contrast, organizations focused on buying talent to perform in a role or looking to accelerate workforce change will be paying for general experience

2. How organizations pay for performance: the extent to which organizations differentiate rewards for above-average talent

3. How pay varies with status: the extent to which pay varies across levels of the hierarchy

The multiple regression model can be represented by the following equation:

$$\hat{Y}_i = \text{Female}_i\, \hat{\beta}_f + X_{i1}\, \hat{\beta}_{i1} + \ldots + X_{ip}\, \hat{\beta}_{ip}$$

[1] Unexplained gaps are not themselves clearly driven by discrimination, as any analysis of this kind suffers from omitted variables – factors that drive pay and may differ by gender.

In the equation, $\hat{Y}_i$ represents the estimated pay for individual i; Female_i represents a “dummy variable” set to 1 for women and 0 for men; $X_{i1} + ... + X_{ip}$ represents *p* individual attributes associated with pay; , $\hat{\beta}_{i1} + ... + \hat{\beta}_{ip}$ represents the impact of each of p attributes on pay; and β_f represents the impact of gender on pay or the unexplained gap. X’s accounted for include:

AGE

Represents general experience

TENURE

Represents firm-specific experience

HIGH PERFORMANCE

Proxied by receipt of more than a target bonus

CAREER LEVEL

Relies on Mercer standards, further described below (on page 9)

JOB FAMILY

Relies on Mercer standards, further described below (on page 9)

THE “PROBABILITY OF AUTOMATION”

Based on research by the Oxford Martin Programme on the Impact of Future Technology (Frey & Osborne, 2013) assessing susceptibility to automation through robotics and artificial intelligence

LOCATION OF WORK

Separate controls for large cities

ORGANIZATION CONTROL

A separate control for every organization in the sample

The probability of automation is a unique control to this analysis. We know that jobs with a high probability of automation are likely to decline, and that women are more concentrated in such jobs in many industries, particularly in administrative roles, which is a concern (World Economic Forum, 2017). Here, we are able to assess the extent to which the probability of automation might also be linked to differential pay outcomes, for all in such jobs and for women in particular.

The organization control simultaneously accounts for differences in pay that would be explained by the employer’s size, industry and unique pay philosophy (for example, pay to the 75th market percentile). This is an important control, as women might be concentrated in different industries and that concentration itself will generally drive part of the pay gap captured by aggregate statistics. For example, according to World Economic Forum research, women represent just 19% of the energy industry workforce, but 51% of the healthcare industry workforce. The perception of a gender wage gap — in this case defined as the percentage of survey respondents reporting that there is a wage gap for equally qualified men and women — is 31% in energy and 15% in healthcare, respectively (World Economic Forum, 2016).

Factors known to be omitted from this analysis include the employee’s actual, relevant experience, details on the employee’s role (which would not be available in our standardized database) and education. Explanatory factors considered in conducting analysis for a specific company would generally be more extensive; hence, one needs to use caution in benchmarking one’s own estimated “pay gaps” against those represented in this report.

DECOMPOSITION

The regression model provides one way to evaluate the effect of gender on pay; it assumes that pay is determined by a set of attributes, including gender, and it seeks to estimate the effects of each separately. That is to say this: Gender may have an impact on an individual's pay, but the impact of age, tenure and other attributes are assumed to be the same regardless of the individual's gender. An alternative view is that gender impacts pay indirectly, by affecting the way individuals are rewarded for these other attributes. In this light, for example, an additional year of tenure may yield a greater increase in pay for a male employee than for a female employee. For those interested in the details of the decomposition approach, we represent them briefly here:

To allow for this variability in the return on attributes, we use another approach that involves fitting separate regressions for women and men. This approach is based on a variation, proposed by Neumark (1988), of the classical Oaxaca-Blinder decomposition. The Oaxaca-Blinder decomposition is a statistical technique widely used by economists to analyze gender- and race-based discrimination. It allows for us to decompose the raw pay gap into an explained part, driven by differences in employee attributes, or "quantities," and an unexplained part, driven by differences in the return on attributes or "prices." Of great value in this approach is the ability to parcel out the impact of differences in specific quantities (attributes) on the overall gap as well as the impact of differences in specific prices for those attributes on the overall gap. As you will see, the gender gap is in part determined by women and men having different quantities of experience and it is in part determined by women and men being rewarded differently, via different prices, for that experience. (For example, the fact that women, on average, are younger than men is a difference in "quantities" that explains the gap; the fact that women receive a smaller increase in pay for each additional year of experience than men would be based on a difference in "prices.")

In this analysis, we assume that the labor market sets the correct "price" for each attribute for the population as a whole — though each group might face a distortion in that overall price, reflective of a difference in treatment.

With this assumption, we carry out the decomposition with three sets of regression estimates:

1	$\bar{Y}_p = \bar{X}_p \hat{\beta}_p$
2	$\bar{Y}_f = \bar{X}_f \hat{\beta}_f$
3	$\bar{Y}_m = \bar{X}_m \hat{\beta}_m$

Equation (1) represents regression results for both women and men together (“pooled sample”), evaluated at the mean attribute values for the population ($\bar{X}_p$), which, by a standard regression property, is equal to the average pay rate in the population ($\bar{Y}_p$); $\hat{\beta}_p$ are the estimated regression coefficients, or prices, for each attribute. Equation (2) represents results for women only, evaluated at the mean attribute values for women ($\bar{X}_f$), and equation (3) represents results for men only, evaluated at the mean attribute values for men ($\bar{X}_m$). Subtracting (3) from (2), then adding two special “zero” terms based results from (1), we have the following:

$$\bar{Y}_f - \bar{Y}_m = \bar{X}_f \hat{\beta}_f - \bar{X}_m \hat{\beta}_m + (\bar{X}_m \hat{\beta}_p - \bar{X}_m \hat{\beta}_p) + (\bar{X}_f \hat{\beta}_p - \bar{X}_f \hat{\beta}_p)$$

Finally, with some rearrangement on the right side, we can transform the equation into the following:

$$\bar{Y}_f - \bar{Y}_m = \underbrace{(\bar{X}_f - \bar{X}_m)\hat{\beta}_p}_{\text{Explained term}} + \underbrace{[(\hat{\beta}_p - \hat{\beta}_m)\bar{X}_m + (\hat{\beta}_f - \hat{\beta}_p)\bar{X}_f]}_{\text{Unexplained term}}$$

Each variable can be broken down into two components: the explained term and the unexplained term. The explained term represents the amount of the pay gap that can be explained by differences in attributes between women and men — with the ability to break out the piece that might be explained by any specific attribute. The unexplained term is the sum of two values: the amount by which men are overpaid and the amount by which women are underpaid, relative to the pooled set of prices, for the same attributes. The sum of these two values represents the total amount of the pay gap that can be explained by differences in treatment between women and men. In other words, it represents the amount of the pay gap that can be eliminated by giving women and men the same returns on attributes — if the prices were the same for women and men, this unexplained term would be zero. Usefully, the unexplained term also can be broken out to show the amount of the overall gap that might be attributable to difference in treatment on specific attributes.

DATA

The data for this analysis come primarily from Mercer's 2015 TRS. The analysis dataset contains over 2.5 million incumbent-level records across 11 countries in 5,451 organizations (that is, companies operating in each of the countries examined). The data are effective as of 2015, though the specific submission dates vary by company.

Although the data are global and come from companies across a variety of industries, the TRS data-collection process ensures comparability. This is driven by Mercer's primary aim in collecting the TRS data: to allow companies to benchmark their employees' pay against the market, focusing on the jobs and locations that are most critical to them. Mercer works with participating companies to standardize the data for this purpose. Companies match each employee's position to a standard job code, based on the Mercer Universal Position Coding System (MUPCS). MUPCS code descriptions include associated job titles, job responsibilities, and typical years of experience and education, which are used to support this match process. From MUPCS codes, we can identify standard employee "career levels" and "job families"– across each of the companies, even when they use very different levels and constructs internally.

The countries selected for this study were chosen because of the common availability of key fields that the analysis requires.

KEY FIELDS

All models in this paper define pay as actual Total Cash Compensation (TCC), which is defined as the sum of base salary, the bonus earned and other guaranteed payments (for example, guaranteed cash allowance). Considered "drivers of pay" include employee, job and employer attributes:

EMPLOYEE ATTRIBUTES

- **Gender**
  - Thirty-three percent of employees in the overall sample are female, yet only 15% of employees in India are female.
- **Experience proxied by age and tenure**
  - Age is a proxy for general experience, notably less accurate for women than for men given women's higher likelihood of employment breaks.
  - Tenure represents firm-specific experience.
  - Comparing age and tenure provides insight on the value of general versus firm-specific experience. In our sample, both age and tenure of employees are lower in the developing countries (Brazil, China and India) than in others.
- **Performance proxied by receipt of more than a target bonus**
  - In France, almost 59% of employees receive a bonus higher than target; in contrast, about 13% of Indian employees' bonuses exceed targets. The number of payouts in excess of target in India, to some extent, might reflect a high number of recent hires and/or greater payouts for high performers.
  - Although men are more likely to be high performers in these data (with the exception of Finland and Italy), we note that our performance measure is directly derived from the compensation outcome (for example, bonus in excess of target); in work that we have conducted for specific organizations, we frequently find that women receive higher performance ratings, though they are not rewarded as well as men for those ratings.

JOB ATTRIBUTES

- **Career level defined from Mercer MUPCS codes**
  - Career levels defined include para-professional, professional, management and executive.
  - The greatest number of employees is concentrated in the professional level. The only exceptions to this are Brazil and China, where the greatest number of employees are found in the para-professional level.
  - Women are clearly concentrated in lower levels in each of the countries examined. Though in Brazil and China, men are more highly represented in para-professional levels (for example, manufacturing jobs), and women are more represented in professional levels — the implication is that, in our data, level works to the advantage women relative to men on pay in these two countries.
- **Job family defined from Mercer MUPCS codes**
- **The *probability of automation*, ranging from 0% to 99%, for most occupations comes from research by the Oxford Martin Programme on the Impact of Future Technology (Frey & Osborne, 2013), mapped to MUPCS codes.**

EMPLOYER ATTRIBUTES

- **Location of work (large cities are accounted for directly, as well as each country)**
- **Organization control (a separate control for every organization in the sample)**
  - The dataset has 5,541 organizations (that is, companies operating in each of the countries examined)

Figure 1 shows baseline statistics on many of the above-defined potential drivers of pay.

FIGURE 1.

	EUROPE							OTHER			
	Finland	France	Germany	Italy	Sweden	Switz.	UK	Brazil	China	India	Japan
Analysis population											
Employees	29,543	137,737	92,054	60,319	69,153	38,095	138,405	602,833	1,078,309	177,639	116,933
% Female	32%	38%	29%	32%	33%	34%	33%	30%	37%	15%	24%
Experience											
General (avg. yrs)	44.0	43.3	44.8	44.3	44.8	43.2	42.4	35.2	32.7	33.4	42.5
Female	43.9	42.5	43.2	43.0	43.5	41.3	40.1	34.2	32.5	30.9	40.6
Male	44.1	43.8	45.5	44.8	45.4	44.1	43.5	35.6	32.8	33.9	43.1
Firm-specific (avg. yrs)	13.2	13.8	13.8	14.0	13.0	11.3	10.0	6.3	5.6	5.3	15.0
Female	13.0	13.2	12.4	13.7	11.6	9.2	8.3	5.3	5.2	4.0	12.7
Male	13.3	14.2	14.4	14.1	13.7	12.3	10.9	6.7	5.8	5.5	15.8
Performance											
% Above target	24.4%	58.9%	17.3%	26.4%	26.5%	38.5%	21.3%	26.5%	31.8%	13.4%	39.4%
% Female	25.8%	57.3%	15.3%	28.9%	26.2%	37.3%	18.7%	18.9%	28.7%	11.5%	36.2%
% Male	23.8%	59.9%	18.1%	25.2%	26.6%	39.1%	22.5%	29.7%	33.6%	13.8%	40.4%
Pay											
Avg. total compensation	$62,197	$59,175	$75,072	$53,749	$61,457	$135,070	$61,653	$14,262	$19,473	$14,297	$60,011
Female	$56,717	$55,892	$65,745	$47,141	$58,290	$124,592	$55,519	$12,679	$19,572	$13,128	$50,183
Male	$64,736	$61,156	$78,944	$56,818	$62,994	$140,409	$64,640	$14,949	$19,415	$14,501	$63,192
Likelihood of job automation											
Avg. % overall	19.7%	32.8%	36.3%	32.8%	28.3%	34.2%	38.4%	66.8%	53.3%	25.3%	29.3%
% Female	25.8%	39.9%	44.4%	43.2%	33.0%	43.5%	43.0%	69.8%	55.0%	22.7%	36.0%
% Male	16.8%	28.5%	33.0%	27.9%	26.0%	29.5%	36.2%	65.4%	52.2%	25.8%	27.1%

	Finland		France		Germany		Italy	
	Female	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**	**Male**
Executive	27%	73%	24%	76%	17%	83%	18%	82%
Manager	28%	72%	33%	67%	22%	78%	24%	76%
Professional	32%	68%	40%	60%	31%	69%	32%	68%
Para-professional	44%	56%	40%	60%	33%	67%	38%	62%

	Sweden		Switzerland		UK		Brazil	
	Female	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**	**Male**
Executive	30%	70%	20%	80%	24%	76%	19%	81%
Manager	31%	69%	25%	75%	29%	71%	28%	72%
Professional	33%	67%	35%	65%	34%	66%	39%	61%
Para-professional	35%	65%	40%	60%	34%	66%	29%	71%

	China		India		Japan	
	Female	**Male**	**Female**	**Male**	**Female**	**Male**
Executive	39%	61%	10%	90%	11%	89%
Manager	39%	61%	11%	89%	13%	87%
Professional	40%	60%	17%	83%	27%	73%
Para-professional	35%	65%	13%	87%	32%	68%

CAVEATS

We acknowledge that there are two data-related limitations.

First, the data used for this analysis are not a random sample of any of these country-based economies. Organizations must choose to participate in Mercer's TRS. Further, organizations may choose to provide data for all of their employees globally or for a subset of their employees by country or job group.

With regard to this point, for the reader's consideration, we present information on the representation of different industries in each of our covered countries, as compared to International Labor Organization (ILO) data (Appendix B). Overall, manufacturing industries are over-represented in the TRS data — between 45% and 90% of the analysis sample work for an organization that belongs in a manufacturing industry, whereas only 10%–20% of the ILO sample fall under the ISIC Economic Activity code for manufacturing. Similarly, we provide the percentage female and the age distribution, by country, as compared to ILO data (Appendix C). Overall, female representation is lower in the TRS sample than in the ILO data, in part due to the over-representation of manufacturing industries. The age distribution is similar between the two datasets and follows similar patterns between countries, although it is less variable in the TRS data.

Second, all models control for a very limited, standard set of controls. Similar models run at the organization level to address gender pay equity would take into account actual career structures, as opposed to standardized career levels and actual performance ratings, as opposed to proxies (derived from payouts compared to targets); they would also account for factors not considered here, such as the employee's education level and actual experience — which would at least include the employee's recent job history at the organization.

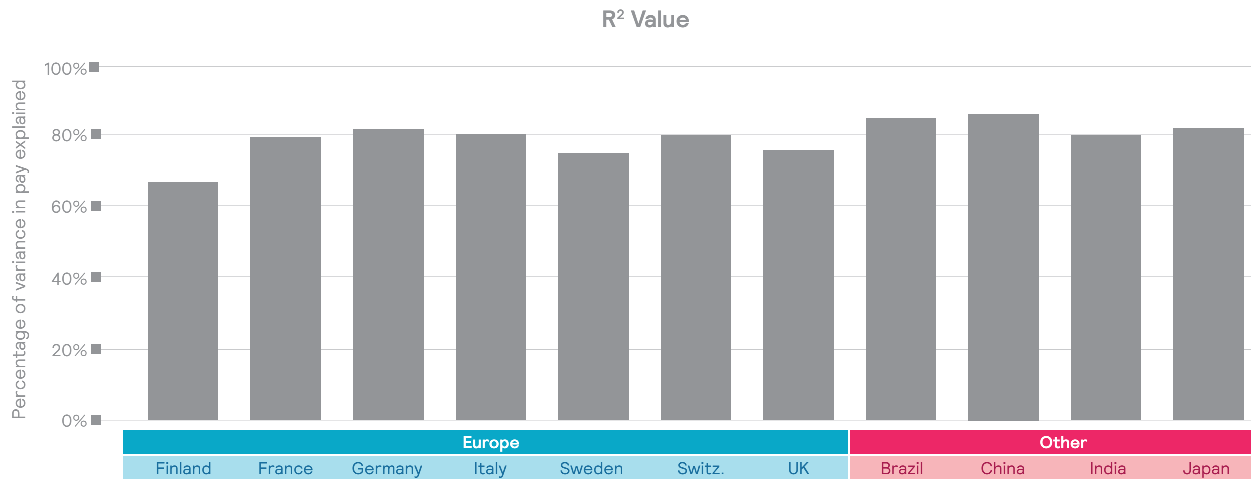
Although the analysis presented here is a helpful starting point, raising potential concerns, we advise that companies conduct their own more detailed analyses to assess pay equity risk and support actions to close gaps, as described in earlier analysis we conducted on this topic (Levine, Park, & Jacob, 2015).

The current analysis provides a "set of estimates" against which recent similar analyses, performed on crowdsourced data and subject to other potential biases, can be evaluated (Chamberlain, 2016). It is our recommendation that such benchmarks be looked at together in any attempt to assess the norm in a given market.

RESULTS

MODEL FIT

FIGURE 2.

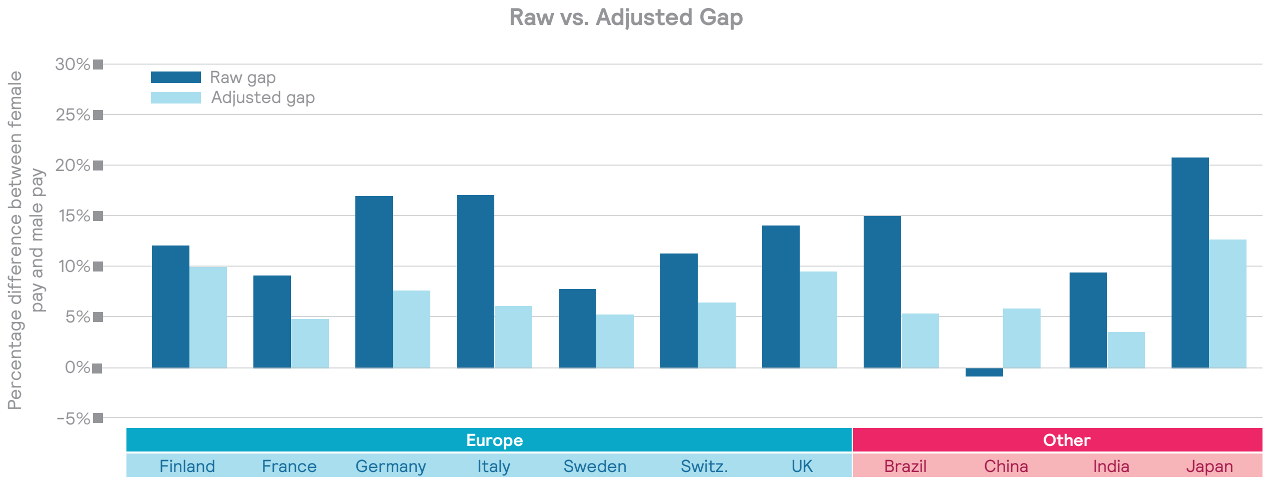


R-squared values	66.6%	79.0%	81.3%	80.0%	74.7%	79.7%	75.5%	84.5%	85.9%	79.5%	81.7%

The R^2 values represent the percentage of variation in pay that is accounted for by the explanatory variables included in each model. Our models perform well; on average, our models explain 80% of variation in pay, which is high for models of this type and reflects the richness of our controls. To represent probability of automation effects, we ran another set of models that excluded job family controls. Those models have only slightly lower R^2 values.

RAW VS. ADJUSTED GAPS

FIGURE 3.

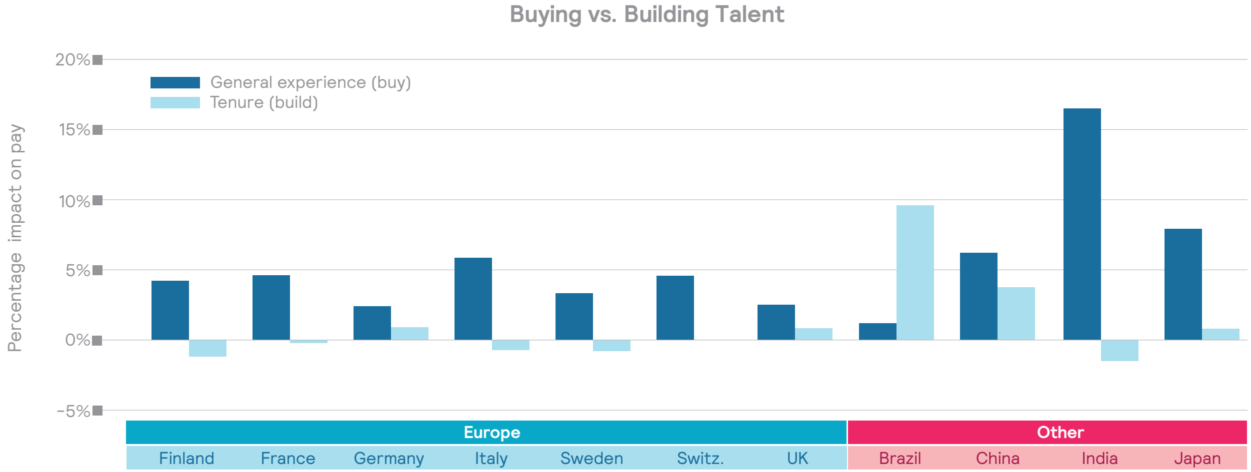


	Finland	France	Germany	Italy	Sweden	Switz.	UK	Brazil	China	India	Japan
Raw gap	-12.4%	-8.6%	-16.7%	-17.0%	-7.5%	-11.3%	-14.1%	-15.2%	0.8%	-9.5%	-20.6%
Adjusted gaps	-9.9%	-4.8%	-7.4%	-6.1%	-5.3%	-6.3%	-9.4%	-5.1%	-5.7%	-3.8%	-12.2%
% Decrease	20.2%	44.2%	55.6%	64.0%	28.6%	44.1%	33.2%	66.2%	-606.3%	59.3%	40.8%

In Figure 3, we present our findings on the gender pay gap — both "raw gaps" and "adjusted gaps." The adjusted gaps account for the various factors defined previously, including employee attributes, job attributes and employer attributes. One might argue that the adjusted gap is overstated, in that we fail to account for factors known to drive pay (for example, education and actual experience); one might also argue that it is understated, in that it accounts for performance, which itself might be affected by discrimination. We account for performance, in this case, because it ultimately provides further insight on the causes of both the raw and adjusted gaps. The reader will, no doubt, note the large difference between the raw and adjusted gaps. Adjusted gaps are largest in Japan, the UK and Finland. These adjusted gaps are similar to gaps estimated on 2012 TRS data (Levine, Park, & Jacob, 2015).

OTHER DRIVERS OF PAY: AGE AND TENURE

FIGURE 4.



	Finland	France	Germany	Italy	Sweden	Switz.	UK	Brazil	China	India	Japan
General experience[1]	4.3%	4.5%	2.6%	5.7%	3.3%	4.5%	2.4%	1.7%	6.3%	16.3%	8.0%
Firm specific experience[2]	−1.1%	−0.1%	1.1%	−0.8%	−0.9%	n/s	0.8%	9.7%	3.6%	−1.7%	0.8%

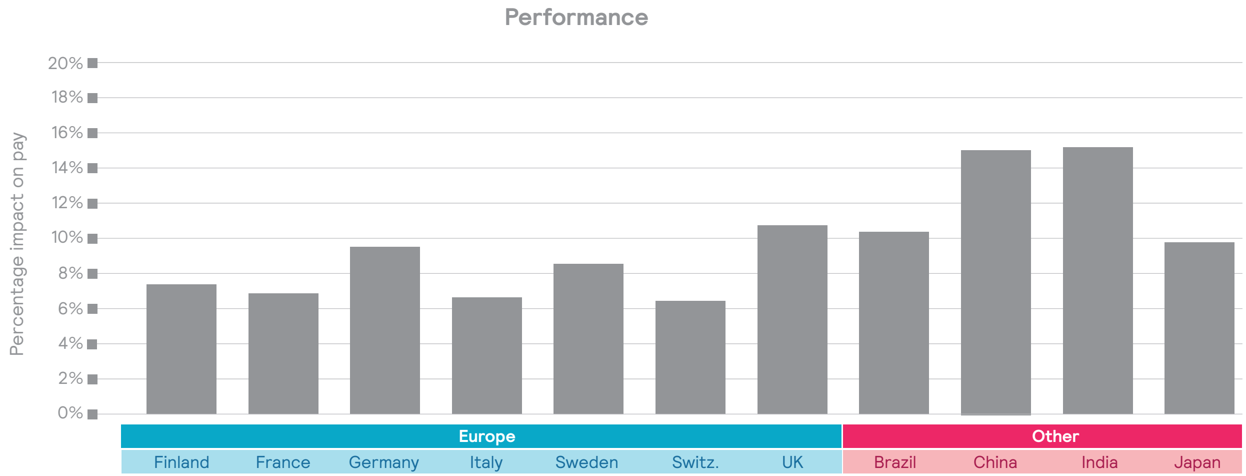
1. General experience is proxied by age. The effect shown are for each additional five years of age.
2. Firm-specific experience is measured by years of tenure. The effects shown are for each additional five years of tenure.

Figure 4 shows the returns for general and firm-specific experience, proxied by age and tenure, respectively, in the models, by country. With the exception of Brazil, general experience is valued more than firm-specific experience, all else equal. Furthermore, tenure has a negative impact on pay in Finland, France, Italy, Sweden and India; a negative effect of tenure on pay is commonly seen when there is “compensation compression” (that is, new hires coming in at premiums), which is common in growing or tight labor markets. In these five countries, organizations pay more for recently bought talent than for built talent.

The extent to which organizations reward general experience (proxied by age) relative to firm-specific experience (represented by tenure at the organization) should align to their talent requirements. Labor economists theorize that firm-specific experience will be valued in organizations where deep knowledge of unique processes or products and/or internal networks are of high value; in contrast, organizations focused on buying talent to perform in a role or looking to accelerate workforce change will be paying for general experience. So it seems that in Finland, France, Italy, Sweden and India, generally speaking, there is less appetite to pay for “company knowledge,” whereas in Germany, the UK, Japan, Brazil and, especially, China, there is greater balance between the rewards allocated to these distinct sources of potential human capital value.

OTHER DRIVERS OF PAY: PERFORMANCE

FIGURE 5.



	Finland	France	Germany	Italy	Sweden	Switz.	UK	Brazil	China	India	Japan
Performance above target[1]	7.5%	6.9%	9.4%	6.4%	8.6%	6.3%	10.7%	10.2%	14.9%	15.1%	9.7%

1. Bonus paid as percentage of target bonus is used as a proxy for performance. When the ratio exceeds one, the employee is flagged as an above-average performer.

Across all geographies, Figure 5 shows that high performance is rewarded with higher pay — that is, in fact, enforced by the analysis, given that high performers are, by definition, paid better than their targets on bonus. The variation in the value of such high-performance across countries, is, however, revealing. The "high performer" premium ranges from 7.5% in Finland to 15.1% in India. Interestingly, the country with the smallest portion of employees identified as "high performers," India, has performance associated with the highest pay reward; the small probability of achieving the target appears calibrated with a more handsome reward.

OTHER DRIVERS OF PAY: CAREER LEVEL

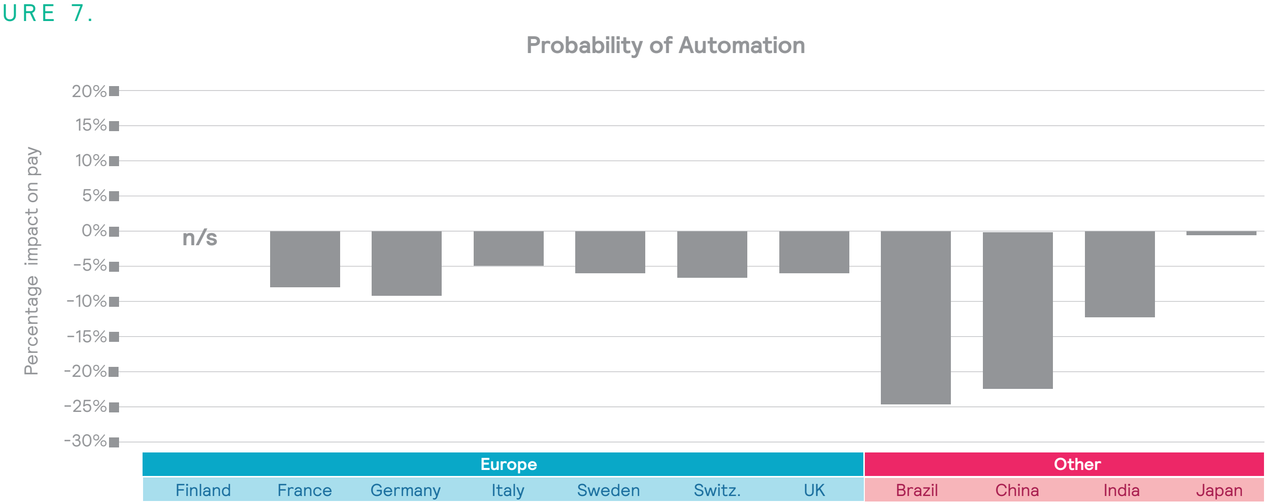
FIGURE 6.

	EUROPE							OTHER			
	Finland	France	Germany	Italy	Sweden	Switz.	UK	Brazil	China	India	Japan
Career level (vs. para-professional)											
Executive	129.5%	190.2%	152.7%	195.4%	144.8%	150.8%	246.8%	1515.8%	773.8%	645.5%	164.4%
Manager	55.0%	75.3%	67.1%	52.3%	60.1%	58.8%	87.5%	351.7%	211.2%	208.1%	65.4%
Professional	17.6%	29.1%	26.9%	14.4%	21.4%	21.1%	31.3%	107.9%	60.3%	59.9%	18.1%

Unsurprisingly, career level is a significant driver of pay; employees in senior levels are paid more than entry-level employees. The pay differentiation by career level is most stark in the developing economies (Brazil, China and India). In Brazil, executives are paid more than 15 times higher than para-professionals.

OTHER DRIVERS OF PAY: PROBABILITY OF AUTOMATION

FIGURE 7.



	Finland	France	Germany	Italy	Sweden	Switz.	UK	Brazil	China	India	Japan
Probability of automation	n/s	-8.0%	-9.1%	-4.7%	-6.5%	-6.8%	-6.5%	-24.9%	-22.7%	-12.2%	-0.7%

Figure 7 shows that the probability of automation is universally associated with lower pay. The magnitude of the effect is largest in the developing countries (Brazil, China and India). In Brazil and China, this is likely due to a concentration of such jobs in manufacturing; in India, the bulk of such jobs are in IT (Figure 8). Note that models focused on the impact of automation do not include separate controls for jobs family — as it is our intent to show the complete impact of being in roles likely to be automated.

JOB FAMILY DISTRIBUTION, BY COUNTRY

FIGURE 8.

	EUROPE							OTHER			
	Finland	France	Germany	Italy	Sweden	Switz.	UK	Brazil	China	India	Japan
Job Family											
Manufacturing	12.6%	14.1%	20.2%	15.1%	13.8%	16.0%	15.6%	48.7%	41.1%	14.1%	15.1%
Sales	10.2%	14.0%	14.4%	14.9%	8.8%	7.0%	10.4%	6.2%	7.1%	13.2%	26.7%
Engineering	13.9%	12.7%	10.9%	15.8%	16.1%	8.2%	11.9%	4.4%	11.1%	10.0%	11.5%
Supply & Logistics	7.7%	11.3%	11.0%	9.3%	8.9%	9.6%	13.4%	9.0%	9.9%	6.7%	5.8%
Finance	6.9%	6.9%	6.4%	8.6%	6.6%	10.4%	7.4%	3.6%	4.3%	6.4%	4.5%
IT	8.4%	4.4%	4.7%	5.1%	7.1%	7.3%	5.1%	2.0%	1.3%	19.1%	3.0%
Administration	4.1%	8.2%	5.6%	5.4%	7.0%	10.4%	6.6%	7.8%	3.5%	3.0%	2.6%
R&D	13.7%	4.4%	5.0%	3.8%	7.4%	4.3%	2.7%	0.1%	2.4%	3.6%	5.8%
Marketing	3.3%	5.0%	4.8%	4.0%	3.9%	5.7%	3.3%	5.5%	2.4%	1.6%	6.1%
HR	3.7%	4.1%	3.4%	3.7%	3.9%	5.2%	4.0%	2.5%	2.3%	3.4%	5.2%
Quality	1.4%	2.4%	2.2%	3.2%	2.1%	4.2%	2.1%	1.2%	6.6%	8.0%	3.2%

Note: Job families shown are the top most represented in the analysis population.

THE DECOMPOSITION: WHAT DRIVES THE GENDER GAP

FIGURE 9.

	QUANTITY EFFECTS (EXPLAINED)					PRICE EFFECTS (UNEXPLAINED)			
Country	Age	Tenure	Performance	Level	Automation	Age	Tenure	Performance	Automation
Europe									
Finland	1.2%	-0.9%	-0.8%	30.3%	1.5%	69.7%	9.0%	2.9%	7.9%
France	18.6%	-0.8%	1.1%	64.3%	15.7%	170.5%	-30.8%	-1.1%	5.9%
Germany	8.4%	1.9%	1.7%	35.9%	7.8%	56.8%	-13.0%	2.2%	-4.7%
Italy	14.7%	-0.8%	-1.1%	38.8%	6.1%	95.2%	-29.6%	1.0%	1.5%
Sweden	20.5%	-7.0%	0.4%	16.3%	7.7%	69.9%	2.9%	0.7%	-7.4%
Switzerland	27.4%	-2.6%	1.4%	68.2%	11.5%	76.9%	-7.5%	0.0%	-13.5%
United Kingdom	12.0%	2.2%	3.7%	22.9%	3.9%	52.2%	-6.2%	0.7%	-5.8%
Other									
Brazil	2.5%	13.2%	4.6%	-15.2%	6.4%	30.9%	6.9%	-6.7%	-69.7%
China	6.2%	3.9%	10.6%	-52.6%	11.8%	65.7%	-13.2%	12.9%	-44.8%
India	129.2%	-10.8%	4.1%	40.2%	-5.7%	-233.5%	-25.7%	3.1%	-11.6%
Japan	18.4%	1.9%	1.9%	37.5%	0.4%	99.3%	-13.8%	4.2%	0.7%

Figure 9 shows the results of our decomposition. For each country, on the left side of the table, we show the impact on the gap of differences between women and men in their “quantities” of employee and job attributes; on the right side, we show the impact on the gap of differences in “prices” women and men face for these attributes. As we are parceling out the effect of likelihood of automation on the gap, the models used to support the decomposition do not account for job family.

In reviewing the quantity effects, the following results are emphasized:

- The gap is significantly driven by differences in career level between women and men (Appendix D). In France, for example, 64% of the pay gap is driven by women being in lower levels. The only countries in our data that show women with pay driven up due to their occupation of higher levels are China and Brazil. This is due to a high concentration of jobs in manufacturing in our data, and a resulting over-representation of men in the para-professional career level. In China and Brazil, career level differences seem to reduce the gap by 15% and 53%, respectively.

- Women are more concentrated in jobs that are likely to be automated, and because such jobs pay employees less, this concentration drives up overall pay gaps.

- The gap is driven by women having less experience — specifically, they are younger.

- Although part of the gap is driven by women having lower levels of performance, we note that the high-performance measure here is directly derived from the bonus outcome (specifically, as bonus exceeding target); in work that we have conducted for specific organizations, we frequently find that women receive higher performance ratings even as they are not rewarded as well for those ratings.

In reviewing the price effects, the following results are emphasized:

- Women are rewarded less well for each additional year of general experience than men. This aligns to a well-known issue with age as a proxy for general experience: that it is less accurate for women who are more likely to experience breaks in employment.

- Women appear to be better rewarded than men for each year of tenure, reflecting what might be a “loyalty bonus” (a reward based on a greater perceived ability to retain tenured women, as opposed to men, into the future); it might reflect greater commitment of women.

- Women appear to be slightly less well rewarded than men when they are high performers.

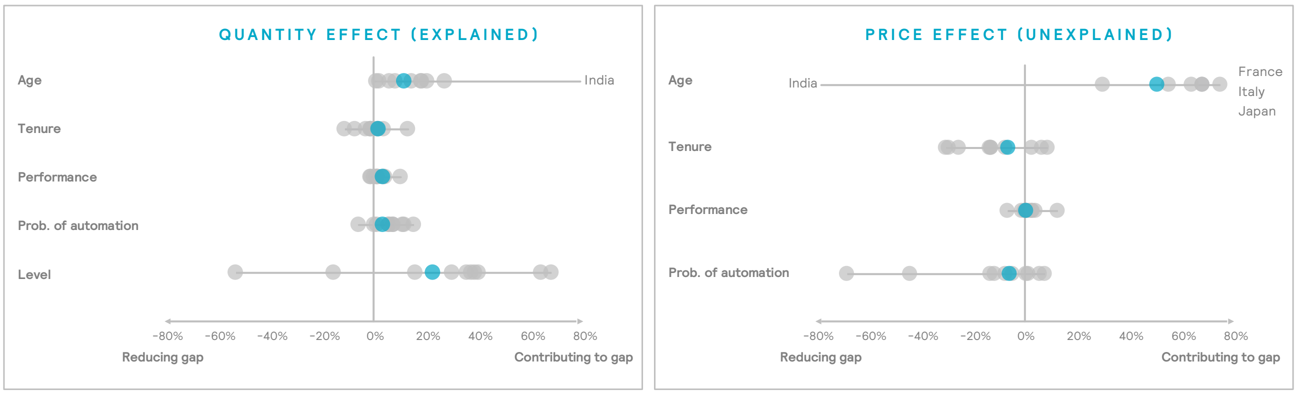
- In three countries (Finland, France and Italy), the pay gap is somewhat larger in jobs subject to automation risk. The last finding seems to imply that women, who are more concentrated in jobs subject to automation risk, face not only the threat of job loss and the lower pay rates associated with those jobs, but also lower pay than men in those jobs; the reality might well reflect a lack of “active management” of pay equity in jobs that are on the decline.

- Generally, the pay gap is reduced in jobs subject to automation risk. This likely reflects a concentration of women in administration roles over men in manufacturing roles (Appendix E; the exception is in Brazil, where women are more concentrated in manufacturing, but in non-production roles in which pay rates are less impacted by automation). Men in manufacturing roles likely to be automated are feeling the pinch.

UNDERSTANDING PAY GAPS IN THE UK

CONTEXT FOR 2018 REQUIRED DISCLOSURES

FIGURE 10.



The charts in Figure 10 show the decomposition results for the UK. The chart on the left shows percentages of the pay gap between men and women driven by the difference in "quantities" of job attributes; the chart on the right shows percentages of the pay gap driven by differences in "prices" of these attributes. The blue dots represent results for the UK, whereas the grey dots represent results for other countries for comparison.

In the UK, we observe the following key quantity effects:

- About 23% of the pay gap is driven by a difference in the distribution of women and men among career levels. Specifically, women are over-represented in lower career levels and under-represented in higher career levels.
- About 12% of the gap is driven by women having less general experience (proxied by age). A much smaller portion of the gap, about 2%, is driven by women having lower tenure, or firm-specific experience.
- About 4% of the gap is driven by a lower percentage of women receiving above-target performance outcomes (estimated with above-target bonus pay).
- About 4% of the gap is driven by a greater percentage of women in jobs that face higher automation risk, as these jobs also tend to be lower paid.

We also note the following key price effects:

- About 52% of the gap is driven by women receiving a lower return on each additional year of general experience (proxied by age). This is somewhat balanced by a higher return on firm-specific experience, which reduces the gap by around 6%.
- About 1% of the gap is driven by high-performing women receiving lower pay than high-performing men. Combined with the quantity effect, this means that women are not only less likely to be designated high performing but that they are also rewarded less for being high performers than their male colleagues. But the effect is modest.
- The gap is reduced by about 12% because women in jobs likely to be automated receive higher pay than men in such jobs; women are more likely to be in administration jobs, whereas men are more likely to be in manufacturing jobs.

CONCLUSION

The analysis points to implications related to, first, compensation management generally and, second, effective strategies to counter pay equity gaps. We address each in turn.

With regard to compensation management:

- For almost all countries examined, we see that organizations reward general over firm-specific experience. Because organizations become what they reward, they need to understand — in their specific circumstances — the value generated by these two types of experience as well as the alignment of compensation to each of them. **It is our perspective that analytics can establish such relationships, and once those relationships are established, that the compensation strategy can be aligned to support the desired, directional evolution of the workforce experience profile**.

- On performance management, we see fairly modest differentiation in compensation between above-average and below-average performers in Europe. That is not to say we are advising greater pay for performance, linked to incentives. But we do believe **the mechanism by which pay-for-performance is enforced should be well-thought-out and validated regularly.** For organizations and jobs within them where teamwork and long-time focus are critical, incentive pay differentiation should be less intensive; for organizations looking to build firm-specific human capital, performance might be rewarded more through career progression than temporary financial awards. Prior Mercer research speaks to such considerations related to pay-for-performance strategy (Nalbantian, Adkins, & Levine, 2014).

With regard to countering pay equity gaps:

- The raw gap is very strongly driven by **differences in the career levels** and roles occupied by women and men. A focus on pay equity within a job has positive effects for building up the representation of women but would be dramatically strengthened by a focus on hiring, promotion and retention of diverse talent throughout the hierarchy. Effective equity strategies need to be focused on more than pay.

- In conducting tailored analyses for specific organizations, we often see that those who have the benefit of occupying **particular roles** (for example, supervisors, customer-facing employees) **do better** in terms of pay increases and advancement. Ensuring access of diverse populations to such opportunities is of paramount importance. Similarly, in such analyses, we see that competencies rewarded are frequently aligned to the traditional strengths of men — it behooves organizations to consider whether such competency models should be updated to reflect critical needs like "collaboration" and "change management" (Mercer, 2016).

- Also in such tailored work, we often see that women receive higher performance ratings than men, but **lower payouts and probabilities of advancement associated with those ratings.** To effectively counter this reality, organizations need to account for performance in their pay equity reviews to ensure that women are rewarded commensurately with their performance; effort should also be taken to clarify desired links between performance ratings and workforce outcomes with managers.

- Organizations need to **manage pay equity actively** across all their populations. That we see women in jobs likely to be automated paid less than men in some countries reveals a need to strengthen review processes, in jobs throughout the hierarchy.

- On a related note, organizations focused on building gender diversity need to **consider proactively the ramifications of automation on female representation**. Providing supplementary training programs to help employees develop new skills and targeting these populations as new roles emerge that need to be filled can perhaps soften the impact of future changes.

- For some jobs, Claudia Goldin notes that **pay inequality based on hours worked and/or flexibility** is a related issue, where “talent continuity” is critical to productivity (for example, where work cannot be transferred easily between employees, where employees need to coordinate with others on teams) (Goldin, 2014). To the degree that companies move to rely on freelancers (for example, contracted tasks) and/or technologies that ensure effective knowledge sharing and collaboration, gaps should decline.

- Although we did not consider the impact of prior employer pay on calculated gaps in this research, our work with specific companies shows that **reliance on prior pay in hiring** can explain as much as half of the “unexplained gap.” To the degree that pay rates can be set explicitly for the roles to be filled, this will lower the risk of inheriting inequities from others.

- Finally, research points to the importance of institutional realities, like minimum wages and labor unions, in promoting equity (Blau & Kahn, 2003). As institutional changes reduce overall wage inequality, they are seen to also reduce the gender gap. Perhaps investor and regulatory pressures will serve a similar function together with more companies moving to proactively assess and address pay inequities.

WORKS CITED

Blau F, Kahn, L. “Understanding International Differenced in the Gender Pay Gap” (2003), *Journal of Labor Economics*, pp. 106–144.

Chamberlain A. *Demystifying the Gender Pay Gap: Evidence From Glassdoor Salary Data*, Mill Valley: Glassdoor (2016).

Frey CB, Osborne M. *The Future of Employment*, Oxford: Oxford Martin Programme on Technology and Employment (2013).

Goldin C. “A Grand Gender Convergence: Its Last Chapter” (2014), *American Economic Review*, pp. 1091–1119.

International Labour Organization. *Key Indicators of the Labor Market (KILM)* (2016), retrieved April 12, 2017, from ILOSTAT.

Levine B, Park M, Jacob T. "Driving Compensation Strategy Alignment: Using Analytics to Benchmark Practices From European Normative Data, *"World At Work Journal"* (2015), pp. 39–45.

Mercer. *When Women Thrive, Businesses Thrive* (2016).

Nalbantian H, Adkins J, Levine B. "Pay-for-Performance Models: Alignment vs. Dysfunction," *Workspan* (May 2014), pp. 33–35.

Neumark D. "Employer's Discriminatory Behavior and the Estimation of Wage Discrimination," *The Journal of Human Resources* (1988), pp. 279–295.

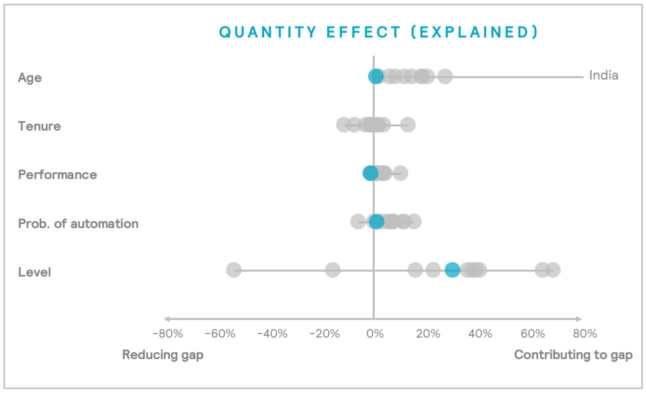
US Bureau of Labor Statistics. *Highlights of Women's Earnings in 2015* (2016). US Department of Labor. *Women's Earnings and the Wage Gap*.

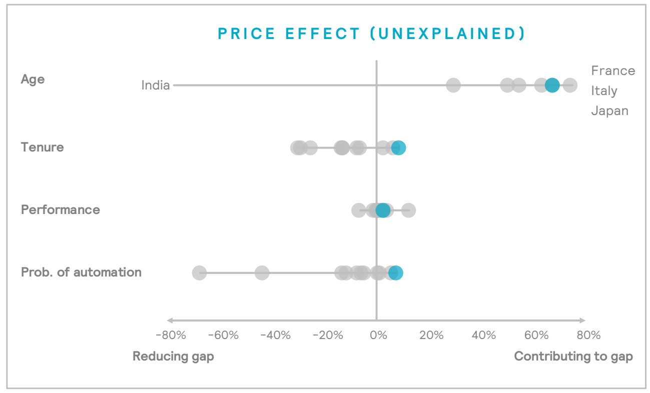
World Economic Forum. *The Future of Jobs: Employment, Skills and Workforce Strategy for the Fourth Industrial Revolution* (2016).

World Economic Forum. *Realizing Human Potential in the Fourth Industrial Revolution* (2017).

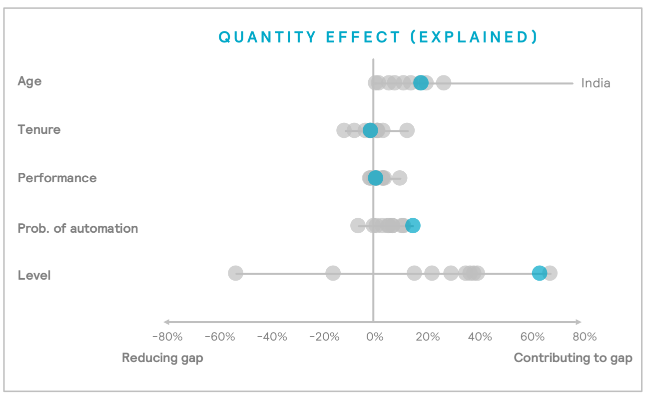
APPENDIX A

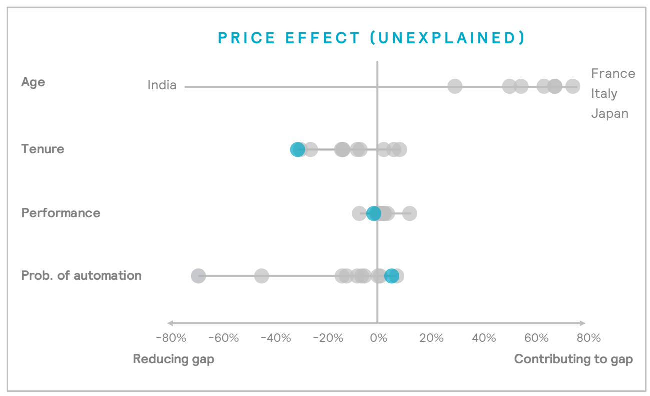
FINLAND



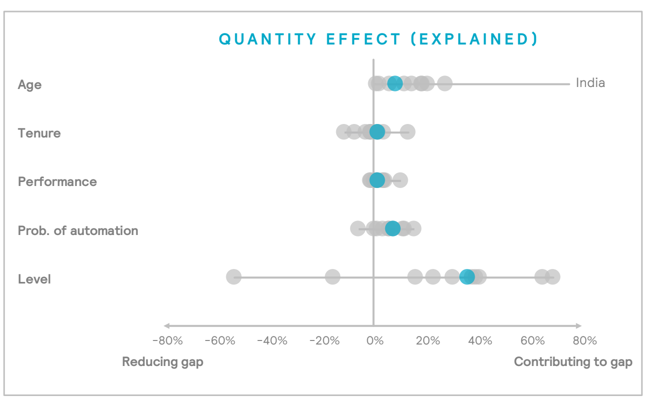


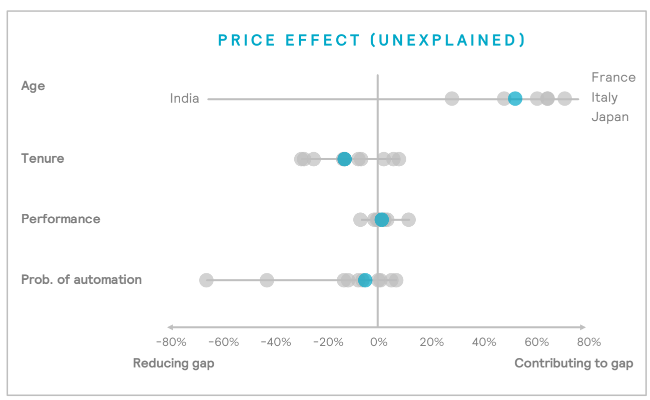
FRANCE



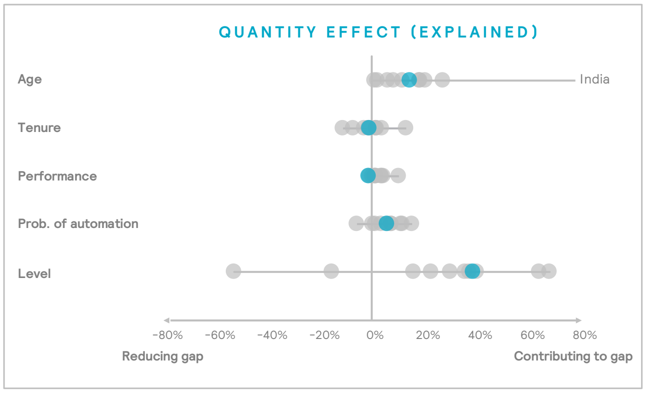


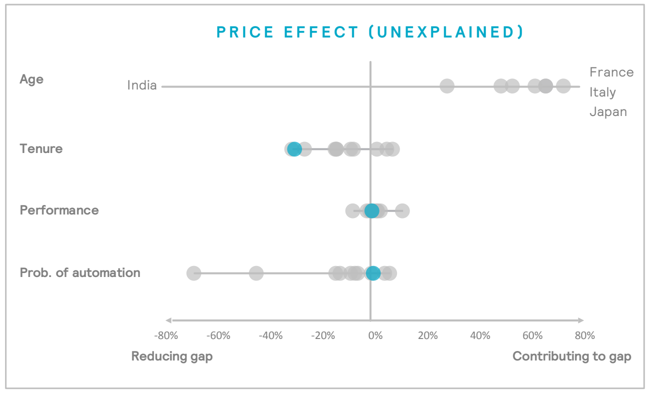
GERMANY



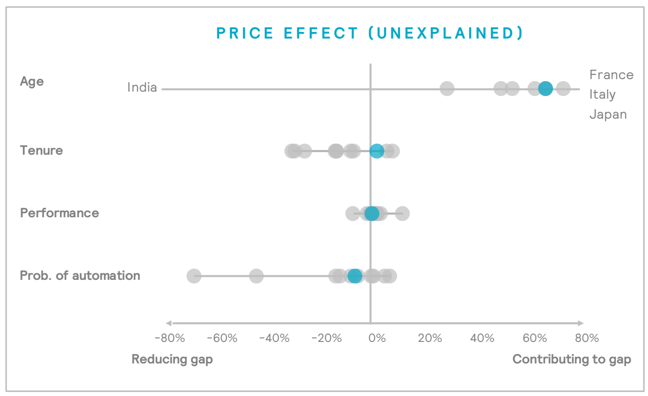


ITALY

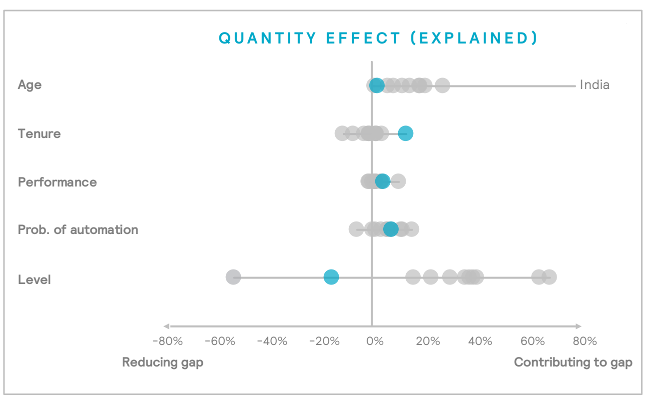


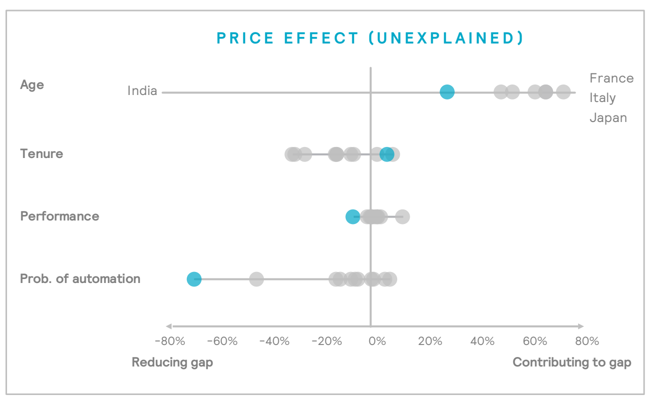


SWEDEN

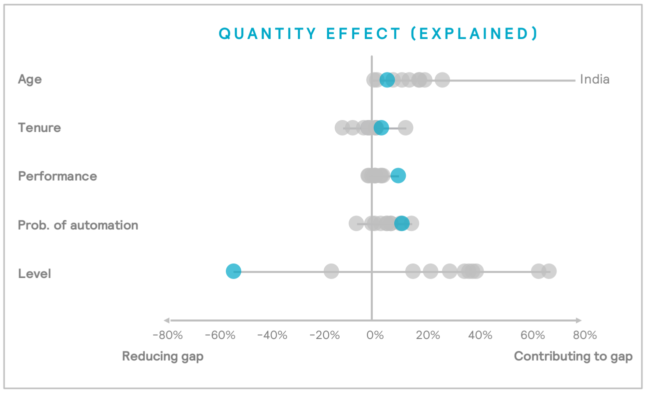


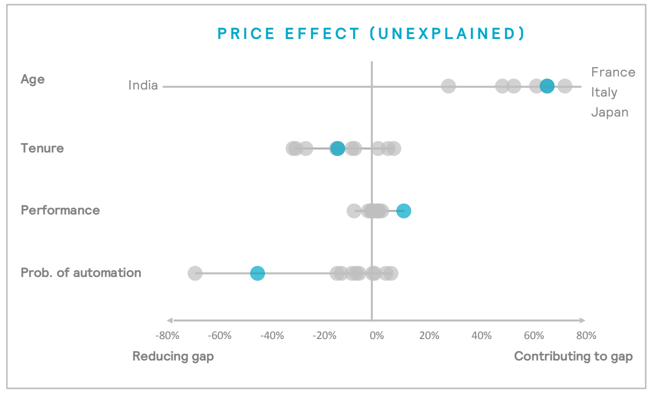
BRAZIL



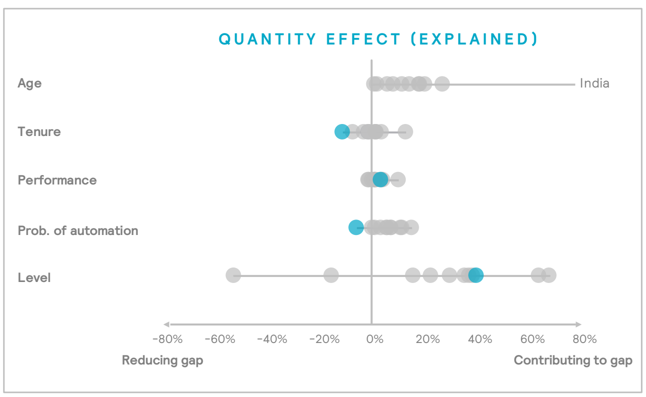


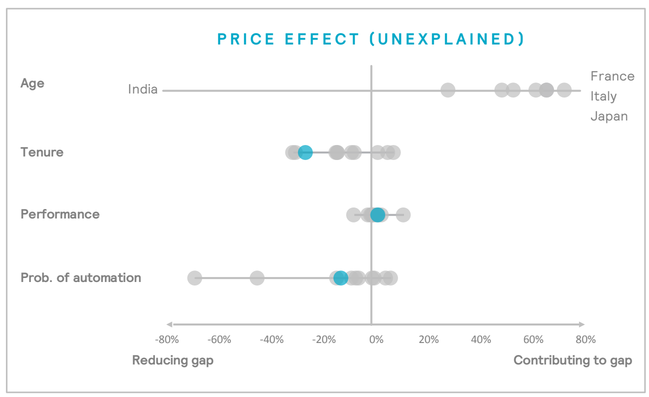
CHINA



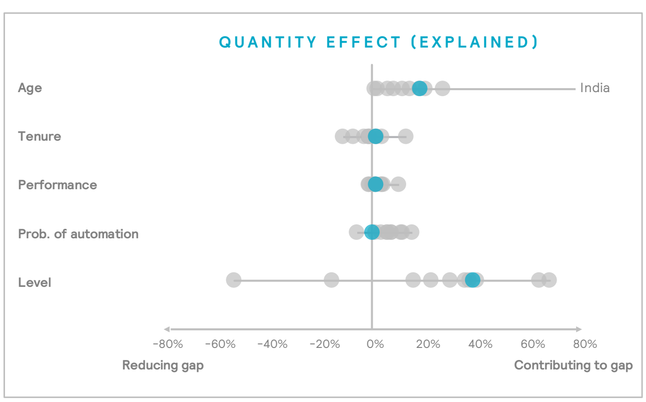


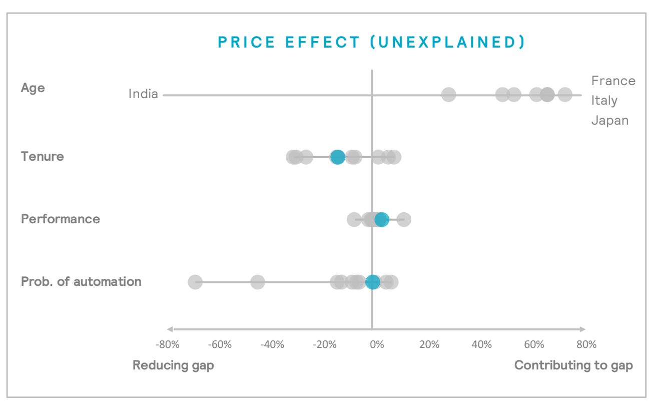
INDIA





JAPAN





APPENDIX B

TRS INDUSTRY REPRESENTATION BY COUNTRY

	EUROPE							OTHER			
	Finland	France	Germany	Italy	Sweden	Switz.	UK	Brazil	China	India	Japan
Industry											
Consumer goods *	6.4%	21.1%	25.5%	15.8%	5.7%	15.7%	17.1%	41.5%	13.9%	15.1%	22.1%
High tech *	17.7%	16.1%	10.4%	15.4%	13.3%	4.1%	7.9%	3.7%	20.2%	22.7%	15.3%
Other durable goods manufacturing *	25.1%	18.9%	20.1%	20.7%	21.5%	9.3%	14.6%	9.2%	20.3%	9.1%	15.3%
Transportation equipment *	0.7%	6.8%	10.7%	10.7%	11.6%	2.9%	11.8%	11.0%	23.8%	15.5%	13.9%
Life sciences	0.9%	10.8%	7.4%	10.2%	5.7%	31.0%	4.0%	2.4%	4.4%	16.0%	11.6%
Other non-durable goods manufacturing *	15.7%	3.7%	5.9%	2.7%	4.3%	13.0%	6.4%	2.3%	9.2%	10.5%	8.6%
Energy	11.2%	4.4%	4.3%	7.9%	15.1%	1.6%	9.1%	5.2%	1.0%	1.5%	0.4%
Other non-manufacturing	17.3%	6.0%	8.8%	6.0%	4.5%	5.8%	15.5%	9.2%	3.6%	1.4%	4.6%
Services (non-financial)	3.0%	2.9%	2.1%	5.5%	7.8%	9.0%	6.5%	2.8%	1.4%	7.0%	0.5%
Retail & wholesale	1.6%	8.1%	3.8%	1.7%	2.7%	1.1%	3.3%	3.4%	2.0%	0.2%	7.0%
Mining & metals	0.2%	0.9%	0.2%	2.5%	5.4%	0.2%	0.1%	9.1%	0.2%	0.0%	0.0%
Insurance/reinsurance	0.2%	0.1%	0.1%	0.5%	1.0%	5.8%	0.1%	0.2%	0.0%	0.0%	0.3%
Banking/financial services	0.0%	0.3%	0.8%	0.3%	1.4%	0.4%	3.5%	0.1%	0.1%	1.0%	0.2%
Specialty retail	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%

* Manufacturing industry

ILO ECONOMIC ACTIVITY REPRESENTATION BY COUNTRY

	EUROPE							OTHER			
	Finland	France	Germany	Italy	Sweden	Switz.	UK	Brazil	China	India	Japan
Economic activity (ISIC-rev.4)											
Manufacturing	13.5%	12.2%	19.3%	18.4%	10.4%	13.1%	9.6%	12.5%	n/a	12.5%	16.7%
Wholesale and retail trade; repair of motor vehicles and motorcycles	11.7%	12.8%	14.1%	14.2%	11.6%	12.5%	13.0%	19.1%	n/a	9.9%	17.0%
Human health and social work activities	16.6%	14.7%	12.7%	8.0%	15.2%	13.5%	13.3%	4.3%	n/a	1.0%	12.3%
Agriculture, forestry and fishing	4.2%	2.7%	1.4%	3.8%	2.0%	3.2%	1.1%	10.2%	n/a	47.0%	3.6%
Construction	6.9%	6.4%	6.8%	6.5%	6.5%	6.4%	7.2%	8.2%	n/a	10.7%	7.8%
Education	7.3%	7.6%	6.6%	6.7%	11.4%	7.1%	10.5%	6.6%	n/a	3.1%	4.8%
Professional, scientific and technical activities	7.0%	5.7%	5.5%	6.3%	8.5%	8.3%	7.0%	3.5%	n/a	0.6%	3.4%
Public administration and defence; compulsory social security	4.4%	9.2%	6.9%	5.8%	6.5%	4.5%	5.9%	5.7%	n/a	1.8%	3.7%
Transportation and storage	5.6%	5.6%	4.9%	4.6%	5.1%	4.5%	5.0%	4.7%	n/a	4.4%	5.7%
Accommodation and food service activities	3.6%	3.8%	3.9%	5.9%	3.5%	4.4%	5.2%	4.8%	n/a	1.7%	6.0%
Administrative and support service activities	4.4%	3.8%	5.0%	4.3%	4.7%	5.0%	4.8%	4.4%	n/a	0.7%	4.6%
Information and communication	4.4%	2.8%	3.0%	2.5%	4.2%	3.3%	4.0%	1.3%	n/a	0.8%	3.3%
Other service activities	3.0%	2.4%	2.8%	2.9%	2.6%	3.0%	2.8%	3.6%	n/a	2.2%	3.2%
Financial and insurance activities	2.0%	3.3%	3.1%	2.9%	2.0%	5.1%	4.0%	1.4%	n/a	1.0%	2.8%
Arts, entertainment and recreation	2.5%	1.7%	1.4%	1.3%	2.4%	1.7%	2.7%	1.0%	n/a	0.2%	1.1%
Activities of households as employers	0.4%	1.1%	0.5%	3.5%	0.0%	1.1%	0.2%	6.6%	n/a	0.8%	0.0%
Real estate activities	1.0%	1.5%	0.5%	0.6%	1.5%	1.1%	1.1%	0.6%	n/a	0.2%	1.4%
Electricity, gas, steam and air conditioning supply	0.5%	0.7%	0.8%	0.5%	0.6%	0.6%	0.6%	0.3%	n/a	0.3%	1.0%
Not elsewhere classified	0.4%	1.2%	0.0%	0.0%	0.7%	1.2%	0.7%	0.0%	n/a	0.0%	1.6%
Water supply; sewerage, waste management and remediation activities	0.4%	0.7%	0.6%	1.1%	0.5%	0.3%	0.7%	0.7%	n/a	0.3%	0.0%
Mining and quarrying	0.3%	0.1%	0.2%	0.2%	0.2%	0.0%	0.5%	0.5%	n/a	0.6%	0.1%
Activities of extraterritorial organizations and bodies	0.0%	0.1%	0.0%	0.1%	0.0%	0.1%	0.1%	0.0%	n/a	0.0%	0.0%

Note: 2015 data used for all countries, except India, where 2012 (latest available) data are used; data not available for China

APPENDIX C

TRS GENDER AND AGE DISTRIBUTION BY COUNTRY

	EUROPE							OTHER			
	Finland	France	Germany	Italy	Sweden	Switz.	UK	Brazil	China	India	Japan
% Female	31.7%	37.6%	29.3%	31.7%	32.7%	33.8%	32.7%	30.3%	37.2%	14.8%	24.5%
Age groups											
15–19	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.1%	1.0%	0.9%	0.1%	0.2%
20–24	0.6%	0.9%	1.4%	0.4%	1.4%	1.4%	3.5%	11.3%	9.8%	6.9%	2.2%
25–29	5.8%	8.1%	6.2%	3.8%	5.9%	6.7%	10.8%	18.7%	27.8%	27.3%	7.5%
30–34	13.9%	13.6%	11.0%	10.6%	10.4%	14.3%	13.8%	21.8%	27.5%	29.3%	11.5%
35–39	17.1%	15.3%	12.6%	16.0%	14.4%	16.5%	14.0%	17.5%	16.7%	17.6%	15.2%
40–44	15.5%	16.2%	13.6%	20.3%	16.7%	16.3%	14.2%	12.1%	9.7%	9.6%	20.3%
45–49	15.2%	15.3%	19.1%	19.4%	17.1%	16.2%	14.3%	8.6%	4.8%	5.2%	18.0%
50–54	13.7%	14.5%	18.0%	15.5%	14.2%	13.7%	13.6%	5.5%	1.9%	2.6%	14.7%
55–59	11.1%	12.0%	12.3%	10.7%	11.1%	9.6%	9.6%	2.5%	0.7%	1.3%	8.5%
60–64	6.6%	3.7%	5.5%	3.2%	7.6%	4.9%	4.9%	0.8%	0.1%	0.1%	1.9%
65+	0.5%	0.3%	0.4%	0.2%	1.1%	0.3%	1.2%	0.2%	0.0%	0.0%	0.1%

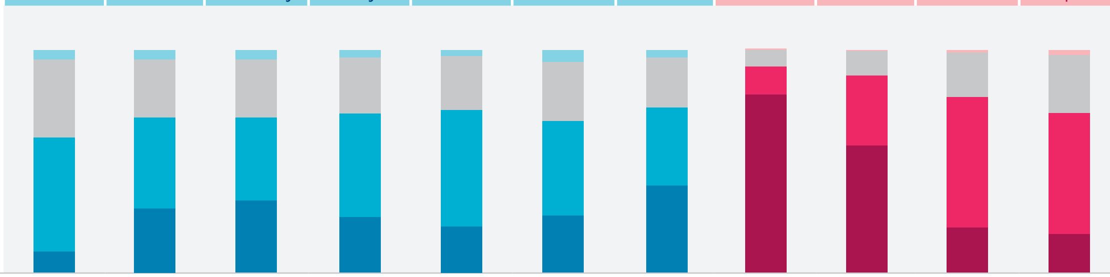
ILO GENDER AND AGE DISTRIBUTION BY COUNTRY

	EUROPE							OTHER			
	Finland	France	Germany	Italy	Sweden	Switz.	UK	Brazil	China	India	Japan
% Female											
Overall	48.7%	48.3%	46.6%	41.8%	47.7%	46.2%	46.7%	42.9%	n/a	22.1%	43.2%
Manufacturing	25.6%	28.6%	27.2%	26.4%	23.5%	29.2%	24.6%	35.9%	n/a	23.4%	29.8%
Age groups											
15–19	2.7%	1.3%	2.6%	0.4%	2.5%	4.7%	3.4%	5.1%	n/a	5.4%	1.5%
20–24	7.7%	6.6%	6.9%	3.8%	8.3%	7.5%	9.0%	10.3%	n/a	10.6%	6.3%
25–29	10.1%	10.6%	9.9%	7.6%	10.9%	10.3%	11.3%	12.1%	n/a	13.1%	8.5%
30–34	11.3%	11.9%	10.4%	10.6%	10.8%	11.0%	11.5%	13.5%	n/a	13.2%	9.2%
35–39	11.4%	12.2%	10.3%	13.4%	10.9%	10.6%	10.8%	13.0%	n/a	14.2%	10.7%
40–44	10.9%	14.0%	11.1%	15.6%	12.0%	11.3%	11.4%	12.2%	n/a	11.9%	12.8%
45–49	12.3%	13.6%	14.0%	15.8%	12.2%	12.5%	12.3%	10.8%	n/a	10.8%	11.5%
50–54	12.6%	13.3%	14.1%	14.4%	11.2%	12.3%	11.9%	9.4%	n/a	7.4%	10.4%
55–59	11.4%	10.9%	11.3%	10.9%	9.9%	9.9%	9.2%	6.6%	n/a	5.7%	9.3%
60–64	6.9%	4.2%	6.9%	5.5%	7.7%	6.2%	5.5%	4.0%	n/a	4.1%	8.4%
65+	2.8%	1.2%	2.6%	2.2%	3.7%	3.7%	3.8%	3.0%	n/a	3.7%	11.4%

Note: 2015 data used for all countries, except India, where 2012 (latest available) data are used; data not available for China

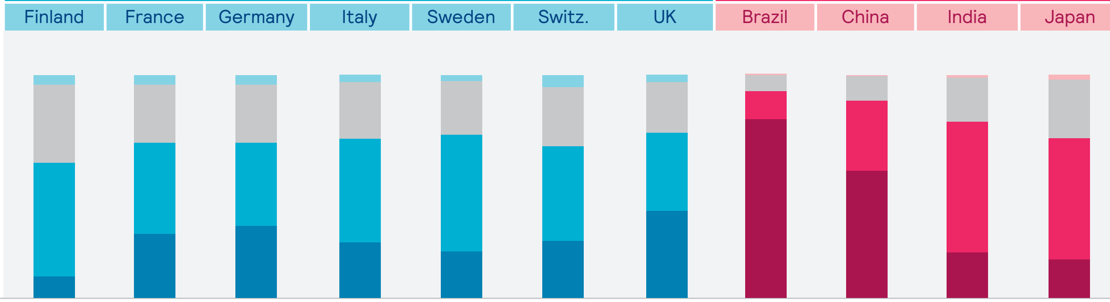
APPENDIX D

FEMALE DISTRIBUTION ACROSS LEVELS



	EUROPE							OTHER			
	Finland	France	Germany	Italy	Sweden	Switz.	UK	Brazil	China	India	Japan
Executive	3.7%	2.3%	2.1%	1.7%	2.7%	2.7%	2.2%	0.2%	0.8%	0.9%	1.0%
Manager	28.4%	21.3%	18.0%	17.2%	22.4%	17.6%	18.8%	6.5%	11.6%	13.7%	11.6%
Professional	52.2%	44.7%	40.8%	47.6%	52.3%	45.3%	37.5%	18.6%	35.7%	67.5%	62.3%
Para-professional	15.8%	31.7%	39.2%	33.5%	22.6%	34.4%	41.5%	74.7%	51.9%	17.8%	25.2%

MALE DISTRIBUTION ACROSS LEVELS



	EUROPE							OTHER			
	Finland	France	Germany	Italy	Sweden	Switz.	UK	Brazil	China	India	Japan
Executive	4.6%	4.3%	4.3%	3.6%	3.1%	5.6%	3.5%	0.4%	0.7%	1.4%	2.4%
Manager	34.5%	26.0%	26.1%	25.0%	23.7%	26.5%	22.6%	7.1%	10.8%	19.5%	26.1%
Professional	51.5%	41.2%	37.2%	46.5%	52.5%	42.0%	34.9%	12.7%	31.6%	58.7%	54.0%
Para-professional	9.4%	28.6%	32.4%	25.0%	20.8%	25.8%	39.1%	79.8%	56.8%	20.4%	17.5%

APPENDIX E

DISTRIBUTION ACROSS JOB FAMILIES, BY GENDER

			EUROPE							OTHER			
Job Family	**Prob. of Automation**	**Gender**	Finland	France	Germ.	Italy	Swede.	Switz.	UK	Brazil	China	India	Japan
Manufacturing	85%	Female	6.2%	11.3%	14.0%	12.0%	9.7%	9.5%	6.4%	51.9%	37.9%	3.6%	9.7%
		Male	15.6%	15.9%	22.8%	16.6%	15.8%	19.3%	20.1%	47.4%	43.0%	16.0%	16.8%
Administration	76%	Female	8.3%	14.6%	12.9%	9.8%	11.7%	22.0%	13.2%	11.5%	5.8%	6.2%	6.4%
		Male	2.1%	4.4%	2.6%	3.4%	4.8%	4.4%	3.4%	6.2%	2.1%	2.5%	1.4%
Finance	49%	Female	14.4%	10.4%	9.8%	15.6%	11.6%	12.3%	11.6%	5.9%	9.1%	8.5%	8.0%
		Male	3.4%	4.8%	4.9%	5.3%	4.2%	9.4%	5.3%	2.6%	1.4%	6.0%	3.3%
Supply & Logistics	47%	Female	7.6%	10.6%	11.8%	9.9%	9.9%	7.9%	10.5%	3.6%	10.0%	4.3%	6.7%
		Male	7.8%	11.6%	10.7%	9.0%	8.5%	10.4%	14.9%	11.4%	9.8%	7.1%	5.5%
Marketing	46%	Female	5.8%	7.8%	8.6%	6.2%	5.8%	8.0%	5.3%	7.6%	3.7%	2.9%	9.7%
		Male	2.1%	3.3%	3.2%	3.0%	3.0%	4.5%	2.3%	4.6%	1.6%	1.3%	5.0%
HR	22%	Female	9.0%	7.7%	6.9%	7.1%	8.7%	9.8%	8.6%	4.8%	4.7%	7.9%	8.2%
		Male	1.3%	1.8%	1.9%	2.1%	1.6%	2.8%	1.7%	1.5%	0.9%	2.6%	4.2%
Sales	19%	Female	10.1%	14.5%	13.1%	13.0%	9.5%	5.6%	12.4%	6.1%	8.3%	6.7%	25.5%
		Male	10.2%	13.7%	14.9%	15.8%	8.4%	7.7%	9.5%	6.2%	6.4%	14.4%	27.1%
Engineering	12%	Female	5.3%	3.7%	3.0%	5.5%	7.9%	2.3%	2.8%	0.8%	4.3%	4.4%	3.9%
		Male	18.0%	18.1%	14.2%	20.6%	20.0%	11.2%	16.4%	5.9%	15.1%	10.9%	13.9%
R&D	6%	Female	10.2%	3.1%	4.3%	2.1%	4.6%	2.8%	3.0%	0.1%	1.8%	3.9%	5.0%
		Male	15.3%	5.1%	5.2%	4.5%	8.7%	5.1%	2.6%	0.1%	2.7%	3.5%	6.0%
Quality	5%	Female	1.7%	3.1%	2.5%	3.5%	2.1%	5.7%	1.6%	1.8%	7.0%	6.6%	4.1%
		Male	1.2%	1.9%	2.0%	3.0%	2.2%	3.5%	2.3%	1.0%	6.4%	8.2%	2.9%
IT	3%	Female	6.0%	2.6%	2.8%	3.3%	5.8%	3.8%	3.1%	1.6%	0.9%	30.2%	2.4%
		Male	9.5%	5.4%	5.5%	5.9%	7.7%	9.1%	6.0%	2.2%	1.4%	17.2%	3.2%

Note: Job families shown are the top most represented in the analysis population

Copyright 2017 Mercer LLC. All rights reserved. mercer.com