Women in the Pipeline
A Dynamic Decomposition of Firm Pay Gaps

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Abstract

This paper proposes a new decomposition method to understand how gender pay gaps arise within firms. The method accounts for pipeline effects, nonstationary environments, and dynamic interactions between pay gap components. This paper assembles a new data set covering all employees at the World Bank Group between 1987 and 2015 and shows that historical differences in the positions for which men and women were hired account for 77 percent of today's average salary difference, dwarfing the roles of entry salaries, salary growth, or retention. Forward simulations show that 20 percent of the total gap can be assigned to pipeline effects that would resolve mechanically with time.

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Women in the Pipeline: 
A Dynamic Decomposition of Firm Pay Gaps

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1 Introduction

Aggregate pay gaps (also known as unconditional or raw pay gaps) can serve as holistic measures of gender disparities in pay, and are often quoted in the press.\(^1\) Assuming innate differences in productivity and preferences are small across genders, large aggregate pay gaps must reflect discrimination and inefficiency in compensation, in job assignment (hires, promotions, retention) or, upstream, in the production of human capital.\(^2\)

In contrast, legal recourse against sexual discrimination in compensation historically relies on the concept of “Equal Pay for Equal Work” (EPEW), which is concerned with pay gaps between equally productive workers in identical occupations.\(^3\) Recently, new transparency regulations are expanding firms’ responsibility beyond EPEW. In the United Kingdom, the “Equality Act 2010 (Gender Pay Gap Information) Regulations 2017” now requires all firms with 250-plus employees to report the difference between the mean hourly rate of pay of all male employees and that of all female employees.\(^4\)

To understand how firms will (or should) respond to these new transparency requirements, we must understand how aggregate pay gaps arise within a firm. This

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\(^1\) For example, gender equality advocates calculate the calendar date at which women start “working for free”, i.e. when the remaining fraction of the year equals the percentage gender pay gap (G.V. (2017)).

\(^2\) The assumptions underlying this argument would include small inherent gender differences in productivity outside the labor market, such as in child rearing or home production.

\(^3\) A large literature has evaluated violations of this principle by statistically controlling for differences in job characteristics and/or measures of a worker’s productivity: See Blau and Kahn (2017) for a survey. As Flabbi (2010) discusses, residual gender pay gaps could be attributed either to discrimination or to unobserved productivity differences, unless economic and distributional assumptions are made to separate those two factors.

\(^4\) Obligations to report pay gaps have also emerged in France, Denmark, Belgium, Germany, Italy, the Netherlands, Ireland, Switzerland, Australia, and Canada (see, for example, Report from the Commission to the European Parliament, the Council and the European Economic and Social Committee 2017). A similar bill (AB-1209) was vetoed by California governor Brown in October 2017.
paper addresses three key considerations that have received little attention in the literature. First, historical patterns in hiring can generate lasting pay gaps long after the original imbalances have disappeared. Consider a firm that satisfies EPEW and applies identical promotion rates to both genders, but hired fewer women than men in the past. Because of “pipeline” effects, it will exhibit an aggregate gender pay gap and an apparent glass ceiling.\(^5\) If the role of pipeline effects is mistakenly assigned to other factors, firm policy responses aimed at fixing the pay gap could create further imbalances. Second, existing gender pay gap decompositions treat firm processes as stationary.\(^6\) In fact, we show in our descriptive section that firm processes, and the gender pay gap itself, exhibit large fluctuations over time. Third, existing studies tend to examine each firm process separately, even though gender disparities in hires, salary growth and exits interact dynamically.\(^7\) As an example, high turnover tends to decrease the quantitative importance of salary growth differences relative to initial salaries differences.

This paper proposes a new dynamic decomposition method that can be applied to aggregate pay gaps to quantify the relative contributions of the gender composition of hires, entry salaries, salary growth, and retention, while accounting for

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\(^5\) Suppose a firm employs two-period-lived male and female workers. In year two the firm hires 50 men and 50 women, but in the previous year it hired more men, say 90 men against 10 women. Each period, half of the workers are promoted to higher paying managerial jobs, with no discrimination against women. Therefore, in year two the firm will employ 45 male managers, 95 male workers, five female managers and 55 female workers. This firm exhibits an aggregate gender wage gap in year two without any discrimination in promotions or within-job salaries.

\(^6\) See Filmer et al. (2005) for an example using a 1997 cross-section of our panel.

pipeline effects and a changing firm environment. The method estimates auxiliary, reduced-form models for each of the decomposition factors in each year, before aggregating them through microsimulations. We then obtain the decomposition through counterfactual simulations of male and female salaries in which each source of pay differences is shut down at a time. The simulations can also be extended forward to quantify pipeline effects. Rather than assume that data are drawn from a steady state, as in traditional wage decomposition methods, our approach accounts for the constant changes in hiring, firing, growth, and shrinkage that are typical in most firms.

To apply our methodology, we assemble a new panel containing 27 years of all personnel records from the World Bank Group (WBG), a multilateral finance organization with more than 16,000 employees in 2015. The panel length, data size, recency, and measurement precision afforded by these personnel records offer the perfect setting for the specific purpose of this paper, which is to analyze the within-firm dynamics of gender pay gaps. The firm is a policy-relevant unit of analysis because firms increasingly bear the legal responsibility of eliminating gender pay gaps.

Our application of the decomposition method to the WBG offers a striking example of how past hiring stocks can affect pay gaps today. Our data show a decline in the aggregate gender gap from 50 cents on the dollar in 1987 to 23 cents on the dollar in 2015. For the mean salaries in our data, this amounts to an annual difference of US$27,400. However, we find that three-quarters of the 2015 gap was due to historical differences in the types of jobs at which women and men were hired. By contrast, less than 10 percent of the pay gap is due to differences in entry salaries; about 5 percent is due to differences in salary growth (including promotions and raises) and

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8The Fortran and Stata programs that implement the methodology are available at https://github.com/clemjoub/Firm-Pay-Gaps-Decomposition
less than 1 percent is due to differences in retention. An implication of this finding is that requiring firms to publish aggregate pay gaps will induce them to outsource low-paid jobs held by women to external partners to satisfy the regulation.

We are also able to quantify how much of the gap reflects historical differences that will, therefore, tend to dissipate over time. When we simulate what would happen to the pay gap if 2015 hiring patterns were kept in place and no changes were made to compensation, we find that over the next 10 years, the aggregate pay gap will decline further by one fifth (or five percentage points) and then stabilize. Historically, most hires in technical positions were men; because these hires formed the pipeline for management jobs today, they continue to exert a negative influence on the gender pay gap. By 2015, the bias in hiring among the technical staff had virtually disappeared, which explains our simulated reduction in the pay gap. The persistent residual gap reflects the continued over-representation of women in support staff positions.

Lastly, we show that the patterns we uncover are not specific to the gender pay gap but also apply to pay gaps associated with employee nationality (broadly categorized in developed versus developing countries). Our methodology could similarly be applied to pay gaps between employees of different races, or disability status, among other examples.

Our main contribution is therefore to propose a simulations-based dynamic decomposition method to understand how gender pay gaps are produced within firms. Studies performing dynamic decompositions based on a fully specified economic model can be found in the literature, applied to different contexts (e.g. Keane and Wolpin 2010, Joubert 2015). In contrast to that approach—but in line with classic decomposition methodologies—we do not account for behavioral responses or permanent unobserved heterogeneity. Therefore, our counterfactual simulations should
not be interpreted as policy experiments but rather as accounting exercises.9

Two non-structural studies share similarities with our approach. Bourguignon et al. (2008) decompose country-level income distribution differences. Although their exercise is static, they also use simulations to aggregate semi-parametric models of each determinant of income dispersion, and generate counterfactual distributions in which the differences in the parameters governing each individual factor are shut down one at a time. Gayle et al. (2012) implement a decomposition that explicitly captures individual career dynamics but the object of their decomposition is the gap in the cumulative earnings of U.S. male and female executives, rather than a cross-sectional firm-level pay gap and hiring pipelines. Also, their approach relies on stationary analytical formulae rather than micro-simulations.

A second contribution of the study is to produce new evidence on where pay gaps are generated within a large, multicultural organization, using an original panel data set of sizable length and width, extracted from recent personnel records.10 The novelty of our approach is to “locate” and quantify, rather than “explain”, pay gaps. It allows to focus follow-up investigations on those organizational processes where the gaps are highest and more malleable. If, for instance, most of the gender gap arose in entry salaries, a classic Oaxaca–Blinder decomposition could then be applied to entry salaries.11 If instead, salary growth was the main pay gap source, follow-

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9In fact, we lack the data to examine such behavioral responses where the gender gap is most salient – historical hiring patterns. For instance, when there is a change in the president of the WBG, churn increases sharply. It may be that the applicant pool changes in anticipation of this churn or immediately after. Unfortunately, the institution does not retain data on the historical applicant pool, and therefore incorporating behavioral responses is currently outside the scope of our work.

10Existing gender pay gap studies using single-firm data separately describe the gender differences in job assignment (Malkiel and Malkiel, 1973; Ransom and Oaxaca, 2005), entry salaries (Gerhart, 1990), salary growth and promotion (Jones and Makepeace, 1996; Hersch and Viscusi, 1996; Barnett-Verzat and Wolff, 2008) and/or retention (Petersen and Saporta, 2004; Giuliano et al., 2005; Gobillon et al., 2014), but they do not provide, as we do, a quantitative comparison of these gender pay gap sources.

11The Oaxaca–Blinder decomposition evaluates the extent to which differences in an outcome vari-
up efforts could investigate gender differences in performance rating, promotions, project allocations, or the impact of career interruptions due to children.

2 Data and Institutional Features

The WBG’s Human Resource Longitudinal Database was assembled for the purpose of this study. It is structured in a panel from 1987 to 2015 with staff uniquely identified through a universal, permanent personnel identifier (UPI). Data from each year are a snapshot taken on June 30 that contains information on the staff’s universal personnel identifier (UPI), compensation and benefits (for instance, salaries), personal background (gender, age), professional situation (for instance, professional grade), location (HQ or country-office based), role and movements within the organization (promotions and lateral moves), and information on the yearly performance rating (SRIs) from 2000 onward.\textsuperscript{12} For the purpose of applying our decomposition, we consider the annual monetary compensation of each employee, the grade at which they were hired, their gender and nationality.\textsuperscript{13}

Our data cover all staff employed by the WBG between 1987 and 2015. Among staff members, the WBG grades run from GA to GL (the president of the WBG). Grades GA–GD are the grade levels for administrative and client support (ACS) staff. GE corresponds to analyst level. GF and GG contain the bulk of professional technical staff. Staff in the GH level, the first leadership position at the WBG, can be either in a technical or managerial role. GI (director) through GK (vice presidents (wages) can be explained by differences in characteristics (experience or education) versus differences in returns to these characteristic (see the seminal papers Oaxaca 1973 and Blinder 1973; Fortin et al. 2011 for a recent survey of the literature; and Filmer et al. 2005 for an application to a 1997 cross-section of World Bank personnel files).

\textsuperscript{12}The Technical Appendix and codebook provide further details.

\textsuperscript{13}Non-monetary benefits (such as health insurance) are substantial at the WBG, but homogeneous within the sample we consider, particularly across genders (described below).
dents) and GL (president) refers to senior management positions. For expository purposes, in the rest of the paper we will use “support staff” to refer to grades GA through GD; “technical staff” for grades GE, GF, and GG and non-manager GH; and “managerial staff” for managers in grades GH and above, sometimes separating GI and above grades under the denomination “senior managers”. The WBG also distinguishes between employees coming from high-income countries (“Part 1”) versus low- and middle-income countries (“Part 2”).

The WBG is a large institution with central headquarters in Washington, DC and country offices in over 100 countries. Unlike other multinational firms, however, special visa arrangements with the U.S. government allow the WBG to hire and bring in staff to central headquarters from all around the world. In fact, U.S. citizens are a minority among hires in the Washington, DC office over our data period (Table 1).

Compensation at the WBG reflects multiple objectives, balancing the need to incentivize performance, allow managerial discretion, and ensure equity. Salary bands for different grades, as well as mean increases each year, are decided with reference to a “comparator group” that includes a mix of other international organizations, private sector firms, and public sector salaries. To promote equity, employees with salaries above the midpoint of their grade receive a lower raise for the same level of performance.

14In addition to staff, the WBG has “unassigned or ungraded” employees who are composed of long and short-term consultants as well as a small number of staff outside the salary and promotion structure of the WBG, such as the WBG’s executive directors, who are representatives of the WBG’s member countries, and their advisers.

15This terminology comes from the way the WBG classifies its country members. Part 2 countries joined the WBG as potential loan recipients and thus roughly correspond to low- and middle-income countries.
2.1 Sample

Although the WBG has more than 100 country offices, we restrict our sample to staff in the Washington headquarters hired on a U.S. dollar salary plan, commonly known as “internationally recruited staff.” The main reason for the restriction is the substantial country-specific expertise required to convert local salaries to dollar equivalents. In doing so, we exclude a growing minority of the WBG employees: the fraction of local hires increases from 7.4 percent to 37.8 percent over the time period of our data.

We make two minor additional sample restrictions. Among the 259,618 records corresponding to the universe of WBG headquarters employees between 1987 and 2015, we exclude the 4,689 records of executive directors and their staff, and of secondments (staff loaned and paid by other institutions). We also exclude a total of 229 records for which missing or anomalous grades were found (6 records), recorded gender changed over time (97 records), recorded salary was 0 (88 records), or recorded salary was clearly outside the grade range in the corresponding year (38 records).

2.2 Three Relevant Historical Trends

Compensation and hiring practices have not remained static over the period of our data. In fact, multiple institutional changes and HR policies could have affected hiring and turnover as well as the salary structure. One advantage of our dynamic decomposition methodology is that it does not assume a stationary environment.

\[\text{Given the starting date of 1987 in our data, the dissolution of the Soviet Union and the emergence of local currencies, the creation of the euro replacing European currencies, as well as multiple spells of hyperinflation through the period of our data in countries ranging from Turkey to Ecuador all need to be addressed on a case-by-case basis. Although this salary conversion is possible, it lies outside the scope of the current project.}\]
Because this feature is likely to characterize most organization over the course of an employee’s career, and is a key motivation for our methodology, we present information on three important institutional dynamics.

First, the period covered by our data exhibits large changes in the staff’s grade composition. Figure 1 shows that over the period of our data, there was an increase in the fraction of technical and managerial level staff as a fraction of total staff from 64 percent in 1987 to 85 percent in 2015. This increase is consistent with both increasing automation of routine tasks and shifting of routine tasks from support staff to technical and managerial staff. The proportional increase in technical and managerial staff was primarily in the technical grades of GE, GF, and GH; no change was seen in the proportion of managers to staff between the years of 2000 and 2015.

A second feature of the data is that exit rates are not stationary. Figure 2 plots annual exits from the institution as a percentage of regular staff, excluding staff exits due to mandatory retirement. Exits at the WBG are an average of 9 percent a year but have fluctuated in cycles between 6 and 11 percent following large institutional reforms. Exits peak in reform years (which are usually associated with new presidential terms) but then drop because reforms bring exits “forward.” It also appears that exits track economic performance in the United States, rising when the economy is strong. Note that the 9 percent exit rate implies that 50 percent of staff leave the institution every 8 years. When we consider long tenures, high rates of attrition leave substantial room for selection effects in the salary gaps of those employees who remain at the institution. Because our methodology only allows exit selection based on the last salary (rather that predicted future career paths), this feature must be kept in mind in the result section when interpreting counterfactuals involving exit patterns.

A third feature of the data is that salaries have not grown at the same pace in all occupations. Salaries in higher grades exhibit much larger progressions over
the span of our data, mimicking similar trends in the US economy over the period. Table 2 shows the mean real salaries of employees at each grade over time. We compare all salaries to a base of 100 for grade GA in 1987. Note the considerable variation in salaries within each grade. Typically, the 10th percentile and the 90th percentile of the within-grade salary distribution differ by 20 to 40 percent. Even within technical grades, the mean real salaries have increased more for grades GI, GJ and GK compared to GF and GG staff. Annual real salaries increased by three-tenths of 1 percent between 1987 and 2014 among GB–GD and GG staff, seven-tenths of 1 percent for GE and GH level staff, and 1.1 to 1.6 percent for GI–GK level staff.

Each of these trends over the period of our data can affect the salary gaps between subgroups. For instance, the decline in support staff, who are predominantly women in jobs with lower salaries, implies that the average salary of women relative to men will rise in the institution. Similarly, differences in the profiles of staff leaving the WBG will affect the salaries of those who remain. Finally, differential increases in salaries for different grades can affect aggregate gaps. First, as support staff tend to be women, their lower salary growth over time will imply that the aggregate gap will also increase. Second, staff are promoted over time. If men are promoted faster to GH (for instance) relative to women and GH salaries are growing faster, this will again induce an increase in the aggregate gap over time.

17To preserve anonymity, we leave blank the cells where there are too few employees and do not present results for grade GK.
3 Decomposition Methodology

3.1 Intuition

The distribution of salaries among individuals employed in a firm in a given year can be recovered from four pieces of information: the initial salaries of incumbent employees in the previous year, the salary raises received by these incumbent employees, the entry salaries received by new hires, and the distribution of salaries among staff who chose to leave the firm in that year. The distribution of salaries in the previous year results from the same four objects in the year before and so on. After iterating this relationship backward, the current distribution of salaries aggregates four components: the salary distribution of incumbent staff at some initial date; the salary growth between that initial date and the present; the salaries of new hires between the initial date and the present; and the salaries of staff who leave the firm between the initial date and the present.

Therefore, we can decompose any salary gap between two groups of employees between differences in each of those four components. We design an algorithm that replicates the evolution of salary distributions through the period covered by the data and then simulate counterfactual salary distributions in which we shut down one source of salary differences after the other. For example, we simulate what women’s salaries would look like if they were hired at the same salaries as men. What would those salaries look like if, in addition, women received the same salary raises as men, etc.? By shutting down one component at a time, we can determine what percentage of the gender gap that component accounts for.

As with most other decomposition methodologies such as Oaxaca-Blinder, the counterfactual simulations we perform are accounting exercises that do not incorporate behavioral responses that reducing male-female gaps in some dimension may
induce. For example, removing disparities in promotion rates across genders could impact the quality of male and female job applicants. Capturing such behavioral responses is outside the scope of this paper, and would require specifying a theoretical model of how job openings are posted, how pool of applicants form, how hiring and job acceptance decisions are made, how salary raises and promotions are determined as a function of effort or other inputs, and how exit decisions are made.

3.2 Decomposition Framework

To formalize our approach, consider a firm that employs individuals of two different types, denoted as $g$. This paper focuses on gender, females ($g = f$) and males ($g = m$), but we show that the framework can also be applied to other categorizations. In year $t$, salaries $\{w_{it}\}_{i}^{n_t}$ are distributed according to the empirical probability density function: $f_t$. We are interested in explaining gender gaps in salaries, defined as the difference between corresponding moments of the male and female conditional densities: $f^f_t$ and $f^m_t$. For example, we may be concerned with the difference in mean salaries across genders.

The process that governs how the salary distribution evolves over time is modeled as follows. At the beginning of year $t$, $n_t$ individuals are employed, comprising $n^f_t$ women and $n^m_t$ men, with salaries distributed according to $f^f_t$ and $f^m_t$. During the year, individuals receive a salary increase. The functions $r^f_t$ and $r^m_t$ map current salaries into salary raises, from which the next year’s distribution of salaries can be generated. At the end of the year, $n^g_{ht}$ individuals of gender $g$ are hired in year $t$, with salaries drawn from the hiring probability density function $f^g_{ht}$. Last, $n_{lt}$ employees leave and the probability density function of their salaries prior to that is denoted as $f^g_{lt}$.
Combining these objects yields the distribution of salaries at $t + 1$:

$$
\begin{align*}
  f_{t+1}^g &= G_t^g\left[n_t^g, f_t^g, r_t^g, n_{ht}^g, f_{ht}^g, n_{lt}^g, f_{lt}^g\right] \\
  n_{t+1}^g &= n_t^g + n_{ht}^g - n_{lt}^g
\end{align*}
$$

(3.1) (3.2)

Iterating backward the equations above to an initial period $t_0$ (say, the first year of available data) yields a relationship between the distribution of salaries for gender $g$ at time $\tau$ as a function of the initial salary distribution of salaries at $t_0$, and the sequence of raise functions, hires, and exits from $t_0$ to $\tau$:

$$
\begin{align*}
  f_{\tau}^g &= H_{\tau}^g\left[n_{t_0}^g, f_{t_0}^g, \{r_t^g\}_{t_0}^{\tau}, \{f_{ht}^g\}_{t_0}^{\tau}, \{n_{ht}^g\}_{t_0}^{\tau}, \{n_{lt}^g\}_{t_0}^{\tau}, \{f_{lt}^g\}_{t_0}^{\tau}\right]
\end{align*}
$$

(3.3)

It follows that any difference in corresponding moments of $f_{\tau}^f$ and $f_{\tau}^m$ can be decomposed into four factors:

1. Legacy factor: differences in the salary distributions of incumbents at $t_0$ ($n_{t_0}^m$ and $f_{t_0}^f$ versus $n_{t_0}^f$ and $f_{t_0}^m$),

2. Hiring factor: differences in the distributions of hiring salaries ($n_{ht}^m$ and $f_{ht}^f$ versus $n_{ht}^f$ and $f_{ht}^m$, $t = t_0, \tau$),

3. Salary growth factor: differences in salary increases ($r_t^f$ versus $r_t^m$, $t = t_0, \tau$), and

4. Retention factor: differences in exits ($n_{lt}^f$, $f_{lt}^f$ versus $n_{lt}^m$, $f_{lt}^m$, $t = t_0, \tau$).

In a large firm, employees are hired at different positions that command very different career paths. Access to these entry positions may differ by gender, a source of gender disparity that is conceptually different from discrimination in entry salaries. Therefore, we separate the hiring factor above into (i) the relative number of men and
women hired in different positions (Composition of hires factor), and (ii) the initial salaries accepted by men and women for each given position upon hiring (Entry salaries factor).

3.3 Microsimulation Algorithm

The pay gaps and decomposition factors are not connected through a simple analytic formula. Instead, we design a dynamic, stochastic microsimulation algorithm that updates salaries from year $t - 1$ to year $t$ in the following way:\footnote{The idea for microsimulations dates back to Orcutt (1957) and modern applications are reviewed in O’Donoghue (2014). The primary use of this technique is to simulate distributional effects of public policies but it is also employed in the context of simulation-based estimation of structural microeconomic models and in some cases to perform decompositions (see Keane and Wolpin (2010) for such a decomposition of black-white differences in women’s economic decisions, or Joubert (2015) for a decomposition of the causes of informality). We are not aware of microsimulations tools applied to modeling an individual firm’s workforce.}

1. Store the salaries carried over from $t - 1$ as a histogram with N bins. In our application, $N = 500$ and each bin represents USD 1,000 in annual salaries.

2. For each bin in the histogram, and for each employee in the bin, draw a salary increase for year $t$.\footnote{Specifically, we recreate a continuous distribution by drawing a salary from a uniform distribution over the support of the bin before applying the salary raise. An alternative is to apply the raises to the midpoint salary $w_m$ in the bin. In our application, the bins are very narrow so that the two procedures are essentially equivalent} Then determine the new bin to which each individual belongs after the salary raise to obtain an interim salary histogram.

3. Sum the histogram of entrants to the interim salary histogram.

4. Determine for each bin of the resulting histogram how many employees exit the sample at the end of $t$.\footnote{In practice, we draw a random number for each employee and compare it to their probability of exiting. That is, the actual number of exits is matched in expectation only.}
5. Go to $t + 1$.

Note that the algorithm keeps track of distributions rather than individual employees. It starts from salary distributions in year $t_0$ that are taken directly from the data. It performs the simulations for each group of employees from the first year when data are available until the year in which the pay gap of interest is measured.

We obtain the decomposition of a salary gap in year $t$ by simulating salary distributions from $t_0$ to $t$ under the baseline and five counterfactual specifications indexed by $c$:

- baseline ($c = 0$): all parameters are gender specific,
- $c = 1$: female employees have the same probability as males of leaving the firm, conditional on their salary;
- $c = 2$: in addition, female employees draw their salary increases from the same distribution as males;
- $c = 3$: in addition, the distribution of female entry salaries is the same as that of males in each hiring position;
- $c = 4$: in addition, the firm hires the same number of female as male employees in each position; and
- $c = 5$: in addition, the distribution of salaries and grades among women is the same as among men at $t_0$.

The female salary distribution in year $t$ obtained in counterfactual $c$ is denoted by $f_{t,c}^f$. Denote the gap of interest $m(f_t^m) - m(f_t^f)$, approximated in our baseline scenario ($c = 0$) by: $m(f_{t,0}^m) - m(f_{t,0}^f)$, where $m(.)$ is a moment of the distribution such
as the mean. The contribution of factor $c$ to the salary gap is defined as the reduction in the gender pay gap as we move from $c - 1$ to $c$, divided by the total gap:

\[
\frac{[m(f_{mt,c}^c)-m(f_{mt,c}^{c-1})]-[m(f_{fm,t}^c)-m(f_{fm,t}^{c-1})]}{m(f_{mt,0}^c)-m(f_{mt,0}^{c-1})}.
\]

Because only female salaries change in the counterfactual simulations, this simplifies to:

\[
\frac{m(f_{fm,t}^c)-m(f_{fm,t}^{c-1})}{m(f_{mt,0}^c)-m(f_{mt,0}^{c-1})}.
\]

In counterfactual 5, female and male salaries have the same distribution, so the contribution of factor $c$ can also be written as:

\[
\frac{m(f_{fm,t}^c)-m(f_{fm,t}^{c-1})}{m(f_{mt,5}^c)-m(f_{mt,0}^c)}.
\]

Other orderings of the decomposition can be performed in analogous ways. We show that the ordering of factors leads to the same qualitative conclusions in section 4.5.

### 3.4 Parametric assumptions

The simulation algorithm can be implemented with various levels of parametrization, depending on the amount of observations in the data set and the statistical regularity of the firm’s processes. Our proposed specification attempts to balance the stability, simplicity, and ease of implementation of the decomposition - by incorporating some parametric assumptions - against the risk of specification error. The stability of the decomposition is assessed by obtaining bootstrapped confidence intervals around the estimated decomposition factors (see section 3.5). Rather than applying statistic tests to each parametric assumption separately, we propose to assess the joint impact of specification error directly on the output of the simulation algorithm through a validation exercise described in section 3.5. We also repeat the exercise using alternative specifications in addition to our preferred one.

We stratify the estimation by year and group of employee, where groups are defined by gender, nationality groups and entry position.\footnote{Nationalities are grouped according to the World Bank classification “Part 1” and “Part 2” described in section 2.} Therefore, we do not impose any restrictions on the way the processes change over time or how they differ
across groups of employees. Also, the number of entrants for each group \( g \) (now including nationality and entry position, in addition to gender) and year \( t \), denoted as \( n_{gt}^{e} \), is directly taken from the data.

For a given position and gender, the salary of a new hire, \( w_{igt}^{e} \), is modeled as a normally distributed random variable with mean \( \mu_{igt}^{e} \) and standard deviation \( \sigma_{igt}^{e} \). The choice of a normal distribution may seem unusual because salaries are usually modeled using a log-normal distribution to capture a right-skewness. However, we are estimating salary distributions within cells that are homogeneous with respect to employer, gender, tenure and type of position. Figure 3 shows that the distributions of entry salaries, aggregated over nationality groups, appear well approximated by a normal distribution for all groups with adequate sample sizes. As a robustness check we redo the exercise assuming that entry salaries follow a log-normal distribution and obtain very similar decomposition results (Table 9, column 3).

Salary decreases are not observed at the WBG but some years saw widespread salary freezes. To capture this feature of the data, salary growth was modeled as a two-step process. With some probability \( p_{igt}^{e} \), an employee’s salary stays constant in a given year. This probability is estimated by the fraction of 0-increases among group \( g \) in year \( t \). Conditional on a strictly positive raise, we model the growth rate of salaries \( r_{igt}^{e} \) using a log-normal distribution with mean \( \mu_{igt}^{r} \) and standard deviation \( \sigma_{igt}^{r} \). Figure 4 shows that this parametric assumption fits salary increases very well overall.

\(^{22}\)External hires at the very top positions of the institution (grades GH and above) are not as well approximated, due to the small cell sizes. However, note that the bulk of the top management is hired into the institution at lower grades and promoted internally, and thus belongs to the well approximated group.

\(^{23}\)Salary raises are also set to zero if there is only one employee in a given cell.

\(^{24}\)We also attempted to estimate a specification in which the raise rate is allowed to depend on the salary level, but the coefficient on that additional regressor was not precisely estimated for all cells, leading to a worse simulation fit than in our preferred specification.
Finally, exits are determined by a linear probability model in which the probability of exiting the sample is allowed to depend on the current salary:

\[ 1_{\text{exit}_{it}=1/1,t,g,w_{it}} = \alpha^ag_t + \beta^ag w_{it} + \varepsilon^ag_t \]  

(3.4)

The linear probability model has the advantage of a faster simulation run time compared to a non-linear probability model, but we verify that using a probit model for exits –also with current salary as the sole regressor– obtains almost identical decomposition results (Table 9, column 2).

### 3.5 Estimation and validation

In our simulation algorithm, all dynamic linkages operate through current salaries, which are observable. As a result, we can separately estimate all the input processes for entry salaries, raises and exits before aggregating them into the current salary distribution. We obtain confidence intervals around the decomposition factors, as well as the parameters of the entry, exit and salary growth processes, by bootstrapping the estimation, simulation and decomposition exercise 250 times.\(^{26}\) The decomposition factors and confidence intervals are reported in section 4.

A benefit of estimating input processes separately is that the end-of-period distributions of salaries are not used in estimation. Therefore, they can be used to jointly validate –out-of-sample– the simulation algorithm and the specifications of the input processes. We take 1987 as the initial year and simulate salaries forward to 2015. We then compare, for each group of employees, the simulated end-of-period distributions of salaries with their data counterpart between 1987 and 2015. Figures 5 and 6 present the difference between the mean and the standard deviations of the

\(^{25}\)For cells with fewer than 20 employees, or fewer than 5 exits, \(\beta^ag_t\) was set to 0.

\(^{26}\)The confidence intervals stop moving significantly after 100 bootstraps.
distribution of salaries of each group of employees in the data and the simulations, respectively. Looking at the means first, we find that simulations can fit the data very well, with no systematic pattern of under- or over-prediction and gaps that are typically less than 1 or 2 percent. Ungraded employees (first column) who are a very heterogeneous group with shorter tenures and were the object of import reforms in the years 1998-2000, are relatively less well captured. Regarding the standard deviations, the dispersion is slightly higher in the simulations than in the data but remains very reasonable around 5 percent on average after running the simulation algorithm for 28 periods (1987 to 2015).

This methodology could be extended to incorporate additional observed and unobserved permanent heterogeneity. Such extensions could have two benefits. The first benefit is to obtain a better approximation of the input processes. For example, if there were two very distinct groups of employees within a cell of the stratification that we consider (which includes gender, nationality group and entry position), entry salaries could have a bimodal distribution that a normal distribution would not be able to approximate. However, as we have shown above, our specifications do an excellent job of fitting the distributions of entry salaries and salary raises with our current level of stratification. In addition, our data do not contain good socio-demographic information such as schooling attainment or schooling quality.

A second benefit of incorporating permanent heterogeneity would be to capture more complex dynamic linkages between processes in our counterfactual. For example, counterfactually improving the retention of women –to match that of men, say– should have an impact on the distribution of raises if the women who leave tend to have steeper salary progressions. This type of linkage is not captured by our procedure. Incorporating permanent unobserved heterogeneity would require a different estimation strategy, in which all parameters are estimated jointly by maxi-
mum likelihood or method of moments. The procedure would pick parameters that maximize the fit of simulations to the data, including all dynamic and cross-process correlations.

We decided to leave this extension out of the scope of the current paper for the following reasons. First, to implement the joint estimation of input parameters, we would need to reduce the number of such parameters by at least an order of magnitude. This would greatly reduce the flexibility of our model and its ability to fit the data, possibly offsetting the expected benefits described above. Second, this exercise would still fall short of capturing behavioral responses due to the absence of a structural model. Third, this approach would make both the practical implementation and interpretation of this method much more complex. Fourth, as discussed in the next section, we find no gender disparity in how the average leaver compares to the average stayer at the Bank, when we consider their last salary or their accumulated performance ratings.

4 Results

4.1 Descriptive Findings: Gender Differences in Hires, Salary Growth, and Exits

In 1987, the mean salary of a female staff member at the WBG was 52 percent that of a male staffer. By 2015, this had increased to 77 percent (Figure 7). As a point of comparison, pay gaps between gender are about twice the size of pay gaps between employees from high-income countries (denoted as “Part 1”) versus middle- and low-income countries (denoted as “Part 2”). Figure 8 interacts gender and country of origin: a clear ordering emerges with the highest salaries for Part 1 males throughout
the period of our data. The differences between men and women within country groups are about twice as large as the differences between Part 1 and Part 2 staff, within gender groups. Contrary to the gender pay gap, the nationality pay gap has not significantly declined over the period.

Occupational segregation among new staff at the WBG has declined significantly. In 1988, women comprised 20 percent of all staff hired into technical and managerial positions, and this number increased to 48 percent by 2015 (Figure 9). This strong convergence toward parity is not fully completed for mid-career hires (GG grade), who were still more than 60 percent male in 2015. On the other hand, among ACS staff hires, women remain the predominant gender to this day, decreasing in share from 92 percent to 78 percent.

In contrast to the large differences in hiring across grades, entry salary differences by gender are relatively modest within a grade. Figure 10 presents the relative entry salaries of women and men at the main entry grades (male entry salary are normalized as the constant line). The largest gap is found in mid-level technical and managerial staff hires (grade GG). Female employees enter at a salary deficit that fluctuates around US$3,000, but this category of hires is less homogeneous, as it requires various levels of previous work experience. For entry-level technical staff, the gap is modest (GF, around US$500) or absent (GE). For support staff, a modest entry salary gap opened up in the middle of the period but disappeared by 2015.

Relatively to men, women’s salary paths show clear declines over years of tenure for most—but not all—entry positions. Figure 11 reports salary paths for the three most common entry grades at the WBG. The graphics aggregate staff according to their tenure, mixing cohorts who joined the institution in different years. The female deficit in annual salary after 15 years is US$2,500 for GB, US$2,000 for GF and non-existent for GG. The evolution of salaries is heavily influenced by the speed and
frequency of promotions, but differences in performance ratings are also rewarded with higher raises in non promotion years.

The salary paths described above will be affected by the gradual attrition of staff over their careers. In fact, all grades combined, less than 60 percent of staff remain at the WBG 15 years or longer (Figure 12). Women are more likely to stay than men in all categories, but the differences are less than five percentage points everywhere. Importantly for the validity of our exercise, we do not gender disparities in how leavers compare to stayers on average. Leavers of both genders seem to have slightly higher salaries (Table 3) and slightly lower performance ratings than stayers (Table 4).

4.2 Decomposition of the Aggregate Gender Pay Gap

Our main task is to decompose the difference between the average salaries of male and female employees in 2015. We start by verifying that this difference is accurately replicated in our simulated salary distributions. Figure 13 compares the pay gaps measured in the data in 2015 with the corresponding statistics obtained by simulating men and women’s salaries in 2015, using the algorithm described in Section 3. Bars 1 and 2 correspond to the aggregate gender gap measured for all employees and show a simulation error of only US$500 out of a gap of US$27,400. After restricting to technical staff (grades GE and above), the simulation error remains at US$500 out of a gap of US$14,600.

The main results of the aggregate gender pay gap decomposition are shown in Table 5. The decomposition (including the input estimation and micro-simulations steps) was replicated 250 times on bootstraps of our main sample. The first column of Table 5 contains the mean of the share of the total gap that is explained by each factor. Columns two and three report the confidence interval obtained by computing the
5th and 95th percentiles of the distribution of bootstrapped estimates. Confidence intervals are narrow around the point estimates for all factors.

We find that retention plays a small role in explaining the aggregate gender pay gap. When we set the parameters governing the probability, conditional on their salary, with which women to exit the institution, in each year and for each entry grade, to be equal to that of men, the overall gap diminishes by less than 1 percent. This finding does not imply that exit rates between men and women are identical. Rather, our descriptive results show that, for both genders, the average leaver is similar to the average stayers, in terms of current salaries (Table 3). As a result, exit patterns do not affect the salary distributions of men and women differently in our exercise.

This result relies on our assumption about the salary progressions forgone by leavers. As discussed in Section 3, the salary progression a leaver would have experienced (conditional on last salary), had she stayed, is estimated from the salary progressions experienced by stayers. Bias to our results would ensue if that assumption were violated differently for men and for women; for example, if men were more likely than women to take into account idiosyncratic career prospects when deciding to leave the institution.

Salary growth and entry salaries also play a modest role. After giving women the same parameters as men in the salary growth model, the aggregate gender gap decreases by 5 percent. Further equating entry salaries within each entry grade accounts for another 7 percent. The latter is easily reconciled with our descriptive findings: entry salaries exhibit very modest differences across genders for most entry grades. As for salary growth, we do find a significant gap in favor of men for the two main entry grades (GB and GF). However, the gap opens up slowly over the career and thus applies to the relatively small number of employees who stay for a
long time at the bank.

The bulk of the gap (77 percent) corresponds to the occupational segregation by gender among hires. Section 4.1 shows that women have been disproportionately hired at lower grades, accounting for nearly 80 percent of ACS staff hired in 2015.

To investigate whether there are hiring composition effects within technical and managerial staff, we implement the decomposition on the sample of employees hired at grades GE and higher. The decomposition factors are shown in columns 4, 5 and 6 of Table 5. The composition of hires remains the most important factor even after excluding ACS staff. That is, the relative mix of entry (GE–GF) versus mid-career (GG–GH) external hires among men and among women generates most of the gap among grades GE and above. Indeed, Figure 9 shows that mid-career hires are still only about 40 percent female. Although this proportion is much higher than it was in 1987, there has also been a strong increase in the proportion of women in entry-level technical grades (GF). The latter trend has reduced the pay gap of the whole institution but contributed positively to the pay gap among technical and managerial staff.

The remainder of the gap (11 percent) corresponds to differences between the stock of men and women hired before 1987, for whom we do not have entry salary, salary growth, or retention information.

4.3 Quantifying Pipeline Effects

Pay gaps reflect changes in hiring and compensation patterns with significant lags. The reason is that employees often stay in the same firm for decades, and individual salary paths exhibit high levels of auto-correlation. This inertia makes it difficult to accurately diagnose the causes of pay differentials, and is indeed one of the main motivations for the approach we propose.
In particular, some of the sources of the current pay gap at the WBG may have already vanished. For example, the fraction of women among all technical and managerial hires (GE and above) has almost reached parity, with a gap remaining only for mid-career hires (GG and GH). More generally, our descriptive results show that an organization such as the WBG is highly non stationary, with strong trends affecting the processes that generate pay gaps. Taking this inertia into account could be very important for policy lest differentials may be over corrected.

By simulating our algorithm forward, we can quantify the inertia exhibited by pay gaps. In doing so, we use the parameters estimated using the last year of the data for all the processes. This procedure allows us to project how much of the gender pay gap would close on its own in the coming years, and at what pace, if nothing changed in the organization.

Figure 14 shows that under that scenario, the aggregate gender pay gap would continue to close but at a slower pace, from 23 percent to around 18 percent over the next decade. Interestingly, Figure 15 shows that this improvement would not come from improvements in the pay gap among technical staff. Gender pay differences for that group level off at 10 percent, reflecting that a higher proportion of women are hired at the entry technical position (GF) relative to men. Since hiring parity has not improved among support staff either (Figure 9), the projected gains in the aggregate gap are likely explained by the diminishing overall fraction of support staff, among which women are still largely over represented.

4.4 Aggregate Nationality Gap

To provide perspective and illustrate alternative applications of the methodology we consider how pay gaps associated with nationality compare with pay gaps associated with gender. That is, we decompose pay gaps between Part 1 and Part 2
employees (Table 6). The aggregate country part gap in 2015 is smaller than the aggregate gender gap at US$14,800, and well approximated by the simulations (see Figure 13, bars 5 and 6).

As with the aggregate gender pay gap, the bulk of the nationality gap (62 percent) corresponds to the fact that Part 2 employees are, on average, hired at lower grades. Equating exit probabilities across Part 1 and Part 2 employees further closes 14 percent of the gap. Equating salary growth closes an additional 6 percent, and equating entry salaries accounts for another 11 percent. The remainder of the gap can be attributed to differences predating 1987. Within the technical and managerial category (Table 6, columns 4-6), the composition of hires factor dominates as well.

4.5 Robustness to the Decomposition Order

The decomposition results we have presented shut down sources of gender gaps in a specific order: retention, salary growth, entry salaries conditional on grade, entry grade, and pre-1987 legacy. This order is the reverse of the order in which each factor is simulated in our algorithm, but is otherwise arbitrary.

To test the importance of this choice, we implement our decomposition in all 120 possible different orders and report the distribution of contributions obtained for each factor in Tables 7 and 8. Although the order does affect the exact contribution of each factor, our results remain qualitatively identical and quantitatively very similar for all decompositions, with the nuance that differential retention tends to have a modest negative contribution to gender pay gaps.
5 Conclusion

We have proposed a methodology to decompose aggregate pay gaps in firms. We used it to analyze salary differences between genders at the WBG between 1987 and 2015. Aggregate gaps can be construed as an interplay between composition and compensation effects and our decomposition results suggest that composition effects play the major role in explaining the aggregate gap in 2015. A policy implication of this finding is that if firms are pressured or constrained to minimize aggregate gender pay gaps, it will generate incentives for them to outsource low-paid jobs held by women to external partners. Such regulation could favor changes to the scope of firms in the direction of greater segmentation by job type.

Identifying where the bulk of the aggregate gender gap comes from, and how persistent it will be—ongoing differences in the gender composition of hires, in the case of the WBG—can also guide data collection and further investigation in the most promising direction. For instance, we do not know whether occupational segregation emerges at the point of hiring (equally qualified men and women have applied, but men are chosen more often) or at the point of job applications (fewer qualified women apply relative to men). If differences arise at the application stage, a very different kind of policy would be required (such as an outreach program) than if the application pool is balanced (anti-discrimination training and penalties).

Lastly, our methodology makes clear that a sizeable fraction of current aggregate pay gaps are the results of past hiring imbalances that no longer exist, akin to a star whose light we perceive after its source has died. Recognizing and quantifying these pipeline effects is necessary to avoid over correcting pay gaps, creating new future imbalances in the process.
References


Bielby, W. T. and Baron, J. N. (1984), ‘A woman’s place is with other women: Sex segregation within organizations’, *Sex segregation in the workplace: Trends, explanations, remedies* pp. 27–55.


# Tables and Figures

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Table 1: Nationality of International Hires at the WBG
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<th>Grade</th>
<th>Mean Salary</th>
<th>Number of Staff</th>
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<td>GA</td>
<td>100 103 96 100 101</td>
<td>122 62 72 74 34</td>
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<tr>
<td>GB</td>
<td>112 116 116 118 121</td>
<td>2,600 3,099 1,828 1,068 381</td>
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<tr>
<td>GC</td>
<td>141 150 148 149 154</td>
<td>4,859 6,212 6,159 5,156 4,155</td>
</tr>
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<td>171 185 185 182 188</td>
<td>1,093 2,088 2,478 3,642 3,506</td>
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<td>GE</td>
<td>193 218 217 214 219</td>
<td>2,618 2,719 2,917 4,000 3,917</td>
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<tr>
<td>GF</td>
<td>256 275 273 278 282</td>
<td>1,822 2,944 3,522 6,017 7,084</td>
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<td>GG</td>
<td>362 378 372 377 389</td>
<td>7,644 10,746 10,323 9,973 11,813</td>
</tr>
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<td>457 492 484 501 534</td>
<td>2,901 4,428 5,407 6,161 6,741</td>
</tr>
<tr>
<td>GI</td>
<td>547 610 610 644 698</td>
<td>548 743 920 1,168 1,160</td>
</tr>
<tr>
<td>GJ</td>
<td>619 706 704 782 851</td>
<td>69 100 160 188 152</td>
</tr>
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Table 2: Salaries by Grade at the WBG (GA in 1987 = 100)
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<th>Gender</th>
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<td>0.99</td>
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<td>1.03</td>
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<td>1.01</td>
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Note: Table entries are ratios of the average salaries of leavers over stayers for each group defined by an entry grade, number of years of tenure and gender.

Table 3: Salary Ratios of Leavers over Stayers by Gender
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<th>Tenure</th>
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Note: Table entries are ratios of the average accumulated performance ratings of leavers over stayers for each group defined by an entry grade, number of years of tenure and gender.

Table 4: Performance Ratings Ratios of Leavers over Stayers by Gender
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<th>Technical Staff</th>
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Note: The table entries are percent contributions for each decomposition factor. The distributions of the factor contributions are estimated by simulating the decomposition using each of 250 bootstraps of the simulation input parameters.

Table 5: Decomposition of the Aggregate Gender Gap: Bootstrapped Distributions of the Percentage Contribution of each Decomposition Factor.

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<th>Technical Staff</th>
<th></th>
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<td>mean  p5  p95</td>
<td>mean  p5  p95</td>
<td>mean  p5  p95</td>
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<td>7.7  6.5  9.3</td>
<td>17.0  13.4  21.9</td>
<td>10.5  8.1  13.1</td>
<td>12.9  7.7  19.5</td>
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<td>55.0  40.5  69.8</td>
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<td>55.0  40.5  69.8</td>
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Note: The table entries are percent contributions for each decomposition factor. The distributions of the factor contributions are estimated by simulating the decomposition using each of 250 bootstraps of the simulation input parameters.

Table 6: Decomposition of the Aggregate Nationality Gap: Bootstrapped Distributions of the Percentage Contribution of each Decomposition Factor.
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</tbody>
</table>

Note: The table entries are percent contributions for each decomposition factor. The decomposition was obtained for each of all 120 possible decomposition orders. The moments reported in the table are computed over the set of results thus obtained.

Table 7: Decomposition of the Aggregate Gender Gap: Robustness to the Decomposition Order

<table>
<thead>
<tr>
<th>All Grades</th>
<th>Technical Staff</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean</td>
<td>p5</td>
</tr>
<tr>
<td>legacy</td>
<td>8.8</td>
</tr>
<tr>
<td>salary_growth</td>
<td>4.8</td>
</tr>
<tr>
<td>retention</td>
<td>16.6</td>
</tr>
<tr>
<td>entry_salaries</td>
<td>11.5</td>
</tr>
<tr>
<td>grade_composition</td>
<td>58.2</td>
</tr>
</tbody>
</table>

Note: The table entries are percent contributions for each decomposition factor. The decomposition was obtained for each of all 120 possible decomposition orders. The moments reported in the table are computed over the set of results thus obtained.

Table 8: Decomposition of the Aggregate Nationality Gap: Robustness to the Decomposition Order
<table>
<thead>
<tr>
<th></th>
<th>Baseline</th>
<th>Probit Exits</th>
<th>Log-normal Entry Salaries</th>
</tr>
</thead>
<tbody>
<tr>
<td>legacy</td>
<td>10.7</td>
<td>10.7</td>
<td>10.5</td>
</tr>
<tr>
<td>salary_growth</td>
<td>5.0</td>
<td>5.2</td>
<td>5.5</td>
</tr>
<tr>
<td>retention</td>
<td>0.4</td>
<td>1.8</td>
<td>0.7</td>
</tr>
<tr>
<td>entry_salaries</td>
<td>7.0</td>
<td>7.2</td>
<td>7.7</td>
</tr>
<tr>
<td>grade_composition</td>
<td>76.7</td>
<td>75.5</td>
<td>75.3</td>
</tr>
</tbody>
</table>

Note: This table presents decomposition results for the aggregate gender pay gap using two alternative specifications. In column 2, exits are modeled using a probit specification, with current salary as the lone regressor. In column 3, entry salaries are assumed to follow a log-normal distribution.

Table 9: Decomposition of the Aggregate Gender Gap: Robustness to Alternative Parametric Specifications

Figure 1: Proportion of Support Staff versus Technical Staff versus Managerial Staff (1987–2015)
Figure 2: Annual Exit Rates from the WBG (1987–2015) and WBG presidents’ tenures
Figure 3: Distribution of Salaries at Entry by Entry Grade 2010–2015
Figure 4: Distribution of Log-Salary Increases by Entry Grade 2010–2015
Figure 5: Fit of the Salary Simulations: Means by Employee Group

Figure 6: Fit of the Salary Simulations: Standard Deviations by Employee Group
Figure 7: The Aggregate Gap: Mean Salaries by Gender Over Time

Figure 8: The Aggregate Gap: Mean Salaries by Subgroups Over Time
Figure 9: Composition of New Hires at the WBG, 1987–2015

(a) Support Staff (GA–GD)
(b) Technical Staff (GE)
(c) Technical Staff (GF)
(d) Technical Staff (GG)

Figure 10: Entry Salaries by Grade and Year of Entry, Selected Grades, 1987–2015, Expressed as Differences with the Male Averages
(a) Staff hired at GB level (31.9% of hires)

(b) Staff hired at GF level (23.5% of hires)

(c) Staff hired at GG level (33.3% of hires)

Figure 11: Salary paths by Grade and Year of Entry, Selected Grades, 1987–2015, Expressed as Differences with the Male Averages
Figure 12: Fraction of Staff Who Remain at the WBG After 15 Years

Figure 13: Actual vs Simulated Salary Gaps
Figure 14: Forward Projection of the Aggregate Gender Gap - All Staff

Figure 15: Forward Projection of the Aggregate Gender Gap - Technical Staff