

EXPECTED WORK EXPERIENCE: A NEW HUMAN CAPITAL MEASURE

Joseph E. Zveglich, Jr., Yana van der Meulen Rodgers, and Editha A. Laviña

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Joseph E. Zveglic, Jr., Yana van der Meulen
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ABSTRACT

Work experience is a key variable in earnings function estimates and wage gap decompositions. Because data on actual work experience are rare, studies commonly use proxies, such as potential experience. But potential experience is identical for all individuals of the same age and level of education, so it ignores labor market intermittency because of childbirth and child-rearing—a critical omission when analyzing gender differences in earnings. This paper constructs a better proxy: expected work experience—the sum of the annual probabilities that an individual worked in the past. This measure can be generated using commonly available data on labor force participation rates by age and gender to gauge the probability of past work. Applying the measure to labor force survey data from the Philippines shows that conventional proxies underestimate the contribution of gender differences in work experience in explaining the gender wage gap.

Keywords: gender wage gap, labor force participation, Philippines, potential experience, wage regressions

JEL codes: J16, J24, J31, O15, O53

I. INTRODUCTION

Work experience is a key observable productivity characteristic in human capital earnings function estimates and wage gap decompositions. Because data on actual work experience are rare, studies commonly use potential experience to proxy for actual experience. This is calculated as age minus years of education minus 6 (assuming most children start school at age 6). This proxy, however, is the same for every individual of the same age and education level, regardless of gender. Many women have some labor market intermittency because of childbirth and child-rearing, and potential experience does not account for this discontinuity in labor force attachment (Miller 1993). For these women, potential experience will overestimate their actual experience and underestimate the male–female gap in actual experience.

Differentials in labor force attachment can also affect the accuracy of potential experience measures for immigrants and minority men (Hum and Simpson 2004, Antecol and Bedard 2004). Moreover, the mean level of potential experience differs across time (or between men and women) only because of changes in education attainment, which push down average potential experience as average education levels rise, and changes in the age structure of the workforce. Potential experience therefore neglects key gender, racial and ethnic, and generational differences in workforce attachment. The problem in obtaining accurate estimates of the determinants of earnings is compounded when the underlying dataset excludes information on participation in training programs, union membership, number and age of children, and other relevant information. Such omissions in country labor force surveys are widespread.

To deal with this problem, we construct a better proxy for actual work experience that relies on commonly available labor market indicators. This new approach will be useful for developing country settings or historical analysis where direct measures of work experience and tenure are not available. While labor force surveys typically do not capture actual work experience, their information can be used to approximate the probability that an individual has worked in a year, contingent on certain observable characteristics. This paper launches a new proxy for actual experience—we call this expected work experience—which is the sum of work probabilities for all years that a person has been of working age. Work probabilities could in principle be made contingent on a range of other factors, but data availability becomes a problem. Our solution is to base work probabilities on long-term historical information on labor force participation rates by age and gender. This paper is not the first to propose an improved proxy for accumulated work experience, but it is the first to use the measure of expected work experience, and it is designed specifically with data-sparse conditions in mind. This measure can be applied to developing countries, such as the example of the Philippines in this paper, and for the historical analysis of labor market outcomes.

II. LITERATURE REVIEW

Labor economists have long recognized the importance of having a measure of labor market experience or on-the-job training in estimations of earnings functions. Mincer (1958) and Becker (1962) wrote pioneering studies on this. In the absence of direct information on work experience in the 1960 United States (US) Census, Mincer (1974) introduced what is now considered the standard measure of potential work experience. This is obtained by subtracting years of schooling and age at the start of schooling (usually 5 or 6) from the reported age. While this method may have worked in early research, this measure of work experience is inadequate for those in the labor force who have

interruptions in their work experience. Hence, it does not fully capture actual work experience when there is work intermittency. The issue of work intermittency is important for women because they are more likely than men to drop out of the labor force for giving birth and child-rearing. These interruptions in work experience translate into lower job tenure and less on-the-job training for women and can contribute to the gender pay gap (Mincer and Polachek 1974). Using the common measure of potential experience overestimates actual years of work experience for women and underestimates the contribution of gender differences in work experience in explaining the total gender wage gap (Regan and Oaxaca 2009). Workforce disruptions are also relevant for some groups of men, such as immigrants and minorities, who experience more work interruptions compared with others. The issue of work disruptions has also become more important in the US labor market after the 2008 financial global crisis because of the increase in long-term unemployment and anemic job recovery (Blau and Kahn 2013). For these reasons, measures of actual work experience are preferable to potential experience in the analysis of the determinants of earnings.

Data on actual work experience are usually sourced from longitudinal datasets. In the US, the most notable datasets that include work history are the National Longitudinal Surveys (NLS), which are focused on specific age cohorts but are not representative of the full population, and the Michigan Panel Study of Income Dynamics (PSID), which is the world's longest running longitudinal household survey. Labor economists use these datasets extensively in their analysis of the US labor market. Garvey and Reimers (1979) noted that to investigate the separate effect of each type of experience on earnings capacity, a dataset such as the NLS and PSID should be used because these contain direct information on training and work history. For example, Mincer and Polachek (1974) used the 1967 NLS to relate women's family and work histories to their market earning power. O'Neill and Polachek (1993) used both datasets to examine changes in the actual work experience of men and women, and Regan and Oaxaca (2009) used both the National Longitudinal Survey of Youth 1979 cohort (NLSY79) and PSID to estimate the bias from using potential versus actual experience in wage analyses. Blau and Khan (2013, 2017) used the PSID to study the importance of including actual experience in earnings estimates and in decompositions of the gender wage gap. Moulton (1986), using a dataset with wider coverage, applied the Current Population Survey Social Security Exact Match file to assess the accuracy of individual experience measures. This dataset matches Social Security work and earnings histories to demographic data from the survey. The Bureau of Labor Statistics (1993) also estimated the work experience of men and women using a matched sample of the 1973 Current Population Survey, Social Security work histories, and Internal Revenue Service records.

In the United Kingdom, the National Child Development Study is a birth cohort study that follows more than 17,000 individuals of both sexes born in England, Scotland, and Wales during the first week of March 1958. Importantly, this study later included retrospective information on work experience. Waldfogel (1995) used the longitudinal feature of the National Child Development Study to control for actual work experience and for unobserved heterogeneity in the human capital earnings function. Another dataset that contains data on employment experience is the British Household Panel Survey. Olsen and Walby (2004) argue that it is preferable to use cohort surveys because they are representative of all age groups and not just a group of young women, as in the case of the National Child Development Study. They used the British Household Panel Survey, supplemented by the Labor Force Survey, to model gender pay gaps. Harkness (1996) also used the British Household Panel Survey to give a detailed account of the changing relative earnings of British women in the early 1990s. Wright and Ermisch (1991) used the 1980 Women and Employment Survey to provide new estimates of gender discrimination. This is the first British survey to collect detailed work histories and earnings

information for a nationally representative sample of British women—and the survey marks another first in that estimates of discrimination are presented based on actual work experience.

In other countries, datasets containing actual work experience include the Survey of Labour and Income Dynamics in Canada (Drolet 2002); the Household Market and Nonmarket Activities Survey in Sweden (Blau and Khan 1996, Edin and Holmlund 1995); the 1984 National Social Science Survey (Rummery 1989) and the Household, Income and Labour Dynamics in Australia; the Longitudinal Labour Market Register and the Integrated Database for Labor Market Research in Denmark; the Socio-Economic Panel in Germany; the Survey of Household Income and Wealth in Italy; and the Personnel Records dataset in Portugal (Harmon, Walker, and Westergaard-Nielsen 2001).

Ideally, measures of actual experience can be built into household surveys or surveys of population segments. Blau and Khan (2013) used labor market and demographic data from surveying 2,513 adults by telephone to study the possibility of adding two retrospective experience questions to a cross-section survey like the March Current Population Survey annual supplement. They concluded that a telephone survey produces credible data on work experience. Surveys of work histories have also been conducted for narrowly defined samples. For example, Noonan, Corcoran, and Courant (2005), focusing on lawyers, surveyed University of Michigan Law School graduates 5 and 15 years after graduation on their earnings, work hours, work histories (including interruptions and years worked part time), work settings, and families. This survey information matched with the lawyers' law school records. Bertrand, Goldin, and Katz (2010) surveyed Master of Business Administration graduates between 1900 and 2006 from the University of Chicago Booth School of Business to examine gender differences in the career dynamics of Master of Business Administration graduates. This approach of adding retrospective experience questions to surveys to obtain information on work experience can be used in developing countries where no reliable information on actual work experience exists. This approach, however, may not be a priority for these countries because of the limited capacity of their statistical offices.

Several research works have attempted to predict or estimate actual work experience. Garvey and Reimers (1979), using a dataset that contains detailed information on work histories, estimated equations that can be used to calculate expected total working-hour experience for individuals based on their demographic characteristics. They found that demographic information can be used to construct an improved measure of predicted experience relative to the standard potential experience measure. Moulton (1986), using their prediction equation to evaluate the validity of the experience measure from Social Security data in the US, concluded that the experience measure obtained by summing quarters of experience is almost as reliable as measures obtained from NLS-type data, provided certain precautions are taken.

In an extension of this strategy, Filer (1993) estimated equations that predict work experience by occupation. To reflect the expected divergence in career patterns across occupations, Filer used work experience data from the NLS and estimated actual work experience separately for women in each 1980 US Census occupation. Experience equations were estimated using ordinary least squares with the number of years of work experience (a woman's cumulative total weeks worked divided by 52) regressed on numerous demographic variables, including age, years of schooling, marital status, number of children, and race. Where a woman's actual work experience is not available, one practical alternative is to estimate experience equations using an alternative dataset that contains actual experience and then predicting experience by applying the coefficients from these equations to observed characteristics from the original dataset. Regan and Oaxaca (2009) used data from NLSY79

and PSID to construct predicted experience measures that were applied to the Integrated Public Use Microdata Sample, a dataset that lacks individual work histories. Their results suggest that potential experience biases the estimated rates of return from schooling and labor market experience. All the studies mentioned in this section, however, still require information on some work history to predict actual work experience.

III. CALCULATION OF EXPECTED WORK EXPERIENCE

Without information on an individual's work history, employers can use rules of thumb to form a general opinion of an applicant's accumulated experience when making a wage offer.¹ To this end, let ρ_{it} denote the probability that person i is working during period t . An employer uses the information on the set of characteristics known today (time T) of the potential employee, Θ_{iT} , to infer the person's actual work experience. That is, expected work experience is equal to the sum of the probability that a person has worked in each period from the usual age of entering the workforce (denoted time zero, for simplicity) to today:

$$\Lambda_{iT} = \sum_{t=0}^T \text{Exp}[\rho_{it} | \Theta_{iT}] \quad (1)$$

Proxy variables like potential experience implicitly assume all individuals accumulate work experience at the same rate over time (that is, $\rho_{it} = 1$ for all years following graduation). This assumption is especially problematic when studying gender differences in labor market outcomes. If women spend less time in the labor force than men due to family responsibilities, they accumulate actual work experience at a slower rate than men. Social changes that see younger women spending more time in paid employment than previous generations will cause the probability of work experience for individuals of a given age to rise over time. Using age or potential experience as a proxy for actual work experience cannot capture these important labor market dynamics.

Employers can improve the accuracy of their guess of accumulated experience with more detail on employee characteristics and better estimates of how these characteristics translate into time at work in the past. Yet the same data constraints that require a proxy to be used for actual experience in the first place come into play when studying developing countries or historical episodes. Labor force participation rates by age and gender are widely available for long periods of time, making them ideal candidates for the expected probability of employment. If an employer knows an individual's age today and gender, the expected work probability can be approximated by the age-gender labor force participation rates that have prevailed since the person reached working age.

As an example of this approximation, let λ_{jt}^f denote the labor force participation rate for women of age j at time t . Limiting the set of known worker characteristics to age and gender, the work experience a woman is expected to have gained in period t is $\text{Exp}[\rho_t^f | \text{age}_t = j] = \lambda_{jt}^f$. For a woman who is age J today and assuming her working age begins at 15, her expected work experience can be calculated from equation (1) as follows:

¹ The discussion in this paper is limited to proxy measures for the quantity of job market experience, not its quality. An expanded view of work experience that considers quality differences would be even more information intensive, requiring data on the type of work as well as time worked.

$$\hat{\Lambda}_{JT}^f = \sum_{j=15}^J \lambda_{j,T-J+j}^f \quad (2)$$

The calculation for men is similar. Expected work experience will differ across men and women of the same age at a given point in time depending on the prevailing labor force participation rates during their working years. Similarly, comparisons of expected work experience for the same age cohort of women at different points in time will vary as the age profiles of the labor force participation rates of women change.

Using potential experience as a proxy does not capture these differences. For a man or woman age J at any point in time t whose postschool work experience begins at age 15, the value of potential experience ($\tilde{\Lambda}$) would be

$$\tilde{\Lambda}_{Jt}^f = \tilde{\Lambda}_{Jt}^m = J - 14 \quad (3)$$

Average gender differences in potential experience would only arise from gender differences in age composition of the workforce and gender differences in average education rates. Average expected work experience would capture these differences as well as other forms of labor market intermittency, such as withdrawal from the labor market related to marriage, child-rearing, or military service. If the same gender-age cohorts are compared at different points in time, potential experience will only capture the negative impact that increased years of schooling has on measured work experience. Expected work experience captures this as well, since increased years of schooling would be reflected in the lower labor force participation rates of the young. However, it also captures the effect of other social changes that influence the labor force attachment of men and women, such as smaller family size or improved access to child care.

How well does expected work experience track actual work experience? We test the proxy measure against reported cumulative work experience collected in NLSY79 (Bureau of Labor Statistics 2016). The survey has tracked the same group of individuals since 1979, including retrospective questions covering 1978. The 1979 sample comprised 12,686 individuals—split nearly evenly between men and women—born from 1957 to 1964. The midyear ages of the initial sample ranged from 14 to 22 years. The respondents were surveyed annually during 1979–1994 and once every 2 years thereafter for a total of 26 rounds as of the most recent survey in 2014. In this survey, respondents' midyear ages ranged from 49 to 52 years. Over time, some respondents were permanently dropped from further interviews while others were not interviewed for other reasons, such that complete work histories can be constructed for only 7,071 respondents from the original sample.² Women make up 52% of the sample with complete work histories.

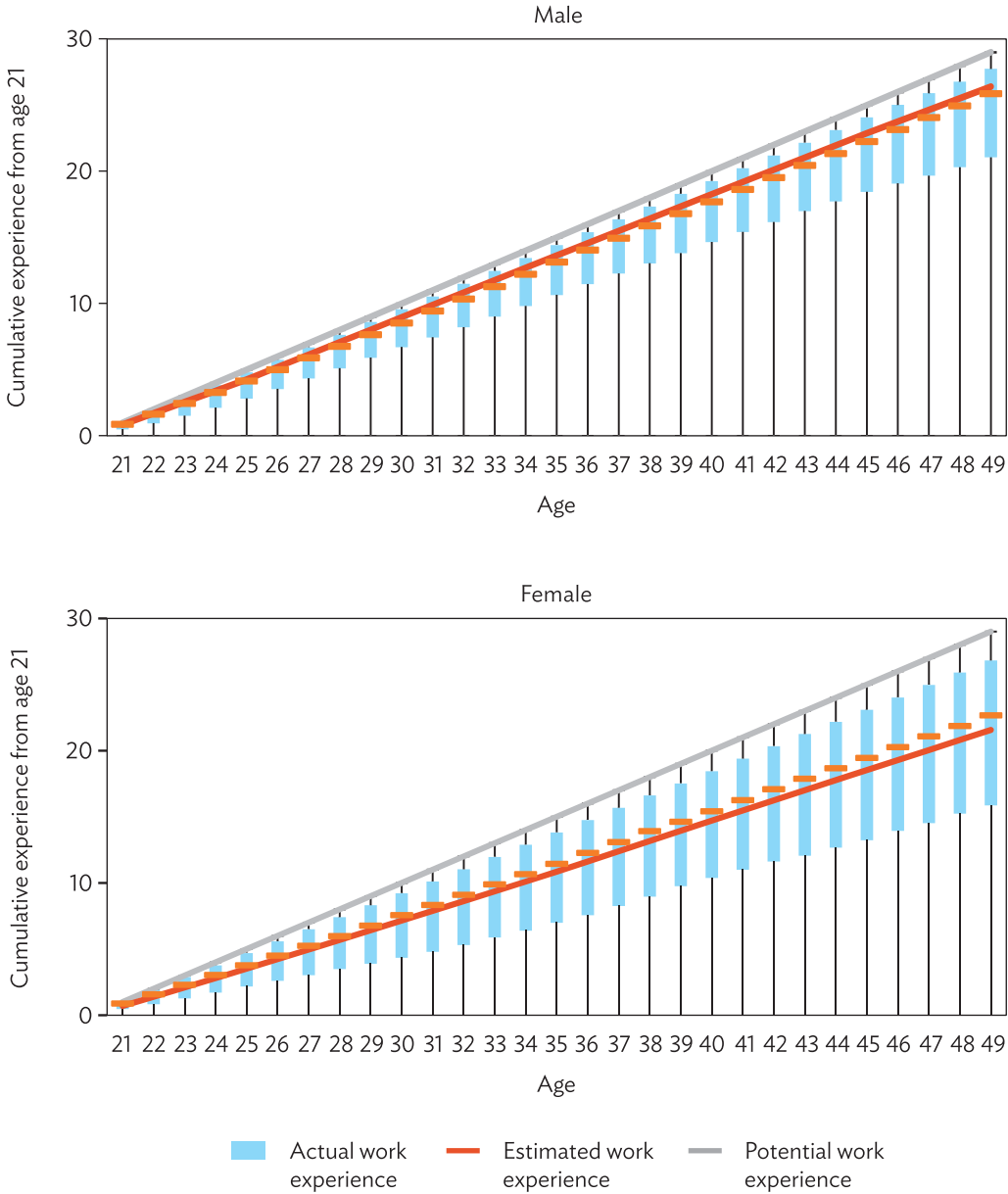
² NLSY79 is composed of three independent probability samples: (i) a sample chosen to be nationally representative of the young, noninstitutional civilian population (6,111 respondents in the first survey round); (ii) a supplemental sample designed to oversample the economically disadvantaged (5,295 respondents); and (iii) a sample representative of those serving in the military (1,280 respondents). After the 1984 survey round, 1,079 members of the military sample were dropped. After the 1990 survey round, 1,643 nonblack and non-Hispanic members of the economically disadvantaged supplemental sample were dropped. In the 2014 survey round, 790 respondents were reported deceased, 515 could not be located, 1,121 refused to be interviewed, and 467 were not interviewed for other reasons.

We calculate actual work in a year as the share of total weeks spent in civilian employment. Cumulative work experience is calculated beginning at age 21 since information for work at younger ages is not available for all NLSY79 respondents. Work histories by age can be calculated for all 7,071 respondents only up to and including age 49. For consistency, expected work experience is also calculated assuming that work experience begins from age 21. Labor force participation by gender and age groups (20–24, 25–35, 36–45, 46–55) for 1978–2014 are used to calculate expected work experience. We also calculate potential experience as a reference, assuming postschool work experience begins at age 21.

Figure 1 shows the distribution of actual work experience in the NLSY79 sample for each age group using box and whisker plots, and it compares the results with the median values for potential experience and expected work experience. By construction, potential experience is the upper bound of the actual experience range, with cumulative work experience equal to age minus 20 in all cases. The range of actual work experience in NLSY79 is quite broad, nearly spanning the possible range of outcomes of no work experience to potential experience regardless of gender or age. The expected work experience proxy performs well, closely tracking the median value of actual work experience for both men and women.³ The relationship is closer for men, with expected work experience overstating actual work experience at the median by less than half a year for men 49 years of age. For women, the proxy somewhat understates actual experience by about 1 year at age 49. Although the expected work proxy does overestimate the NLSY79 gender experience gap by 1.6 years at age 49, it does capture the fact that the experience gap tends to widen with age, unlike the potential experience gap.

³ We also calculated cumulative work experience for the full sample of 12,686 NLSY79 respondents by setting unreported work experience at zero. As expected, the resulting work experience distributions had lower values at the 25th, 50th, and 75th percentiles for all age groups. In this case, expected work experience tended to track the 75th percentile of the distributions for men and closer to the 60th percentile for women.

Figure 1: Comparison of Work History with Estimated and Potential Work Experience in the National Longitudinal Survey of Youth, 1979



Source: Authors' calculations.

IV. APPLICATION: EXPECTED WORK EXPERIENCE IN THE PHILIPPINES

To illustrate the usefulness of this proxy, the technique is applied to labor force data from the Philippines. Data availability—and even its limitations—make the country an ideal test case for the feasibility of the methodology. While the Philippines does not have panel data documenting actual work experience, it does have relatively long time series data on labor force participation by age and sex from a variety of sources. The need to deal with data gaps and shifting definitions of labor force participation illustrates the types of problems that are faced in constructing expected work experience in a typical developing country setting.

A. Expected Work Experience Results

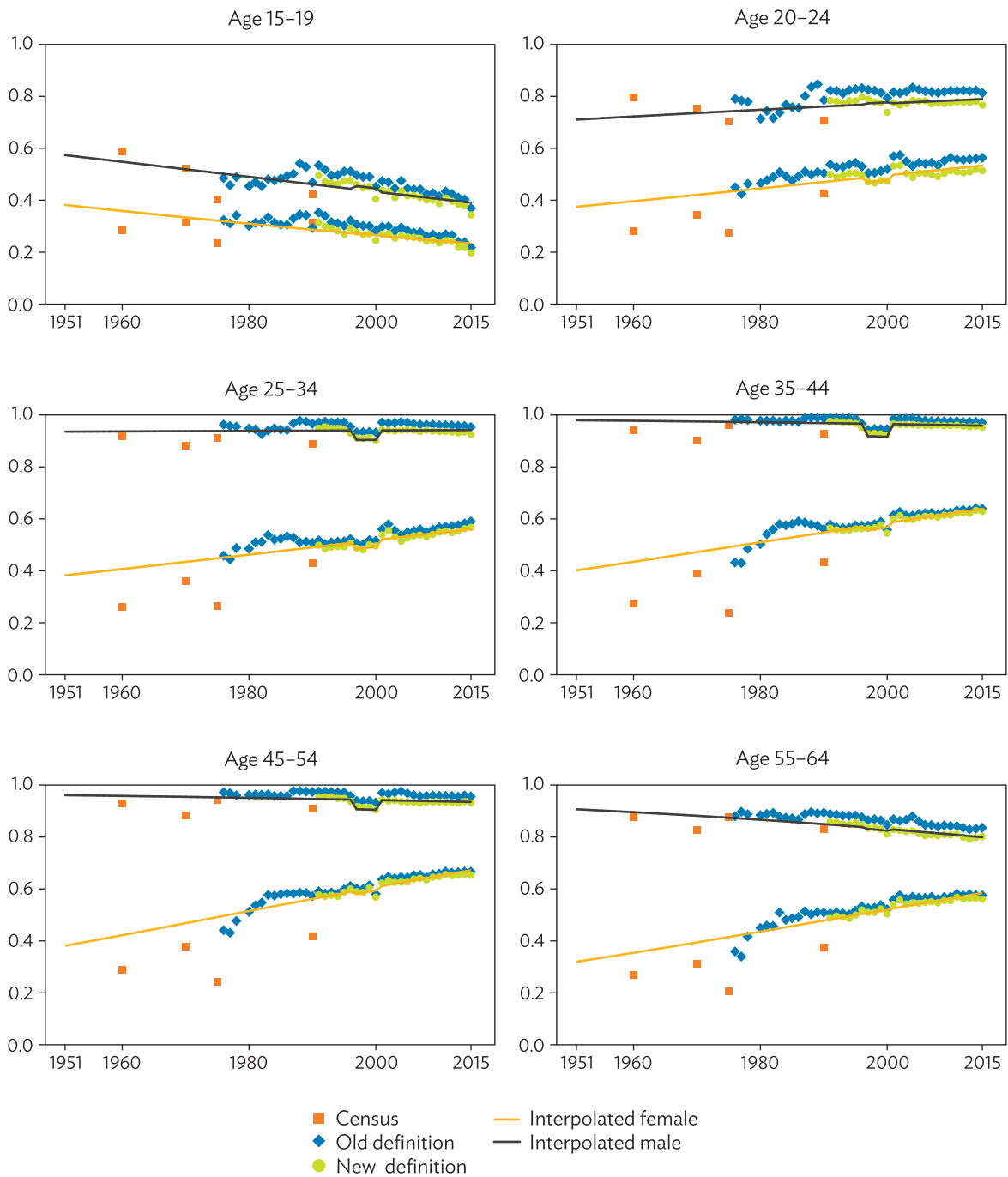
This analysis uses labor force participation rates for age–gender groups to proxy for work probabilities. These rates for the Philippines are constructed from census data, published labor force statistics, and household survey data. We construct rates for six consistent gender-disaggregated age groups: 15–19, 20–24, 25–34, 35–44, 45–54, and 55–64. The process is not without its challenges. Notably, historical data are missing in some cases, largely because expected work experience for older workers requires long time series. To calculate the expected experience for the oldest age group in 2001, the earliest year for which wage data are available, we need labor force participation rates for the youngest age group going back to 1952. Another challenge is comparability in definitions of work over time and across the census data and household survey data.

Data from all sources were used to generate a complete annual series of labor force participation by age and gender. Logit transformations of age–gender labor force participation rates were regressed on a linear time trend plus dummy variables for the changes in the definition of work in the census and household surveys and a dummy for the years of the Asian financial crisis and its immediate aftermath (1997–2000).⁴ The logit transformation was used to ensure that extrapolated fitted values range between 0% and 100%. The constructed series implicitly adopt the latest definition of labor force participation by setting the values of the census and old definition dummies to zero when generating fitted values.

The constructed series are plotted with the published data from the various sources in Figure 2. The figure shows the Philippines has seen increasing labor force participation rates of women across most age groups, but not men. This finding is similar for many other developing countries. Only women ages 15–19 have seen declining participation rates, reflecting their increasing likelihood of staying in school longer. Unlike the pattern for women, labor force participation rates for men have fallen across most cohorts. Because the rates are rising for women and falling for men, women’s accumulated work experience at a given age will be higher for more recent cohorts compared to cohorts of the same age in the more distant past. Hence, the gender gap in accumulated experience is narrowing over time.

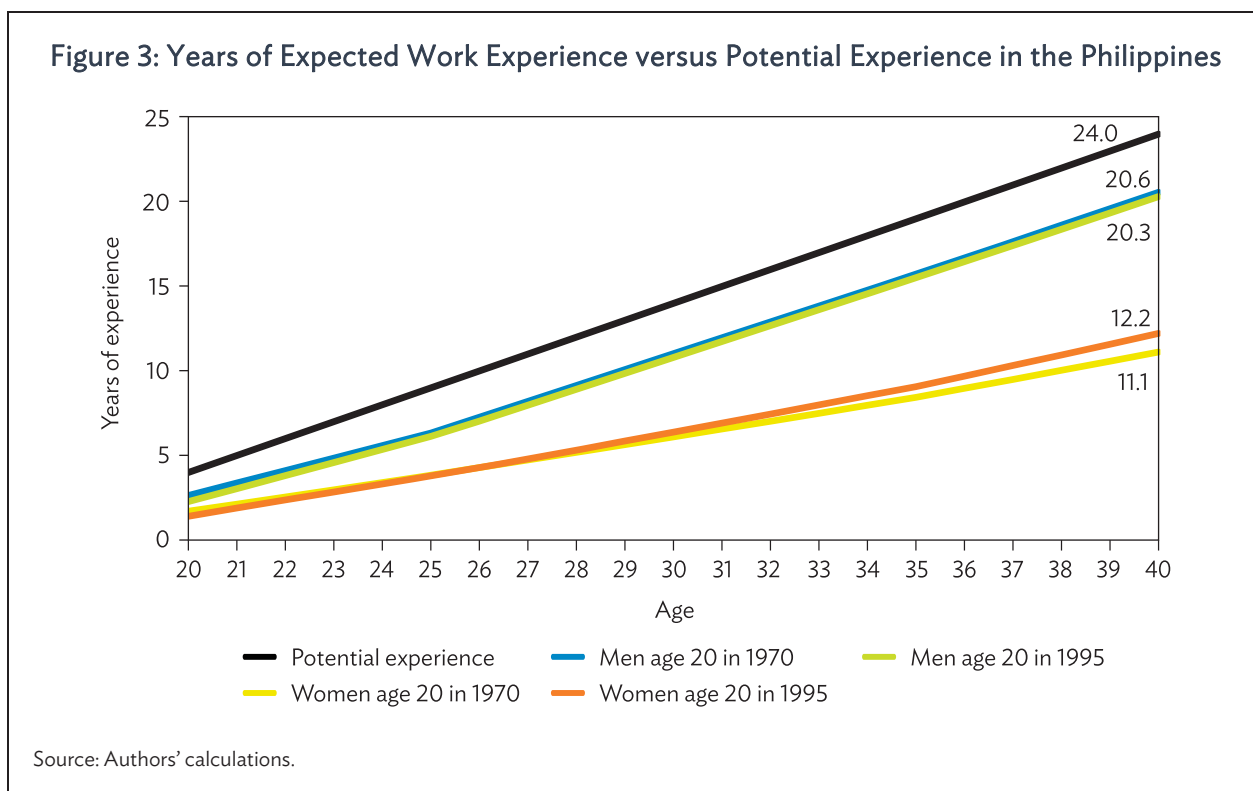
⁴ The logit transformation of the labor force participation rate λ is defined as $\text{logit}(\lambda) = \ln(\lambda) - \ln(1-\lambda)$.

Figure 2: Estimated Labor Force Participation Rates by Age and Sex in the Philippines, 1951–2015



Source: Authors' calculations.

These changes in actual work experience are unlikely to be captured in typical proxy variables, such as age or potential work experience. Figure 3 shows that the gap between potential work experience and expected experience in the Philippines is considerably larger for women than men. It also shows that the expected work experience of women has increased over time across age cohorts, while expected experience has stayed virtually the same for men.



B. Wage Decomposition Methodology

The strength of the expected work experience proxy is best illustrated in a practical example: a decomposition of gender wage differentials. This analysis uses microlevel data from the National Statistics Office's quarterly Labor Force Survey. The data constitute a nationally representative sample and are used by the government to construct official labor market indicators. For the empirical work, we pooled repeated cross-sections of the quarterly releases of the Labor Force Surveys from 2001 to 2015. The full sample retains all civilians ages 15–65 with observed values for the key regressors. The wage sample draws from the employment sample and keeps all individuals with positive reported daily basic wages, including wage workers and salaried employees but excluding live-in domestic workers.⁵ Nominal daily wage rates are deflated using the value of the National Statistics Office's monthly consumer price index corresponding to the reference period of the survey to compute real wages.

Because the wage sample excludes people out of the labor force and the self-employed, who do not report a daily basic wage, it is considerably smaller than the overall sample. To the extent that women are more likely than men to select out of paid employment, our wage estimates could be

⁵ The daily basic wage is the pay for normal work time before deductions for taxes, social security, and other withholdings. The concept excludes nonregular cash payments such as allowances, commissions, and overtime; it also excludes in-kind benefits and compensation.

subject to sample selection bias in which women's earnings are overstated and the gender earnings gap is understated. Typically, individuals from the lower end of the earnings distribution are more likely to select out of paid employment than are those from the upper tail. This result is common for women, since they have lower labor force participation rates than men. Although the magnitude of this selection effect is often larger for women, the selection effect declines over time as labor force participation rates for women increase.⁶

The gender wage gap can be decomposed into an explained and an unexplained portion. Using a fairly standard application of the Oaxaca–Blinder procedure, we decompose the gender wage gap in each year into a portion explained by average group differences in productivity characteristics and a residual portion that is commonly attributed to discrimination (Oaxaca 1973, Blinder 1973). The explained gap is the portion of the gap attributed to gender differences in measured productivity characteristics; the residual gap is the portion attributed to gender differences in market returns to those characteristics. To perform the decomposition, a human capital earnings function is estimated for male employees in each year in each economy, and the coefficients from the male regression are used to calculate predicted log wages for male and female workers. An argument for using male coefficients—the approach followed by most studies of this type in the literature—is that they more accurately reflect competitive returns to measured characteristics than female coefficients. Residual log wages are simply the difference between actual log wages and predicted log wages.

The determinants of real wages for men are expressed as follows:

$$W_i = a + \beta_1 T_i + \beta_2 Edu_i + \beta_3 Exp_i + \beta_4 Ind/Occ_i + \beta_5 X_i + \vartheta_i \quad (4)$$

where i denotes an employee. The dependent variable W_i represents the real value of wages received, and the remaining variables are individual and household characteristics that influence people's wages. These characteristics include time inputs, such as hours per day or days per week, (T_i); a set of dummy variables for educational attainment (Edu_i); and a measure of experience and experience squared (Exp_i). The matrix Ind/Occ_i represents controls for industries and occupations where industries include agriculture (hunting, forestry, and fishing, among other sectors); mining and quarrying; manufacturing; electricity, gas and water; construction; wholesale and retail trade; restaurants and hotels; communications; financial and real estate services; and community, social, and personal services. Occupational categories include professional, technical, and related workers; administrative, executive, and managerial workers; clerical and related workers; sales and service workers; farmers, fishermen, hunters, and loggers; production and related workers; and transport equipment operators and laborers. Most of these variables are fairly standard control variables in wage regressions across countries.

The matrix X_i includes geographic indicators, such as urban residence and state or province of residence, and other demographic variables. The geographical variables control for local labor market conditions that may affect people's employment and earnings. The term ϑ_i is an individual-specific idiosyncratic error term. All regressions are weighted using sample weights provided in the data sources.

⁶ A common procedure to deal with selection bias is to use a two-step Heckman correction procedure that first estimates the likelihood of inclusion in the wage sample and calculates what is known as an inverse Mills' ratio, and then includes this ratio as an explanatory variable in the wage estimations. The effectiveness of this procedure hinges on the inclusion of additional variables that are plausible predictors of paid employment but are not associated with wages. Our dataset for the Philippines did not contain such variables so we did not perform the correction procedure. Previous research we conducted for Taipei, China for the 1978–1992 period indicated that the Mills' ratio accounted for a negligible portion of the gender wage gap (Zveglich, Rodgers, and Rodgers 1997).

Table 1 provides sample means of the variables used in the analysis of labor market trends and in the wage gap decomposition analysis. The sample statistics are demarcated by gender, the first year and the last year of the data, and by the sample used (wage and full sample). The table shows that real weekly pay has fallen over time in the Philippines. The high incidence of part-time work among wage earners for both women and men is also noteworthy. Women do have an advantage over men in formal education. For industries, 8% of women and 18% of men in the Philippines work in agriculture. But once we look at all individuals of working age, including unpaid family workers, the dominance of the rural sector becomes more apparent. The importance of manufacturing as a sector of employment declines over time for men and women, being replaced instead by mining, utilities, and construction. Among the other variables, paid workers live predominantly in urban areas. About two-thirds of men and women in the samples are married, and the number of preschool children (0–5 years) has declined in households.

Table 1: Wage Function Estimation Variable Definitions and Averages in the Philippines
(%, unless otherwise indicated)

Variable	Women				Men			
	2001		2015		2001		2015	
	Wage Sample	Full Sample	Wage Sample	Full Sample	Wage Sample	Full Sample	Wage Sample	Full Sample
Log of real basic daily pay (P, 2006 prices)	5.4		5.4		5.4		5.4	
Log of normal daily hours worked (hours)	2.0		2.1		2.1		2.1	
Part time work	23.9		20.9		23.0		21.0	
Education								
No formal education	0.8	2.3	0.4	1.3	0.9	2.0	0.6	1.5
Primary incomplete	8.2	11.7	5.5	7.7	13.7	15.4	11.8	12.8
Primary graduate	12.5	17.1	7.8	10.4	16.6	16.2	11.8	12.0
High school incomplete	8.8	17.1	7.8	15.1	14.4	18.5	13.2	16.5
High school graduate	21.5	22.8	32.0	34.4	26.9	23.1	36.8	32.8
College incomplete	13.2	15.6	9.4	14.2	14.1	15.6	9.4	12.4
College graduate	35.1	13.4	37.2	17.0	13.3	9.3	16.4	12.2
Experience (years)								
Age	34.8	34.8	34.4	34.0	34.8	33.9	34.4	33.9
Years of schooling	10.3	8.8	10.8	9.6	8.8	8.4	9.2	8.9
Potential experience	18.2	19.5	17.4	18.2	19.5	18.9	18.8	18.5
Estimated work experience	8.9	9.0	9.2	9.1	15.6	15.1	15.1	14.9
Industry								
Agriculture, forestry, and fishing	10.8		7.8		21.4		18.3	
Manufacturing	18.0		13.4		14.4		12.1	
Mining, utilities, and construction	1.2		1.3		18.9		23.2	
Wholesale and retail trade	13.4		15.2		9.6		12.4	
Transport, storage, and communications	1.6		1.7		11.8		6.2	
Business services	5.9		10.4		4.2		8.6	
Personal services	49.2		50.3		19.6		19.2	

continued on next page

Table 1 *continued*

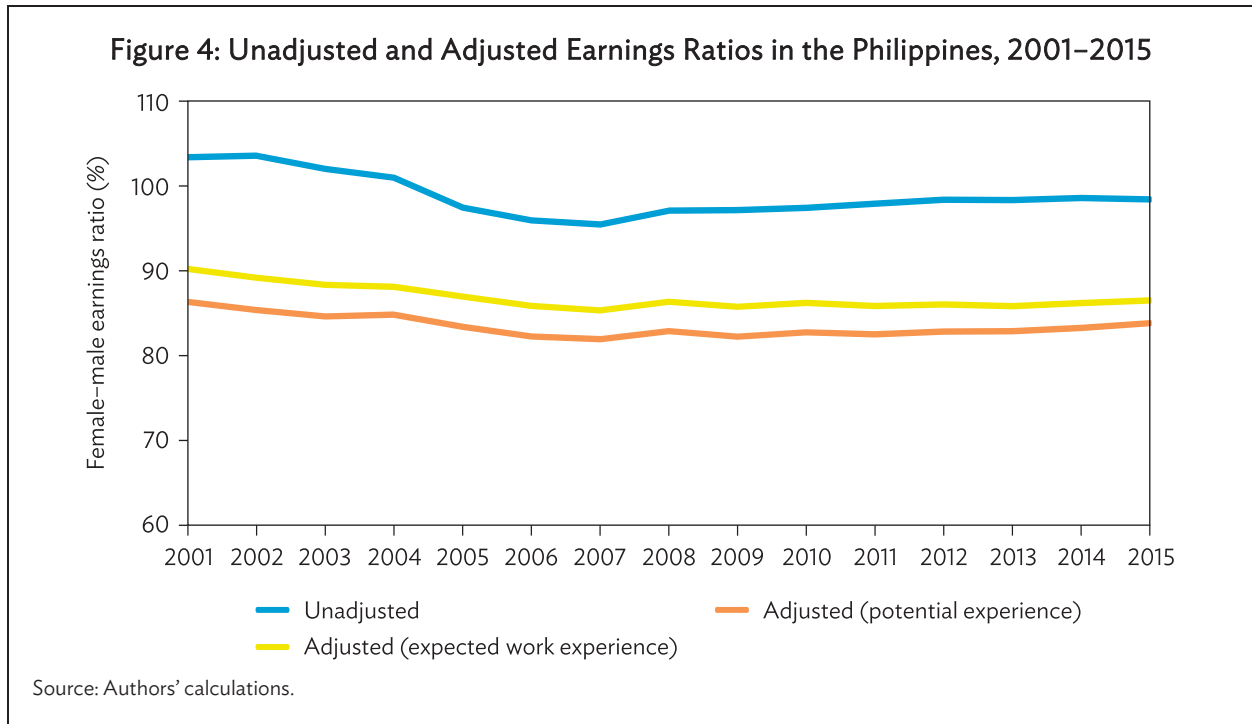
Variable	Women				Men			
	2001		2015		2001		2015	
	Wage Sample	Full Sample	Wage Sample	Full Sample	Wage Sample	Full Sample	Wage Sample	Full Sample
Occupation								
Executives and managers	5.3		4.0		5.0		3.4	
Science professionals and technicians	5.7		6.1		3.3		4.3	
Other professionals and technicians	18.4		16.2		4.4		4.3	
Clerical workers	15.0		18.9		4.4		6.9	
Service and sales workers	30.3		36.2		17.0		21.7	
Agriculture, forestry, and fishing workers	10.6		7.7		20.4		17.9	
Light production workers	10.2		6.4		14.8		11.9	
Heavy production workers	4.6		4.4		30.6		29.7	
Location								
Northern Luzon	9.4	10.8	10.1	10.8	9.4	11.0	10.2	11.1
Metro Luzon	28.7	24.2	30.6	26.3	28.4	24.3	27.9	26.0
National Capital Region	19.2	15.8	17.3	13.1	17.6	14.2	16.0	12.3
Central Philippines	25.4	27.6	25.8	27.5	26.1	28.3	26.6	28.2
Mindanao	17.3	21.6	16.3	22.2	18.5	22.2	19.3	22.4
Urban area	60.7	52.5	61.4	51.5	57.0	49.9	55.8	49.4
Married	52.1	57.8	52.4	57.2	62.9	54.4	59.8	52.9
Preschool age children (number)	0.6	0.7	0.5	0.6	0.7	0.6	0.6	0.6
Number of observations	49,308	244,702	56,844	258,117	85,642	245,224	93,651	265,260

Notes: Weighted averages from pooled quarterly survey data. Consumer price index (2006 = 100) used to deflate nominal basic daily pay. Sources: Philippine Statistics Authority, Labor Force Survey 2001, 2015; authors' calculations.

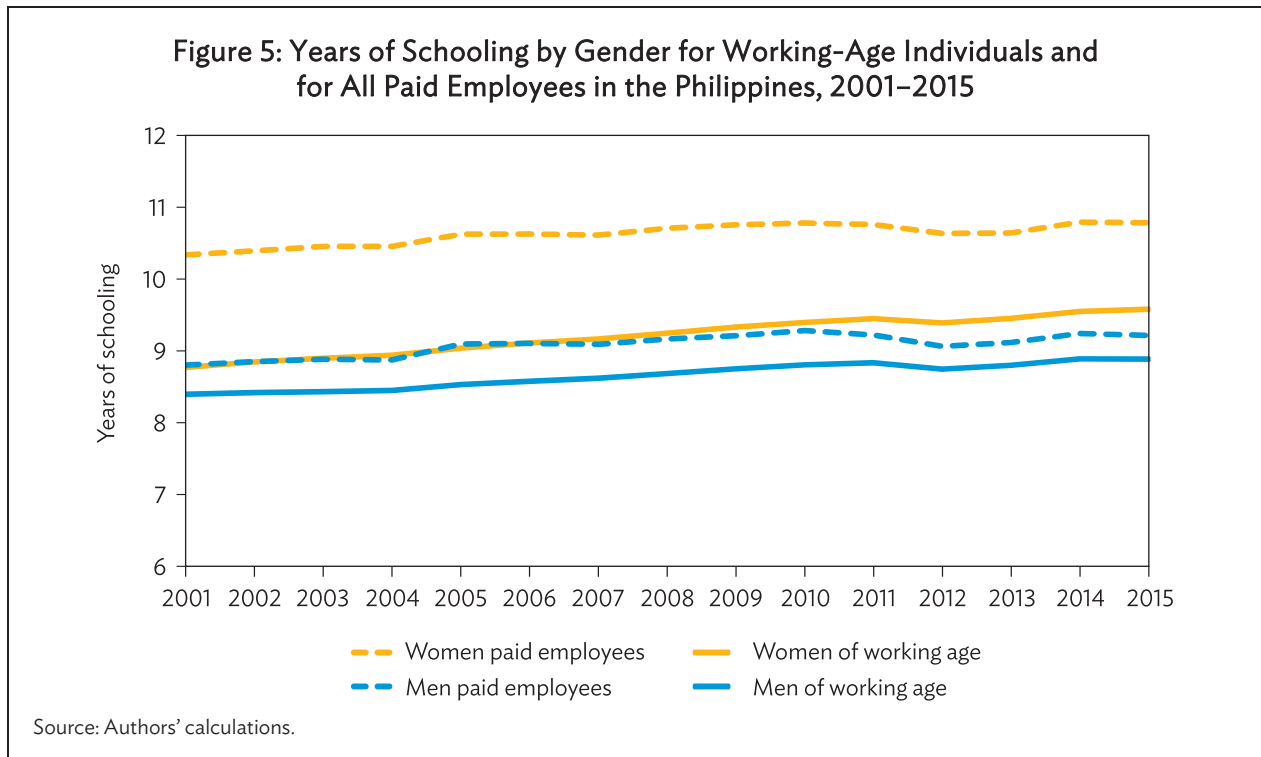
C. Wage Decomposition Results

The empirical analysis for trends in gender pay gaps begins by examining changes in the mean unadjusted female-to-male earnings ratio. Because changes in this ratio can arise from changes in gender differences in observed characteristics, such as education and experience, we also calculate adjusted earnings ratios. These ratios are constructed as the ratio of female to male residual wages, where residual wages are the portion of wages that cannot be explained by observed productivity characteristics.

The Philippines is an unusual case compared with many other economies because it has near gender wage parity over time, with women earning relatively more than men on average in the early 2000s and slightly less than men thereafter (Figure 4). The main explanation for this is that women cluster in higher-paying occupations and industries than men. Women also have a relative advantage over men in educational attainment. These relative advantages for women kept the unadjusted earnings ratio close to parity over the sample period. Once all productivity characteristics are considered, including potential experience as the proxy for work experience, the adjusted female-to-male earnings ratio is considerably lower, hovering slightly above 80% in the early 2000s and slightly below or at this level for the remainder of the period.



One potential answer to the differences in gender earnings ratios over time comes with gender gaps in education. In the Philippines, paid employees are more educated than the overall working-age population: half of all female employees have a college education compared with less than a third of all women of working age. But note that educational attainment has improved substantially over time for men and women (Figure 5).



Gender differences in occupation and industry distributions are another source of gender disparity in earnings. Globally, women are often clustered in lower-paying jobs, while men are clustered in higher-paying positions. This source of gender disparity is explored in Table 2, which shows employment shares for women and men across major industry and occupation categories in the Philippines ranked according to average total basic pay. Unlike the common pattern in other countries, men in the Philippines tend to be employed in lower-paying industries and occupations, while women are employed in higher-paying industry and occupation categories. For example, half of all paid female employees work in personal services, the country's third-highest paying industry, compared with just 20% of men. In contrast, 20% of paid male employees work in agriculture, the lowest-paying industry, compared to just 10% of women.

Table 2: Average Industry and Occupation Compensation and Gender Employment Shares in the Philippines, 2001–2015

Industry/Occupation	Mean Basic Pay (₱)	Women		Men	
		Employment Shares (%)	Cumulative Shares (%)	Employment Shares (%)	Cumulative Shares (%)
Industry					
Business services	332	7.6	7.6	6.7	6.7
Transport, storage, and communications	246	1.9	9.6	7.9	14.7
Personal services	239	49.9	59.4	19.4	34.1
Mining, utilities, and construction	231	1.0	60.5	20.2	54.3
Manufacturing	223	15.7	76.2	13.5	67.8
Wholesale and retail trade	189	14.5	90.7	11.4	79.2
Agriculture, forestry, and fishing	118	9.3	100.0	20.8	100.0
Occupation					
Executives and managers	486	4.3	4.3	3.9	3.9
Other professionals and technicians	446	17.2	21.6	4.4	8.3
Science professionals and technicians	407	5.6	27.1	3.7	11.9
Clerical workers	286	16.9	44.1	5.7	17.7
Heavy production workers	221	4.5	48.6	28.3	46.0
Light production workers	193	8.3	56.8	13.3	59.2
Service and sales workers	157	34.0	90.9	20.6	79.9
Agriculture, forestry, and fishing workers	116	9.1	100.0	20.1	100.0

Note: Industry and occupation groups listed in descending order of mean basic pay.

Sources: Philippine Statistics Authority (2001–2015) Labor Force Survey; author's calculations.

Changes in gender earnings ratios may be because of changes in the productivity characteristics of women and men, as well as changes in the returns to these characteristics. Table 3 shows the results from the Oaxaca–Blinder decomposition. The first panel shows results when potential experience is included as an explanatory variable; the second panel shows the decomposition results using expected work experience to proxy for actual experience. The difference between the two panels is striking. When potential experience is used to proxy for actual experience, the gender gap in experience accounts for only 1.7 log points of the gap. But when experience is measured by expected

work experience, the gender gap in experience is considerably larger, at 4.5 log points. The table shows near gender parity in wages because of the concentration of women in high-paying jobs. This concentration may be mostly due to the relatively higher levels of education of women compared with men. The explained gap actually accounts for a negative proportion of the overall earnings gaps, indicating that the proportion due to gender differences in returns to characteristics and to other unexplained factors exceeds the total wage gap. Hence, women would be paid more than men if they were paid male returns for education, experience, and their occupations and industries.

Table 3: Oaxaca Decomposition of Gender Earning Differentials in the Philippines, 2001–2015
(male–female difference in log earnings times 100)

Years	Total Gap	Gap Explained by Differences in Observables					Total Explained	Residual Gap
		Time	Education	Experience	Industry and Occupation	Other		
Potential experience								
2001–2007	0.2	0.3	-12.4	1.8	-6.7	-0.2	-17.1	17.3
2008–2015	2.1	0.2	-13.3	1.6	-4.6	-0.6	-16.6	18.8
All years	1.2	0.3	-12.9	1.7	-5.5	-0.4	-16.9	18.1
Expected work experience								
2001–2007	0.2	0.4	-11.3	4.8	-6.7	0.0	-12.9	13.1
2008–2015	2.1	0.2	-12.2	4.2	-4.6	-0.6	-12.9	15.0
All years	1.2	0.3	-11.8	4.5	-5.6	-0.3	-12.9	14.1

Source: Authors' calculations.

V. CONCLUSION

This paper launched a simple methodology for improving measures of labor market experience when the actual accumulation of experience is unknown. Using readily available information on labor force participation rates by age and gender can provide greater insights into the drivers behind gender wage differences and their evolution over time, as illustrated using data from the Philippines. Like many other developing countries, the labor force participation rates for women in the Philippines have been rising while they have been falling for men. So, for more recent cohorts, the accumulated work experience of women at a given age will be higher relative to the same age cohorts in the more distant past. This means the gender gap in accumulated experience is narrowing over time. These changes in actual work experience are not, however, captured in traditional proxy variables, such as potential experience. More troubling, the gap between potential experience and expected experience is considerably larger for women than men. Moreover, women's expected experience has risen over time across age cohorts while it has remained virtually unchanged for men. These patterns imply that using potential experience to proxy for actual experience has become increasingly problematic.

The expected experience variable can be a useful tool in empirical studies of labor markets in developing countries that lack extensive data on work histories and job tenure. That said, even the expected work experience has limitations as a proxy for actual work experience, particularly in a developing country context. Compared to more industrialized countries, developing countries have more fragmented labor markets with higher incidences of multiple job holdings, seasonal work, underemployment, unpaid family work, and self-employment. To the extent that this labor market fragmentation affects women more than men, the expected experience proxy may not fully capture

gender differences in years of full-time job tenure in paid employment. Additional variables to measure these particular issues would need to be added to decomposition procedures to try to identify more clearly the sources of the gender wage gap.

With this caveat in mind, our results for the Philippines show that when potential experience is used to proxy for actual work experience, the contribution of gender differences in work experience is considerably smaller than when expected work experience is used. Hence, using expected work experience as a proxy for actual work history results in a smaller residual gender wage gap. This outcome can be used to help pinpoint policy recommendations in the Philippines and in other developing countries for improving the labor market status of women. Policies that promote women's attachment to the labor force, such as paid parental leave, should in particular help to reduce gender differentials in work experience and, according to our results, will have a substantial effect in narrowing the gender wage gap. A similar conclusion applies to other policies that provide more opportunities for on-the-job training and workforce development.

Appendix: Wage Decomposition Data and Variable Definitions

Item	Description
Data source	Labor Force Survey <ul style="list-style-type: none"> • Source: Philippine Statistics Authority • Pooled quarterly surveys with reference months January, April, July, October • Time span 2001–2015 (1991–2015 for labor force statistics other than wage) • Full sample includes civilians ages 15–65 with no missing information on observable characteristics • Wage function estimation subsample includes only paid workers with reported daily basic wage, but excludes live-in domestic helpers
Dependent variable	Log real daily basic wage <ul style="list-style-type: none"> • Logarithm of the daily basic wage deflated using the monthly consumer price index (base year = 2006)
Time variables	Log daily hours worked <ul style="list-style-type: none"> • Logarithm of normal daily hours worked in the reference week Part-time work dummy <ul style="list-style-type: none"> • Equal to one if respondent worked less than 40 hours in the reference week
Education variables	Education dummies [associated years of schooling in square brackets] <ul style="list-style-type: none"> • One if no formal education (omitted) [0] • One if elementary education incomplete [3] • One if elementary education complete [6] • One if high school education incomplete [8] • One if high school graduate [10] • One if college education incomplete [12] • One if college graduate [14]
Experience variables	Potential experience <ul style="list-style-type: none"> • The lesser of age minus years of schooling minus 6 or age minus 12 (negative values set to zero) Potential experience squared
Industry variables	Industry dummies <ul style="list-style-type: none"> • One if agriculture, forestry, and fishing (omitted) • One if manufacturing • One if mining, utilities, and construction • One if trade • One if transport, storage, and communications • One if business services • One if social services
Occupation variables	Occupation dummies <ul style="list-style-type: none"> • One if legislators, senior officials, and managers • One if science, engineering, and health professionals, and associate professionals • One if other professionals and associate professionals • One if clerical workers • One if service and sales workers • One if agriculture, forestry, and fishing workers • One if light industry production workers • One if heavy industry production workers (omitted)

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Appendix *continued*

Item	Description
Other variables	Marital status dummy <ul style="list-style-type: none"> • One if married Number of preschool-age children <ul style="list-style-type: none"> • The number of children ages 0–5 in the household Location dummies <ul style="list-style-type: none"> • One if Northern Luzon (omitted) • One if Metro Luzon • One if National Capital Region • One if Central Philippines • One if Mindanao Urban dummy <ul style="list-style-type: none"> • One if in an urban area as defined by the statistical authority Survey month dummies <ul style="list-style-type: none"> • One if January (omitted) • One if April • One if July • One if October

Source: Authors.

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Expected Work Experience: A New Human Capital Measure

This report uses commonly available data on labor force participation rates by age and gender to gauge the probability of past work experience. The data show that conventional proxies underestimate the contribution of gender differences in work experience in explaining the gender wage gap. Work experience is a key component of human capital, but data on actual work experience are rare. Potential experience, the most common proxy for actual experience, ignores labor market intermittency because of childbirth and child-rearing—a critical omission when analyzing the gender wage gap.

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