ANALYSIS OF THE GENDER PAY GAP AND GENDER INEQUALITY IN THE LABOUR MARKET IN ARMENIA

UN WOMEN
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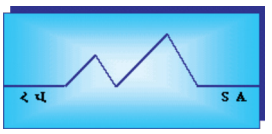

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ABBREVIATIONS AND ACRONYMS

Armstat	Statistical Committee of Armenia
CIS	Commonwealth of Independent States
Eurostat	European Statistical Office
ILO	International Labour Organization
ISCO	International Standard Classification of Occupations
LFS	Labour Force Survey
NACE	Statistical Classification of Economic Activities in the European Community
OLS	ordinary least squares
p.p.	percentage points
SDGs	Sustainable Development Goals

EXECUTIVE SUMMARY

The gender wage gap is the difference between the hourly wages earned by men and women in the labour market, expressed as a percentage of men's wage. This raw gap does not take into account the characteristics of the individuals used in the comparison, most notably education. When these are considered, the gap becomes "adjusted". The objective of the present study is to calculate the adjusted gender pay gap and the associated economic inequalities of women in the labour market in Armenia. The study is based on the Labour Force Survey of 2018. This executive summary presents the main findings.

The employment rate in Armenia is 44.8 per cent for individuals aged 15–64. Women experience a 11.1 percentage point (p.p.) employment gap. The employment rate is the lowest for the youth, with a gender employment gap less than half that of the overall population, while the rates for the other age cohorts are similar. The gender employment gap is the largest for the 35–44 and 55–64 age cohorts. The gender unemployment gap largely exists for the younger labour force (aged 15–34), while the gender inactivity gap stands at 6–37.4 p.p., hence sizable. It is apparent at any age.

Women are slightly more present in agriculture, which corroborates their larger share as unpaid family workers. Mining and especially construction, on the one hand, are more "masculine" sectors, as well as public administration. On the other hand, education and health and social care are dominated by women. Women are less frequently found in managerial positions, which may be an early sign of the glass ceiling effect, despite the fact that women dominate the next three skill levels (i.e. professionals, technicians and associate professionals, and clerical support workers).

The raw (unadjusted) gender pay gap in Armenia is estimated at 23.1 per cent. The raw gap calculated on monthly wages is 40 per cent, however, it captures the gender pay gap and the gender gap in hours worked. Specifically, Armenian women are found to work less than men by about 14.3 per cent, which explains a third to half of the gender pay gap when calculated with monthly wages.

The adjusted gender pay gap in Armenia is estimated at 28.4 per cent. It is larger than the unadjusted gender pay gap, suggesting that working women have better labour-market characteristics than men. This also relates to women's potentially more positive selection into the labour market, despite the fact that non-working women (unemployed and inactive) also do possess considerable levels of education. Therefore, qualifications cannot explain the gender pay gap in Armenia; quite the contrary, they amplify it. The addition of sectors and occupations does not affect the resultant gap, suggesting that potential sectoral and/or occupational segregations likewise cannot explain the gap.

The adjusted gender pay gap cleaned for selectivity in Armenia is estimated at about 10 per cent. It suggests that once we control for characteristics and selectivity, the gap declines at this level. Hence, this is a residual gender pay gap that could be ascribed to labour-market discrimination and the work of unobservable factors.

There is a potential glass ceiling effect in Armenia: the top 1 per cent of earners face a gender pay gap of around 19 per cent, which is almost double the average.

Women work fewer hours than men and such differences are spread among ages, occupations and economic statuses. However, the inequalities are more important given family structure. Women spend comparatively more time than men in household chores; caring for sick, elderly and disabled family members; and caring for children, with the most pronounced difference evident for household chores. Mothers in couples are most prone to low employment incidents and large gender employment gaps, especially at a young (childbearing) age. Results find evidence for horizontal gender segregation, as at least three quarters of women and men employees would need to trade places across the job categories for their distribution to become identical. Vertical segregation is quite forceful as well.

1 INTRODUCTION

The gender wage gap is the difference between the hourly wages earned by men and women in the labour market, expressed as a percentage of men's wage (Blau and Kahn, 2003). This is the definition employed by Eurostat and other international organizations. The gap is a broader reflection of the work-related and economic inequality of women in the labour market, including their economic dependence, decision-making power both in the household (e.g. spending decisions) and in society (e.g. managerial decisions), tolerance to violence and so on (Blunch, 2010). Understanding the gender pay gap and its determinants may support awareness-raising among employees, employers and policymakers; bring actions for the mitigation of economic inequalities; and support women in realizing their productive potential and ultimately support growth.

> Adjusted Gender Pay Gap – the differences between average men's and women's wages, accounting for their different endowments, most notably education, as well as a range of job characteristics

The gender pay gap – estimated as a pure difference between men's and women's wages – is known as the unadjusted or raw gender pay gap. It is "raw" since it does not take into account the characteristics of the individuals used in the comparison, most notably education. Hence, the gender pay gap may exist simply because individuals have different personal endowments (e.g. education, experience, age, etc.) but also due to discrimination (e.g. because employers think women are less productive than men). General-equilibrium effects – stemming from economy-wide changes in wage structure, structural reallocation and globalization patterns – may also shape the gender pay gap. However, the most important influence on the gender pay gap is expected from personal traits (Ehrenberg and Smith, 2003). When these are considered, then the gap becomes "adjusted", meaning adjusted for personal and labour-market characteristics. The latter is a more reasonable reflection of the gender pay inequality in the labour market.

A progressive number of countries – both industrialized and developing – have passed laws mandating the equal treatment of women in the labour market, and with the objective to reduce gender economic inequalities. The labour and anti-discrimination laws, as well as the laws and policies governing parental leave and childcare availability, have all been on the agenda in various countries worldwide, mainly transposing several key ILO Conventions. Most notably, the Equal Remuneration Convention, 1951 (No. 100), stipulates that men and women are entitled to equal remuneration for work of equal value. The key concept of this ILO Convention is "equal value", suggesting that the work could come in two forms: (a) equal or identical work in equal, identical or similar conditions; or (b) different kinds of work that, based on objective criteria, are of equal value. The latter implies that, at first sight, the jobs may look different, though they may be of equal value in terms of the weight and difficulties in task performance, i.e. in terms of the required skills, effort, responsibilities and working conditions. Two other related ILO Conventions include the Workers with Family Responsibilities Convention, 1981 (No. 156), promoting non-discrimination, work-family balance and the access to vocational training for mothers and fathers; and the Maternity Protection Convention, 2000 (No. 183), which sets minimum standards for maternity protection.

At the global level, the Sustainable Development Goals (SDGs) also aim to achieve gender equality within Goal 5, which stipulates, "Achieve gender equality and empower all women and girls". SDG 5 treats the inequality more broadly than simply the gender pay gap: its ambition is to achieve gender equality in the labour market (e.g. equal access to jobs and top decision-making roles); in education (e.g. achieving gender parity in primary education); in access to health; and in an array of targets to reduce gender-based violence and discrimination and to empower women and girls. As such, SDG 5 has nine targets and 14 indicators. While quite significant progress has been made on the majority of these indicators, a large amount of work is still needed as, for example, women at the global level still earn 77 cents for each U.S. dollar earned by men[1]. Beyond SDG 5,

[1]See: https://www.unwomen.org/en/news/in-focus/csw61/equal-pay

gender equality in pay importantly fares in target 8.5. of SDG 8: "By 2030, achieve full and productive employment and decent work for all women and men, including for young people and persons with disabilities, and equal pay for work of equal value".

A tremendous set of empirical research has been produced to investigate gender pay gaps in various countries, over various time horizons and potentially to correlate it with different outcomes. Examples of cross-sectional studies include: Alaez-Aller et al. (2014); Dupuy and Fernández-Kranz (2011); Simón (2012); Matteazzi et al. (2014); Arulampalam et al. (2007); and many others. Stanley and Jarrell (1998) were the first to conduct a meta-analysis of the gender pay gap in the U.S. and identified 12 factors that affected the pay differential, powered to explain 80 per cent of its variation. In particular, they identified that the omission of experience and the failure to correct for the selectivity bias may significantly impinge on the calculated gender pay gap. Similarly, Jarrell and Stanley (2004) arrive at a similar conclusion through an expanded set of underlying studies; however, they document a reduced need for selectivity-bias correction, implying lessened discrimination. Weichselbaumer and Winter-Ebmer (2005) analysed more than 260 published papers covering 63 countries over five decades (from the 1960s through the 1990s) and found that the pay gap may be significantly influenced by cohort-to-cohort analysis (e.g. analysing only married individuals) and by missing key variables (e.g. experience). On the other hand, they do not find that different econometric approaches produce significantly different results. In particular, the studies with time dimensions have widely documented the persistent though declining gender pay gap. Hence, the gap remains a persistent characteristic of every labour market and is increasingly researched, and policies and measures are being adjusted for its attenuation.

To our knowledge, one study dealt with the gender pay gap in Armenia (Rodriguez-Chamussy et al. 2018), as well as one covering the whole CIS region (Khitarishvili, 2015). They generally corroborate our findings. The former study is based on the 2015 Labour Force Survey in Armenia and finds a gender wage gap of 20 per cent, based on hourly wages.

The objective of the present study is to calculate the adjusted gender pay gap and the associated economic inequalities of women in the labour market in Armenia. The final objective is to understand the existence and structure of the gender pay gap in Armenia, so as to be able to propose clear amendments and measures to tackle it. In achieving this objective, we use the latest wave of the Labour Force Survey in Armenia in order to calculate and decompose the gender pay gap – as well as to provide a broader set of work-related inequalities in light of SDG 5 and 8 – so that the reader has a fuller comprehension of the gender gap in the country.

The study is structured as follows. Section 2 provides an extensive literature overview on the notions behind the gender pay gap and reviews a strand of empirical findings in the global literature. Section 3 presents the underlying methodologies for calculating and decomposing the gender pay gap. Section 4 devotes attention to the data used and points to some caveats. Section 5 discusses the obtained results for Armenia in light of their economic and policy importance. Section 6 presents a descriptive overview of the other work-related gender inequalities in the labour market in Armenia. Section 7 concludes and offers some policy recommendations. The annex of this document provides guidelines for calculations in Stata, with specific codes that a reader who is not expert in Stata may easily apply to reproduce the calculations underlying this study. The study contains a glossary of the gender-inequality terminology used throughout.

2 OVERVIEW OF THE RELATED LITERATURE

The literature on the economics of discrimination dates back to the seminal work of Becker (1957). Since then, a large corpus of empirical evidence has been created on the gender wage differentials, also reflecting the proliferation of the availability of micro-data. Thus, many reviews or surveys of the development of gender pay gaps have been done focusing on a single country or in a cross-sectional manner. With the proliferation of panel data techniques, the gender pay gap has been analysed in both cross-sectional and time dimensions, providing more space for understanding not only its determinants but also its dynamics.

2.1 Explained gender pay gap

The general notion of the gender pay gap in the global literature has been that it stems from two particular sources: (a) individuals have different labour-market characteristics (i.e. they work in different sectors and workplaces) and human capital (i.e. women may have less experience than men because of career interruptions related to child-rearing); and (b) the labour market may discriminate against women, causing them to receive lower returns for the same individual characteristics that men have. Both elements could be reinforcing each other, since women may be inclined to invest less in their human capital when they observe discrimination in the labour market.

The gender pay gap arising from the different endowments of individuals with human capital is known as the explained part. In other words, the average employed woman may not be identical to the average employed man according to her level of education, work experience, productivity levels, occupation, industry sector or other factors, and this has to be taken into account in the discussion on and estimation of the gender wage gap (Cukrowska and Lovasz, 2014; Lips, 2012; Manning, 2011). It may be that women, especially in the past, have been consistently underinvesting in their education, or that their career interruptions to devote time to their household and children are penalized by the labour market. It is also well known that women segregation exists in some lower-paying occupations (e.g. textiles), which likely explains part of the gender pay gap (Ehrenberg and Smith, 2003). The literature that tries to explain the gender pay gap with reference to personal and labour-market characteristics is abundant. We mention the most-cited studies: Gronau (1974); Beblo et al. (2003); Blau and Kahn (2003); Albrecht et al. (2004); Azmat et al. (2006); Neal (2004); Fortin (2005); and Olivetti and Petrongolo (2008).

Education constitutes the main explanatory power over wages and, hence, over the gender pay gap. The declining gap at the global level, to a large extent, is due to the increasing education of women (Weichselbaumer and Winter-Ebmer, 2005), especially in the upper deciles of the earnings distribution (Kassenboehmer and Sinning, 2014). Education worked for the gender pay gap by stimulating increased participation in the labour force, especially of married women (Katz et al. 2005). On the other hand, however, the choice of educational fields may still follow gender lines and therefore may aggravate the contribution of the increased levels of education. For example, Glover et al. (1996) argue that women still have a lower propensity to study science, engineering and technology. Likewise, the educational field may determine a woman's career path, thereby provoking gender segregation. For instance, Langdon and Klomegah (2013) argue that gender stereotypes still direct women into the traditional lower-pay careers, irrespective of the notion that women could equally cope with the responsibilities of jobs and sectors that are dominated by men. Furger (1998) goes further, arguing that even teachers and families discourage women early in their life from entering technology, science and maths fields and, instead, suggest that they choose a field that is "easier" or "female", like cosmetology, care work, medical transportation and nursing, among others.

Equally important as education is experience. In particular, women tend to have more interruptions in the workplace than men, especially related to childbirth and child-rearing. This not only determines their actual accumulation of experience but may also affect their devotion to taking on-the-job training as a vehicle to keep their skills up to date. Blau and Kahn (2007), for instance, argue that women tend to have less motivation to invest in market-oriented educa-

tion, given their expectations for interruptions, which then affects their wages.

Marriage and children may determine the gender pay gap, despite the fact that their inclusion in earnings functions has been frequently disputed. It is, however, a notional idea that wives and mothers may have chosen occupations or sectors that provided sufficient flexibility to take care of their families; these are usually lower-paid jobs, though not necessarily because they are women-friendly. Taniguchi (1997) argues that for women to advance in their jobs and wages, they need to minimize the burden on their household responsibilities. Even Becker (1985) recognized the traditional division of labour that may put women at a disadvantage with regard to hours spent on household chores, thus implying lower productivity and wages. He hypothesized that wage differentials between men and women may be a consequence of the household roles specialized by both genders. Generally, single or unmarried women should have higher hourly earnings than married women for the same working hours and job positions because married women are expected to have more household responsibilities, which would lead these women to prefer more convenient and less energy-intensive work obligations. Moreover, the role of women as mothers may prevent them from working overtime or accepting extended travel assignments, thus leading to segregation to occupations that require less effort and, therefore, are less paid. Epstein et al. (1999), for instance, link this tendency of the gender pay gap – women's reluctance to work longer hours due to their household duties – indirectly to vertical segregation by limiting the entry of women into higher-paid occupations. Overall, marriage and children likely affect married women's wages on the basis of productivity, as wage is significantly correlated with effort, which in turn is inevitably determined with how a woman allocates attention between her household and labour-market duties (Waldfogel, 1998; Cukrowska and Lovasz, 2014).

Despite the importance of education and experience, still a significant portion of the gender pay gap could be explained by occupation and industry differentials (Blau and Kahn, 2003, 2007). Educational fields and family-constrained stereotypes, mentioned above, likely result in women pursuing careers in sectors that are usually lower-paid. By choosing these sectors, women may experience lower risk but are aware that they miss significant financial rewards. Along the same line, occupations that are considered "easier" or "feminine" are considered less prestigious and hence deserve lower pay (Lips, 2012). According to Thomson (2006), occupational segregation produces horizontal or vertical segregation. Horizontal segregation implies that a sector, occupation or workplace is dominated by men or women, while vertical segregation suggests that opportunities for career progression in a particular occupation, sector or workplace are limited by gender, age or race. Both types of segregation often cause substantial differences in wages between genders, as men tend to work in the higher-paying "masculine" jobs, while women in the lower-paying "feminine" jobs (Hill and Corbett, 2012). Moreover, even if wages are observed at the occupational level – so that segregation is ruled out – gender pay gaps may still exist within occupations or sectors (Giapponi and McEvoy, 2005), particularly those cases when men in "feminine" occupations/sectors are paid more than women (e.g. textiles). This boils down to societal norms and attitudes, or what Chafetz (1978) describes as a labour force structured by society to the advantage of men.

2.2 Unexplained gender pay gap

Albeit a large portion of the gender pay gap could be explained by key personal traits – most notably education and experience – and job characteristics, still a substantial part may remain unexplained (Budig and England, 2001; Blau and Kahn, 2003, 2007; Ehrenberg and Smith, 2003; Janssen et al. 2016). The unexplained gender pay gap is often thought to represent discrimination. Yet, this is often a naïve approach to the discussion and understanding of the gender pay gap, for a few reasons: (a) the estimation of the adjusted pay gap may still be missing important personal or labour-market characteristics that may significantly impact the gender pay gap; (b) unobservables – notably ability, motivation, devotion, attentiveness, risk aversion, attitude to work, ties and social networks, among others – may all affect the wages of men and women distinctively and yet cannot be captured by observed variables; and (c) women with particular characteristics (e.g. more-educated, career-minded women) may tend to self-select into the labour market.

The role of unobservables is frequently discussed in relation to the individual traits or human capital characteristics of women. Budig and England (2001), Weichselbaumer and Winter-Ebmer (2005), Blau and

Kahn (2003, 2007) and Cardoso et al. (2016) argue that other than discrimination, unobservable productivity differences between the genders could give rise to the unexplained part of the gender or motherhood wage gaps. In addition, less investment in formal and non-formal education, more time devoted to household chores and lower occupational attainments could all be personal and voluntary choices of women, rather than a reflection of labour-market frictions, including discrimination.

2.3 Selectivity bias

Aside from the role of unobservable traits, studies similarly may overlook the role of the potential non-random selection of men and women into the labour force (Orloff, 2009). For example, employed women may consistently be better educated than employed men, or inactive women (who, accordingly, do not feature in the wage distribution) may have worse labour-market characteristics than employed women. In such cases, controlling for such characteristics may not actually reduce or "adjust" the gender pay gap. The effects of the non-random selection of women on the labour market is called selection bias. The importance of selection bias in calculating wage differentials has long been recognized since the seminal work of Gronau (1974) and Heckman (1976). Conceptually, selectivity bias works along the relationship between the gender pay and participation gaps. Namely, many countries, especially those in the developing world, experience an ample differential in labour-market participation rates between men and women. Differential participation rates may be related to various factors, among which include household and child-rearing chores, stereotypes and prejudices, and stable flows of income like remittances or social assistance. Thus, the idea goes back even to Roy's (1951) model, applied to the choice between market and non-market work in the presence of rising dispersion in the return to market work (Olivetti and Petrongolo, 2008). The practical implication of this is that women who do not feature in the labour market do not have an observed wage, i.e. they do not feature in the wage distribution. If they are systematically different than women for whom a wage is observed, then there is grounds for concern that the absence of the former significantly impacts the gender wage gap.

Studies have been progressively accounting for this selectivity and finding that selectivity-bias correction has important implications for the gender pay gap, as described in prominent articles by Altonji and Blank (1999); Blau and Kahn (2003); Beblo et al. (2003); Albrecht et al. (2004); Neal (2004); Fortin (2005); Azmat et al. (2006); Machado (2012); and many others. In general, the issue of selection bias also raises the importance of considering labour-market gaps in employment, unemployment and participation as equally important in the comprehension of gender-related inequalities as the gender pay gap itself.

2.4 Gender pay discrimination

After considering personal and labour-market characteristics, correcting for selectivity and allowing for ways (at least, qualitatively) to capture the unobserved workers' characteristics in econometric models, the gender pay gap may still persist. Undoubtedly, the very remaining part of the unexplained gender pay gap could only be "explained" on the grounds of discrimination. Namely, employers – and the labour market in general – observe women with the same characteristics differently than men, for work of equal value, due to different perceptions, expectations, stereotypes and prejudices. Janssen et al. (2016), Budig and England (2001), Correll et al. (2007) and Altonji and Blank (1999) consider four types of gender pay discrimination: stereotyping, taste-based, statistical and normative discrimination.

Stereotyping and social prejudice could directly affect personal preferences over genders when human capital investment and choices are considered (Janssen et al. 2016). In cases where some jobs are considered typically "masculine" and society opposes gender equality (or, at best, has little awareness of it), then there will be fewer women applying for such jobs. Firms will also tend to assign men and women to workplaces based on these stereotyped views, which is an indication that such firms often do have large gender pay gaps. Likewise, societal expectations about what women should and should not do would significantly impinge on their decisions related to job applications, labour-market participation and even how they negotiated their wages. For higher-paying jobs in particular – e.g. managerial or board positions – women may feel inferior in negotiations and less deserving of higher-paying jobs and, therefore, may undervalue their worth (Fortin, 2008; Babcock and Laschever, 2003).

Taste-based discrimination arises from the notion

that employers, but also customers and employees, may have a certain level of distaste towards women (Altonji and Blank, 1999; Budig and England, 2001; Janssen et al. 2016; Sano, 2009). Such discrimination arises because employers simply consider it distasteful to employ women and mothers, rather than make assumptions about their lower productivity due to marriage or motherhood. Such an approach is based on prejudices. Taste-based discrimination often breaks through social prejudicial and discriminatory contexts where firms have monopsonic power and where search frictions and barriers to entry are larger for women than for men (Altonji and Blank, 1999).

In statistical discrimination, employers have limited information about the personal traits and productivity of job candidates, so they simply concentrate on observable characteristics, which is a fairly easy and less costly task (Budig and England, 2001). Simple observation is used as a screening device to predict individual probability among applicants. Such an approach may seem an unbiased method of judging one's productivity, but it may hide two important biases: the first relates to stereotypical cultural beliefs that distort cognition, while the second relates to the precision of information that employers use as input in assessing productivity. Based on these two biases, women and mothers are less likely to be evaluated as favourable. Consider, for example, work experience: Due to career interruptions, a lower level of experience in the statistical model will predict lower wages for women and mothers, implying a gender pay gap. Gangl and Ziefle (2009) argue that motherhood is not related to lower productivity among mothers, while statistical models will implicitly suggest so, resulting in the stigmatization of working mothers with regard to their performance in the labour market.

Finally, in normative discrimination, there is an underlying cultural belief that mothers should remain home and take care of their children, which does not mean that they are inexperienced or incompetent in their paid job (Correll et al. 2007). The idea behind it is that employers, maybe unconsciously, discriminate towards mothers because of their beliefs that success in the paid labour market, especially for those jobs that are considered masculine, signals stereotypical masculine qualities such as assertiveness and dominance. It is a rather normative expectation that mothers should prioritize the needs of their dependent children above all other activities. In such decisions, mothers are affected not only by their employers but also by their husbands. Benard and Correll (2010) claim that when mothers break these norms, they are held to stricter standards and penalized on recommendations for hiring, salary level and promotion since they are viewed as interpersonally deficient in the work setting.

2.5 Other work-related gender inequalities

While the gender pay gap plays a dominant role in capturing work-related gender inequalities, it should be recognized that such inequalities affect areas beyond pay equity. For example, target 5.5 of SDG 5 (Gender Equality) stipulates, "Ensure women's full and effective participation and equal opportunities for leadership at all levels of decision-making in political, economic and public life". Therefore, besides equal pay, to achieve gender equality, companies should strive to provide broadly the same outcomes and privileges to both men and women, some of which include: no barriers to women's full participation in the workplace; no discrimination against women with regard to their family and caregiving responsibilities; and equal access to leadership positions.

> Sticky Floor – A discriminatory employment or wage pattern that keeps workers, mainly women, in the lower ranks of the job or wage scale, with low mobility and invisible barriers to career advancement

Most notably, women could face multiple barriers as they climb the corporate ladder, as a result of their underrepresentation at the top of the labour market (Baxter and Wright, 2000; Bertrand et al. 2010). A prominent 1986 article in the Wall Street Journal popularized this phenomenon as the glass ceiling effect. The literature extensively treated this issue mainly through the restrictive approach, i.e. by considering this type of work-related inequality as an absolute barrier for women from higher positions of workplace power simply because they are women (Jacobs, 1992; Morrison and von Glinow, 1990; Reskin and McBrier, 2000). In this vein, women face an invisible line below which they achieve a modest degree of workplace power (e.g. supervisory roles) and above which they do not (e.g. managerial control). Then, this line materializes into conscious and subconscious discriminatory practices (Lee, 2002; Ridgeway, 2001). Such discriminatory practices have also been labelled as the "concrete ceiling" (Ogilvie

and Jones, 1996), "sticky floor" (Padavic and Reskin, 2002; Tesch et al. 1995), "glass door" (Cohen et al. 1998) and "tokens" (Cox, 1990; Frankforter, 1996; Kanter, 1977).

Women and men also differ in the contractual relationships involved in work. As women are those who primarily undertake household and caregiving roles – particularly in patriarchal-minded societies – they apparently spend more time at home, compared to men, and more frequently are engaged in unpaid family work (Acevedo, 2002; Messing and Elabidi, 2003). Similarly, in many countries, other forms of precarious employment – e.g. short-term contracts or subcontracting (Quinlan et al. 2001), or even working in the absence of a written contract – have been more prevalent among women, another phenomenon related to their propensity to look for part-time engagements given their household responsibilities. The ILO (2000) finds that women are more likely to suffer from the growing competitive pressures and cost-saving strategies, which can be associated with a lack of security, limited possibilities for training and career advancement, and inadequate social security coverage in terms of old-age pensions, sickness insurance and maternity protection. Likewise, women are less likely to be unionized.

3 UNDERLYING METHODOLOGIES

3.1 Calculation of the gender pay gap

The gender wage gap is the difference between the hourly wages earned by men and women in the labour market, expressed as a percentage of men's wage (Blau and Kahn, 2003):

$$\text{Gender Wage Gap} = \frac{\text{(Men's average hourly wage - Women's average hourly wage)}}{\text{(Men's average hourly wage)}} \times 100\%$$

Eurostat uses the gross values of wages in the above formula, although net amounts are widely used when gross are not available. In the applied work, the difference between the log hourly wage of men and of women is used to calculate the gender pay gap, despite mathematically assuming a comparison to the overall average wage, rather than men's average wage.

This simple calculation will produce the *unadjusted* or *raw* wage gap. However, as we discussed previously, such a gender pay gap would hide important information on how personal and labour-market characteristics interfere with the wage differential.

> The gender wage gap is the difference between the hourly wages earned by men and women in the labour market, expressed as a percentage of men's wage (Blau and Kahn, 2003)

Jacob Mincer was the first to introduce a novel way of analysing individual earnings, in his prominent book *Schooling, Experience, and Earnings.* Since then, a tremendous body of research has been produced based on what became known as the *Mincerian earnings function* (Mincer, 1974). The substance of the function is rooted in Becker's human capital theory, whereby an individual's wage rate is a reflection of the productive capacity of the individual, i.e. it depends on his/her human capital characteristics accumulated with education, time and on-the-job training, which in turn affect productivity (Budig and England, 2001; Lemieux, 2006). Hence, in its most generic form, the Mincerian earnings function models the natural logarithm of hourly earnings as a function of the years or levels of education and the years of potential labour-market experience. Rosen (1992) claimed that the function captured the empirical variation in earnings over one's life cycle, which although increasing, indicated a concave shape of the path of earnings with age, called "age-earnings profile". For modelling purposes, therefore, age is included with its quadratic term as well. This change puts the emphasis from age to labour-market experience by interpreting it as on-the-job training, in order to include schooling as well as participation in traineeships, job investment and other firm-specific training that were better at capturing labour-market exposure than just age.

Therefore, it became very customary for the Mincerian earnings function to include gender as an explanatory variable of the wage rate, to account for the potential differences between the log hourly wages of men and women. Hence, the Mincerian earnings function takes its most generic form as

$$ln(y_i) = \alpha + \beta_1 gender_i + \Sigma y_j * X'_i + \varepsilon_i \quad (1)$$

whereby $ln(y_i)$ is the log of the hourly wage of person i; $gender_i$ is a dummy variable taking a value of 1 for females and 0 for males; and X'_i is a vector of other personal and labour-market characteristics (including but not limited to: education, age and its square, experience, tenure, occupation, sector and the like) (Budig and England, 2001). The coefficient β_1 measures the *adjusted* gender pay gap. If the vector of explanatory variables X'_i is not included, then β_1 would measure the unadjusted gender pay gap, i.e. the calculation would boil down to estimating a simple difference of logged mean wages. The term ε_i is the idiosyncratic error, capturing all influences on the gender pay gap not captured by the observable variables, i.e. the *unexplained* part of the gender pay gap.

This equation is the fundamental part of empirical research on earnings determination (Lemieux, 2006). The tendency of this equation to be used and estimated on thousands of data sets for a large number of countries and time periods, has made this equation the most widely used model in empirical analysis.

To estimate equation (1), studies have frequently relied on ordinary least squares (OLS). OLS estimates

are based only on the sample of employed workers for whom wage is observed (Beblo et al. 2003). Hence, this simple approach compares individuals at the mean of the distribution, i.e. the wage of the "average" man compared to that of the "average" woman, given their characteristics. However, the key potential problem is that unemployed and inactive individuals are ruled out of the estimation, simply because their wage is unobserved. The question is whether or not selection into employment is fully random. In practice, this is unlikely to be the case, as persons who feel more capable (likely determined also by their education), more motivated, more encouraged by family and so on, will have a greater propensity to look for and find a job. Hence, selection is endogenous, i.e. in such circumstances, the calculated β_1 will suffer selection bias and the OLS would be biased and inconsistent towards working women. The sample selection bias is determined by the gap between workers and non-workers since some parts of the decisions to work are relevant in determining the wage process.

Heckman's (1976, 1979) selection model has been widely used in the literature, allowing for the selection into the labour force not to be random and for the unobservables determining observed wage not to be independent of the decision whether or not to work. The method considers the relationship between the gender pay gap and the gender participation gap as crucial in determining gender inequalities. Statistically, if selection is ignored, the unobserved parts of the wage and participation equations will be correlated, leading to biased OLS coefficients.

The Heckman selection method is a two-staged method: the wage equation and the selection equation. The wage equation is our equation (1), whose coefficients could be estimated consistently provided we include the inverse Mills ratio $(\lambda(Z'_i\phi_m))$, calculated using the first stage probit coefficient estimates, as an additional regressor in the wage equation, in order to correct for any selectivity (endogeneity) in the sample of workers. In a more formal sense, the wage equation is

$$y_i^* = X_i'\Theta_k + \varepsilon_i \qquad (2)$$

where y_i^* is the log of hourly wage and is not observed for people who are not working (hence the *); X_i' encompasses the labour-market characteristics (e.g. gender, education, prior work experience, etc.) and an intercept; Θ_k is a vector of the coefficients to be estimated; and ε_i is the error term.

The selection equation is a probit model determining labour-force participation (i.e. the probability of being employed). It takes the form

$$h_i^* = Z_i'\phi_m + u_i \qquad (3)$$

where h_i^* is the number of working hours and is not observed for people who are not working (hence the *); ϕ_m is a vector of the coefficients to be estimated; and u_i is the error term. The vector Z_i' encompasses the variables in X_i' plus variables that determine the decision to participate, but not the wage directly. These are called exclusion restrictions and require that the number of explanatory variables included in the wage regression must be a strict subset of the number of explanatory variables included in the probit regression. That is, any variable that appears as an explanatory variable in the wage regression should also be an explanatory variable in the selection equation, and there must be at least one element in the selection equation that does not appear in the wage equation (Wooldridge, 2009, chap. 17). Commonly used exclusion-restriction variables in the literature include: an indicator of whether or not the spouse earns income and, if so, its size; the number of children aged up to a specific age; and an indicator of whether or not the mother has at least one daughter.

The Heckman two-stage model, despite being widely used, is not without criticism. Heckman (1979) himself considered this estimator to be useful for giving good starting values for maximum likelihood estimations and that "given its simplicity and flexibility, the procedure outlined … is recommended for exploratory empirical work" (p. 160). A first line of criticism is that estimated coefficients are sensitive to the distributional assumptions placed on the error term in the outcome equation and especially in the selection equation (Little and Rubin, 1987). However, the Monte-Carlo simulations summarized in Puhani (2000) and conducted to examine this assumption do not find a superior estimator. However, the correlation between the error terms of the outcome and selection equations has been found to reduce the efficiency of Heckman's model. A second – and probably the most important – line of criticism is related to the exclusion restrictions, i.e. the variables explaining the selection equation but not the outcome one (Beblo et al. 2003). In practice, the selection equa-

tion needs variables that are not included in the outcome equation, i.e. those that affect the decision to participate in the labour market but do not affect the wage. There is no guarantee that such variables do not affect the wage directly, nor that they are a good predictor of labour-market status. Leung and Yu (1996) investigated this issue in detail and found that the collinearity between the outcome-equation regressors and the inverse Mills ratio may be the main source of the Heckman estimator's high inefficiency. It could be caused either by the exclusion restrictions or by the large share of missing data, which may frequently be the case.

As the Heckman (1979) selection method requires [arbitrary] exclusion restrictions (which may lead to biased estimates), we use an alternative empirical approach: repeated imputations. This technique is based on median regressions (Rubin, 1987) and does not require assumptions on the actual level of missing wages, as usually required in the matching approach, nor does it require arbitrary exclusion restrictions and the lack of robustness (Manski, 1989) raised in Heckman (1979) models. Hence, wages for those who do not work are simulated/imputed based on observable labour-market characteristics. Afterwards, the gender pay gap, which constitutes our base sample, is compared to the sample based on the imputed wages, which is the sample where all individuals are assumed to be employed, i.e. all individuals have an observed wage.

One plausible characteristic of the median regressions is that, if missing wage observations fall completely on one side of the median regression line, the results are only affected by the position of wage observations with respect to the median, not by the precise values of imputed wages. Hence, we can make an assumption referring to the economic theory on whether an individual who is not in work should have a wage observation below or above the median wages for his/her gender; and we extend the framework of Kitamura et al. (2000) and Neal (2004) by using probability models (probit) to assign individuals to either side of the median of the wage distribution. The imputation rule assumes

$$F(m, I_i = 0, X_i) = \hat{P}_i \qquad (4)$$

where $F(m)$ is the cumulative distribution function of the low median wage; $I_i = 0$ refers to the case when person i is non-employed and hence has a non-observed wage; X_i is a vector of observable characteristics; and $\hat{P}_i$ is the predicted probability to be found below the median, based on probit estimates.

First, we estimate the probability that an individual has a wage above the median wage, based on observable characteristics: age, experience, education, gender and marital status. For the sample of observed wages, we define $M_i = 1$ for the individuals earning more than the median and $M_i = 0$ for the others. We estimate a probit model for M_i with the explanatory variables X_i. Using the probit estimates, we obtain predicted probabilities of having a latent wage above the median; $\hat{P}_i = \Phi(\hat{\gamma} X_i) = \Pr(M_i = 1 | X_i)$ is for the non-employed subset, where Φ is the cumulative distribution function of the standardized normal distribution and $\hat{\gamma}$ is the estimated parameter vector from the probit regression.

The predicted probabilities $\hat{P}_i$ are then used in the second step as sampling weights for the non-employed. In other words, we construct an imputed sample in which the employed are featured with their observed wage and the non-employed are featured with a wage above the median with a weight $\hat{P}_i$ and a wage below the median with a weight 1- $\hat{P}_i$. Then, the statistic of interest is the coefficient on the duration of unemployment.

Despite early suggestions (e.g. Schafer and Olsen, 1998; Schafer, 1999) that three to five imputations are sufficient to obtain good results, some more recent contributions (Graham et al. 2007) document that increasing the number of imputations increases the efficiency of the estimations. Therefore, we use variants of 5, 10 and 50 imputations. In the final step, we use the estimated gender pay gaps from each of the simulated data sets to obtain the part of the variance reflecting missing-data uncertainty. This method has the advantage of using all available information on the characteristics of the non-employed and of taking into account the uncertainty about the reason for missing wage information (Rubin, 1987; Olivetti and Petrongolo, 2008).

3.2 Decomposition of the gender pay gap

The early and standard decomposition technique, widely applied to the gender pay gap, is due to Blinder (1973) and Oaxaca (1973). Plasman and Sissoko (2004) claim that this wide use of the model is due

to the fact that it is based on the Mincerian earnings function and that it combines the two schools of thought that were introduced by Mincer and Polachek (1974) – according to whom the gender gap depends on the endowment effect – and Becker's (1971) idea that economic agents belonging to a specific group might have discriminatory preferences against members of another group. If hiring a person of a discriminated group implies an additional psychological cost for the employer, then the employer will offer a lower wage to that worker; therefore, the discriminated worker would accept the lower wage in order to be employed.

The method enables decomposition of the mean differences in log wages based on linear regression models in a counterfactual manner. The procedure divides the wage differential between males and females into two parts: one that is "explained" by group differences in productivity characteristics, such as education or work experience; and a residual part (the "unexplained" part) that cannot be accounted for by such differences in wage determinants. This "unexplained" part is often used as a measure for discrimination, but it also includes the effects of group differences in unobserved predictors (Jann, 2008). As we explained in Section 2.2, the unexplained component in the method should instead be named remuneration. Note that we are conducting the Blinder-Oaxaca decomposition on our basic and imputed data sets, so that in the latter case, the selection will be automatically considered and the decomposition will be selection-unbiased. The decomposition we are interested in could be written as

$$\bar{y}^M - \bar{y}^F = (\bar{X}^M - \bar{X}^F)'\hat{\theta}_k^M + \bar{X}^{F\prime}(\hat{\theta}_k^M - \hat{\theta}_k^F) \quad (5)$$

whereby $\bar{y}^M$ and $\bar{y}^F$ are the observed averages of log hourly wages of men and women, respectively; $\bar{X}^M$ and $\bar{X}^F$ are the averages of individual characteristics; and $\hat{\theta}_k^M$ and $\hat{\theta}_k^F$ are the regression coefficients for the model explaining hourly wages, estimated separately for men and women. The left side of equation (5) refers to the raw gaps; the first term on the right side refers to the explained part, while the last term, to the unexplained part.

Though a very popular and much used method in the literature, the Blinder-Oaxaca decomposition has been the subject of much scrutiny and criticism. Beblo et al. (2003) point out two problems. First, the endowment effect is based on one of the sexes (the male, in most applications); therefore, a problem of potential dissymmetry in the effects may arise. Though true, Oaxaca and Ransom (1994) apply a matrix of combinations of both male and female prices in decomposing the wages. However, Olsen and Walby (2004) claim that this two-term approach is incoherent and does not contribute to sensible findings in the analysis of the gender wage gap since it only partially solves the problem but still has deep difficulties with the unexplainable part of the gender wage gap. The second problem with the Blinder-Oaxaca method is that it considers only the wage decomposition at the mean, meaning that it does not catch potential variations of the different effects on the wage distribution. Conversely, the Juhn-Murphy-Pierce decomposition (Juhn et al. 1993) is far more reliable in this respect.

As a result, the decomposition literature has seen an evolution. Fortin et al. (2011) review the decomposition methods that have been developed since the seminal work of Blinder and Oaxaca. In that regard, we use two advancements of the gender pay gap decomposition.

First, the research moved to estimating gender pay gaps at different percentiles of the wage distribution. The quantile regression was developed as a semi-parametric method used to analyse wages, considering wage structure and distribution (Buchinsky, 1998). While the Blinder-Oaxaca decomposition investigates the mean effects, the quantile regression method allows for study of the marginal effects of covariates on the dependent variable at various points in the distribution, not only the mean. Important contributions include: Machado and Mata (2005); Firpo et al. (2007, 2009); and Chernozhukov et al. (2013).

Second, semi- and non-parametric methods, such as matching or weighting, have been proposed, against the inherently parametric character of the Blinder-Oaxaca decomposition. Due to the problems mentioned in the Blinder-Oaxaca decomposition, Barsky et al. (2002) provide an alternative non-parametric approach that reweights the empirical distribution of the outcome variable by using weights that would equalize the empirical distributions of the explanatory variable between genders. Frölich (2007) argues that such an approach differs from the parametric approach in two ways: firstly, the regression function is not specified as linear; and secondly, the adjusted mean wage is simulated only for the common sup-

port subpopulation.

The alternative to the weighting approach is the matching approach, which allows for matching comparisons through probability weights to find matched samples with similar observable features, except for the treatment that is used to group observations into two sets, the treated and the control group (Ñopo, 2008; Goraus and Tyrowicz, 2014). By controlling the differences in the observed characteristics, the treatment of the impact could be measured. Frölich (2007) claims that the method allows for estimating the average treatment effects when selection is on observables. Moreover, it allows using one-dimensional non-parametric regression to estimate the effects, even with many confounding variables. In this method, matching on one-dimensional probability is sufficient, instead of matching on all covariates. Ñopo (2008) considered the gender variable as a treatment and used matching to select subsamples of males and females by finding complete matches (no differences) between the observable characteristics of the matched males and females. In this way, a method was developed to measure four components of the overall wage differences: wages of men identical to women in the sample; wages of women identical to men in the sample; wages of men for whom there are no identical women in the sample; and wages of women for whom there are no identical men in the sample (Ñopo, 2008; Goraus and Tyrowicz, 2014). Goraus and Tyrowicz (2014) assert that the two components could be considered similar to the Blinder-Oaxaca decomposition, while the other two explicitly tackle the problem of overlapping and measure the quantitative effect of overlap on the overall wage differential.

Finally, we opt to decompose the gender pay gap (a) at percentiles, especially at the corner deciles/quintiles of the wage distribution, and (b) by utilizing weights that equalize the empirical distributions of the explanatory variable as in Barsky et al. (2002). The former, in particular, will help us in identifying sticky floors and/or glass ceilings.

4 DATA AND THE ASSOCIATED CAVEATS

We make use of the Labour Force Survey of Armenia for 2018. It comprises 18,553 individuals of working age (15–64), of which 8,388 persons were employed. However, only 6,631 reported a non-zero wage. The key question we use from the LFS is "How much wage/income did you receive during the last month worked?" However, if the respondent could not define the exact value, s/he was asked to respond in intervals: "If you do not want to say the exact amount of your wage/income during the last (previous) month, please specify the approximate amount according to the below-mentioned table (after deductions)." The intervals were as follows: AMD 55,000 or less; AMD 55,001–110,000; AMD 110,001–220,000; AMD 220,001–440,000; AMD 440,001–600,000; AMD 600,001–700,000 and AMD 700,001 or more. Thus, for the respondents who answered with an interval, we specified the weighted average amount of the interval obtained from the observed exact wages. These respondents constituted 20.8 per cent and none of the non-zero wage receivers. Within the non-zero wage receivers, 4.3 per cent refused to report their wage, while 6.4 per cent did not know the answer.

In general, surveys are prone to non-response. If those who did not respond to the survey (i.e. either declined or were not reached to respond) are systematically different than those who responded (one of the few potential reasons being that they earn high wages and would not like to speak about it), then the results may suffer non-response bias. In particular, household surveys are known to imprecisely capture the highest wages (especially compared to establishment-level surveys). Some of the reasons may be the difficulties with interviewing the richest households (non-response bias), as well as the tendency to attenuate the real figures more when they are quite high (response bias).

Underreporting of wages, however, is not a characteristic of the top earners only, but happens along the entire wage distribution and is known as a response bias. A quick look at survey versus administrative data on wages across many countries attests to this, thereby motivating a greater inclination to use establishment-level data (which could again be collected by a survey but filled out by the firm accounting, or which could be collected by pure administrative data, e.g. from the tax administration). However, Moore et al. (2000) conclude that "wage and salary income response bias estimates from a wide variety of studies are generally small" (p. 342). Similarly, Marquis et al. (1981) conclude that "the overall picture that emerges … is that self-reports of wage and salary data are relatively unbiased" (p. 29), who in addition find very little random measurement error.

In this study, we are bound to use survey data, mainly because establishment-level microdata are not available in a form usable for such analysis. This is our point of departure from, e.g., the Eurostat methodology for calculation of the gender pay gap, which relies on establishment-level data. Moreover, currently the establishment data in Armenia are obtained from the tax authorities at the level of the firm, which means that the company is only asked about the average wage earned by men and women in the firm. Also, average hours worked are currently not obtained, despite the fact that the tax authorities must have this variable. Therefore, the use of these data for gender wage analysis in Armenia is presently constrained. Ultimately, establishment-level data do not usually track the key observable characteristics (like education and age), which makes adjusting the gender pay gap impossible.

Therefore, in the usage of these data, we just need to bear in mind the measurement errors and the potential underreporting and non-response biases. However, the objective here is not and should not be the comparison of survey data with any administrative data. As Moore et al. (2000) point out, administrative and survey data are almost never completely comparable, due to sampling frame differences, timing differences, definitional differences and other dissimilarities.

5 GENDER PAY GAP IN ARMENIA

5.1 Data and stylized facts

The employment rate in Armenia is 44.8 per cent for individuals aged 15–64 (working age). **Table 1** looks at the employment rate by gender and shows that women experience a 11.1 percentage point (p.p.) employment gap. The employment rate is the lowest for the youth, with a gender employment gap less than half that of the overall population, while the rates for the other age cohorts are similar. The gender employment gap is the largest for the 35–44 and 55–64 age cohorts. The lower part of the table suggests that Armenia has a significant share of self-employed persons, despite the large gender gap in self-employment in favour of men. The picture is opposite for unpaid family workers, though the share is very low. With regard to wage employees – which constitute about two thirds of the employed – women are more likely than men to be in this category.

TABLE 1:
Employment characteristics of men and women

	Men (%)	Women (%)
All	50.8	39.3
Age group (employment rate)		
15–24	22.8	17.9
25–34	59.5	45.1
35–44	61.1	49.2
45–54	57.5	51.0
55–64	51.8	40.7
Professional status (structure)		
Employee	60.1	70.9
Employer	1.7	0.5
Self-employed	37.6	26.8
Contributing family worker	0.7	1.8
Other	0.0	0.1

Source: Author's own calculations based on LFS.

Similarly, **Table 2** observes the gender unemployment and inactivity gaps, overall and by age. The gender unemployment gap largely exists for the younger labour force (aged 15–34), while the gender inactivity gap stands at 6–37.4 p.p., hence sizable. It is apparent at any age.

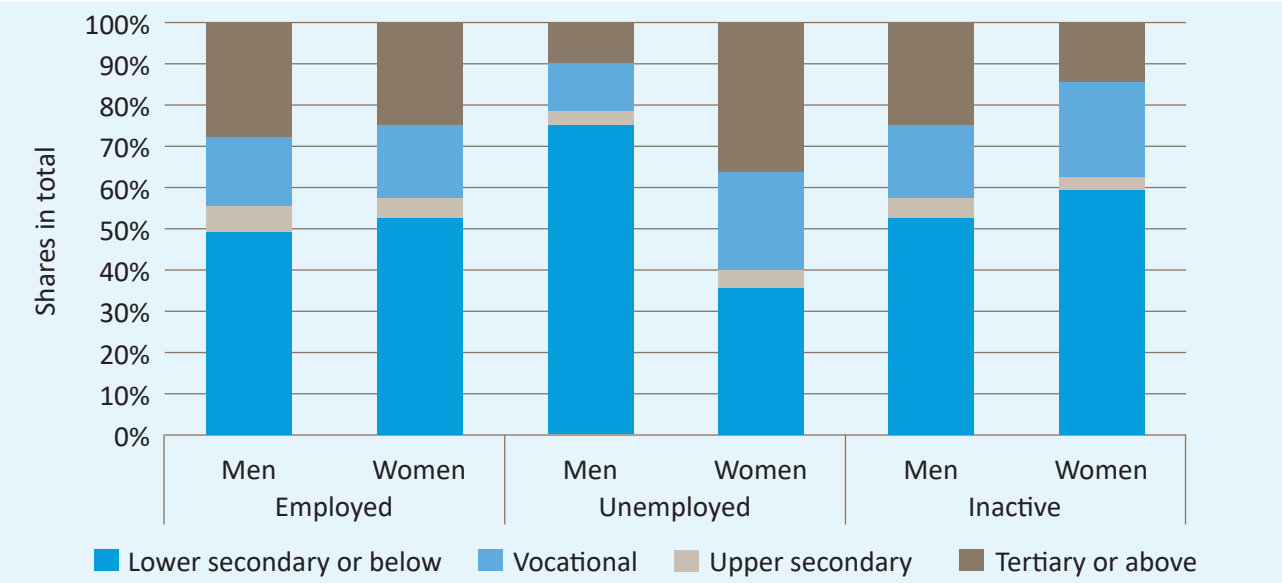
TABLE 2:
Non-employment characteristics of men and women

Age group	Men (%)	Women (%)
Unemployment rate		
ALL	20.2	21.7
15–24	33.9	41.1
25–34	19.8	27.3
35–44	19.9	21.0
45–54	17.0	15.4
55–64	17.0	13.9
Inactivity (non-participation) rate		
ALL	24.3	48.0
15–24	58.2	67.2
25–34	10.9	48.3
35–44	10.5	35.6
45–54	14.8	37.6
55–64	28.3	51.7

Source: Author's own calculations based on LFS.

Figure 1 presents the educational structure of the labour force by gender. It suggests that employed women have similar characteristics to employed men. Unemployed women have considerably better characteristics than unemployed men and employed women in Armenia. On the other hand, inactive women are performing slightly worse than inactive men and working women.

FIGURE 1:
Educational structure of the labour force, by gender



Source: Author's own calculations based on LFS.

Table 3 presents the sectoral and occupational structure of employment in Armenia. Women are slightly more present in agriculture, which corroborates their larger share as unpaid family workers. Mining and especially construction, on the one hand, are more "masculine" sectors, as well as public administration (though it is potentially driven by the defence sector). On the other hand, education and health and social care are dominated by women, as is usually the case in other countries. These patterns may reveal important aspects of the sectoral segregation of women. Women are less frequently found in managerial positions, which may be an early sign of the glass ceiling effect, despite the fact that women dominate the next three skill levels (i.e. professionals, technicians and associate professionals, and clerical support workers). Then, as the skill level approaches the lower end (heading towards elementary occupations), men start to predominate. Overall, women are more likely to be found in high-skill occupations than men.

TABLE 3:
Sectoral (NACE) and occupational (ISCO) structure of employment, by gender

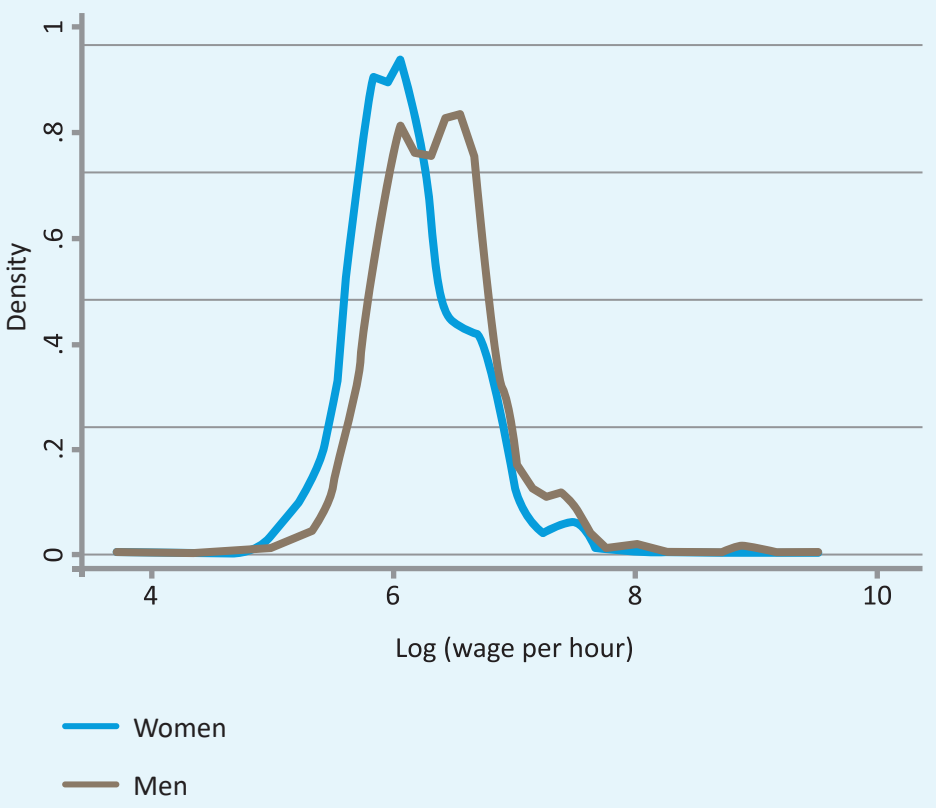
	Men (%)	Women (%)
Sector		
Agriculture, forestry and fishery	20.3	24.6
Mining and quarrying	1.6	0.2
Manufacturing	10.3	9.6
Electricity, gas, steam and air conditioning supply	3.0	0.8
Water supply; sewerage, waste management and remediation activities	0.4	0.3
Construction	16.2	0.3
Wholesale and retail trade; repair of motor vehicles and motorcycles	12.2	11.7
Transportation and storage	6.7	1.5
Accommodation and food service activities	2.4	3.2
Information and communication	2.5	1.7
Financial and insurance activities	1.2	2.0
Real estate activities	0.2	0.3
Professional, scientific and technical activities	1.1	2.0
Administrative and support service activities	0.5	0.5
Public administration and defence; compulsory social security	11.2	5.7
Education	3.7	19.4
Human health and social work activities	1.3	9.7
Arts, entertainment and recreation	1.6	2.0
Other service activities	3.0	3.4
Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	0.2	0.8
Activities of extraterritorial organizations and bodies	0.4	0.3
Occupation		
Managers	4.2	1.9
Professionals	10.7	24.2
Technicians and associate professionals	5.9	12.7
Clerical support workers	1.9	5.9

Services and sales workers	15.9	15.5
Skilled agricultural, forestry and fishery workers	19.3	24.1
Craft and related trades workers	20.0	6.3
Plant and machine operators and assemblers	11.4	0.5
Elementary occupations	10.7	8.7

Source: Author's own calculations based on LFS. Weights used accordingly.

For the purpose of the wage analysis that follows, we drop all employed persons who have reported positive working hours but for whom a wage is not observed, including employers, own account workers and unpaid family members.[2] **Figure 2** shows the distribution of the log hourly wages of men and women. The blue line, representing women, appears to the left of the brown line, representing men, suggesting that women are more likely to appear at lower wage levels. The peak of the female wage distribution, likewise, appears to the left of the peak of the male wage distribution.

FIGURE 2:
Distribution of log hourly wages, by gender



Source: Author's own calculations based on LFS. Weights used accordingly.

[2]Had these respondents been used in the analysis, we would have addressed the gender earnings gap.

There is a gender pay gap of 23.1 per cent in Armenia (**Table 4**). This is the unadjusted or raw wage gap (see Section 2.1). It is crucial here to highlight that hourly wages enter the calculation of the gender pay gap because women usually work shorter hours than men. If not properly accounted for, the resulting gender pay gap would reflect the difference in wages between genders and the differences in mean hours worked. As this is an important aspect for Armenia, we revisit this issue in the grey box at the end of this section. The gap exists at all levels of education, though it is quite persistent and wide at the vocational level and slightly lower at the tertiary level.

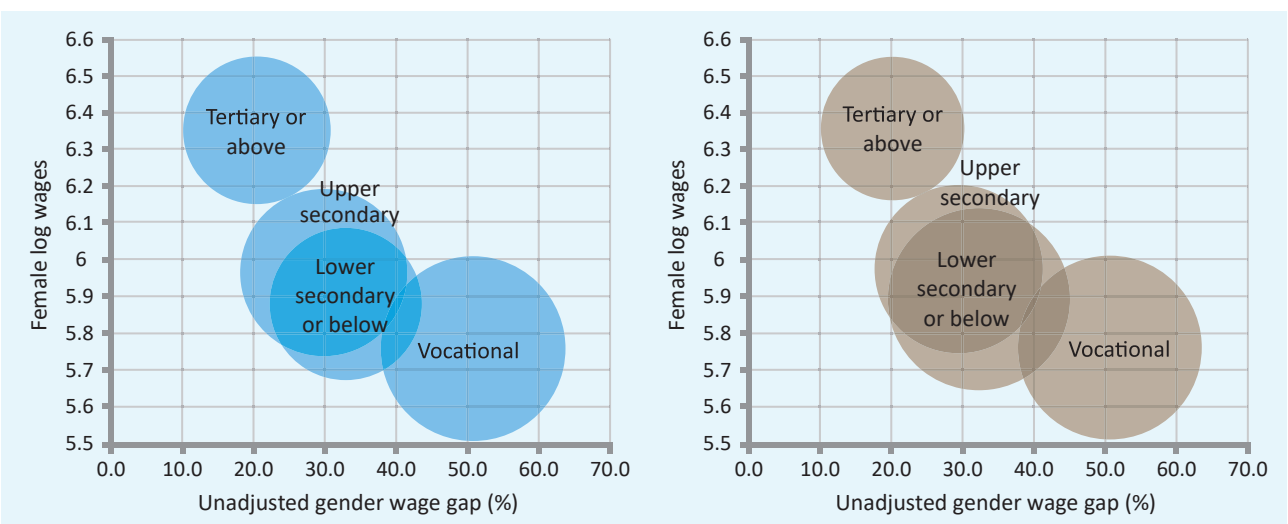
TABLE 4:
Raw gender pay gap (hourly), by education

	Males	Females	Gender pay gap
	Log wage per hour		%
All	6.359	6.128	-23.1
Lower secondary or below	6.216	5.887	-32.9
Vocational	6.268	5.757	-51.1
Upper secondary	6.272	5.970	-30.2
Tertiary or above	6.564	6.358	-20.6

Source: Author's own calculations based on LFS. Weights used accordingly.
Note: The gap is a simple difference between the logged mean wages per hour for each gender. Where negative, males are exhibiting higher wages than females, at the mean, and vice versa.

Figure 3 contrasts the gender pay gap with the gender employment and participation gaps. It implies a positive correlation between the gender pay gap on the one hand and the gender employment and participation gaps on the other (with correlation coefficients ranging between 0.93 and 0.88). Namely, in general, the circles get larger as we move to the right along the x-axis. Such positive correlation between the gaps may reveal sample selection effects in observed wage distributions.

FIGURE 3:
Gender pay gap against (a) gender employment gap (left) and (b) gender participation gap (right), at different levels of education



Source: Author's own calculations based on LFS.
Note: The size of the circles represents the size of the respective gaps.

The raw gender pay gap amplifies for manufacturing, while hovering around the average for the rest of the sectors (**Table 5**). In agriculture, the gap is 15.7 per cent, although it is potentially influenced by the prevalence of women as unpaid family workers.

TABLE 5:
Raw gender pay gap (hourly), by sector

	Males	Females	Gender pay gap
	Log wage per hour		%
All	6.359	6.128	-23.1
Agriculture	6.147	5.990	-15.7
Manufacturing	6.387	6.086	-30.1
Construction	6.379	6.158	-22.1
Market services[3]	6.290	6.043	-24.7
Non-market services[4]	6.420	6.195	-22.5

Source: Author's own calculations based on LFS. Weights used accordingly.
Note: The gap is a simple difference between the logged mean wages per hour for each gender. Where negative, males are exhibiting higher wages than females, at the mean, and vice versa.

Likewise, **Table 6** presents the raw pay gaps by occupation. The gaps exist within all occupations. It is higher than the average for occupations like technicians, service and sales workers and craftsmen, while lower in skilled agricultural workers. For the rest of the occupations, it is around the average, and a pattern between skill level and gender pay gap cannot be derived.

TABLE 6:
Raw gender pay gap (hourly), by occupation

	Males	Females	Gender pay gap
	Log wage per hour		%
All	6.359	6.128	-23.1
Managers	6.723	6.482	-24.1
Professionals	6.705	6.425	-28.0
Technicians and associate professionals	6.433	6.086	-34.7
Clerical support workers	6.328	6.045	-28.3
Services and sales workers	6.267	5.898	-36.9
Skilled agricultural, forestry and fishery workers	6.155	6.043	-11.2
Craft and related trades workers	6.280	5.959	-32.1
Plant and machine operators and assemblers	6.271	5.996	-27.5
Elementary occupations	6.075	5.846	-22.9

Source: Author's own calculations based on LFS. Weights used accordingly.
Note: The gap is a simple difference between the logged mean wages per hour for each gender. Where negative, males are exhibiting higher wages than females, at the mean, and vice versa.

[3]For the sake of compactness of the exposition, the following sectors are grouped in market services: wholesale and retail trade; hotels and restaurants; transport and communication; financial intermediation; ICT; real estate, renting and business activity; professional, scientific and technical activities; private households employing domestic services; and extraterritorial organizations and bodies.

[4]For the sake of compactness of the exposition, the following sectors are grouped in non-market services: public administration; education; health and social work; and the arts, entertainment and recreation.

The important difference between expressing wages per hour or per month, for the gender pay gap

If we use the monthly instead of the hourly wages (**Table 7**), we get amplification of the pay gap (40 per cent). However, such a calculated gender pay gap incorporates the different pay between men and women, as well as the large differences between them regarding mean hours (14.3 per cent), as is evident in the table:

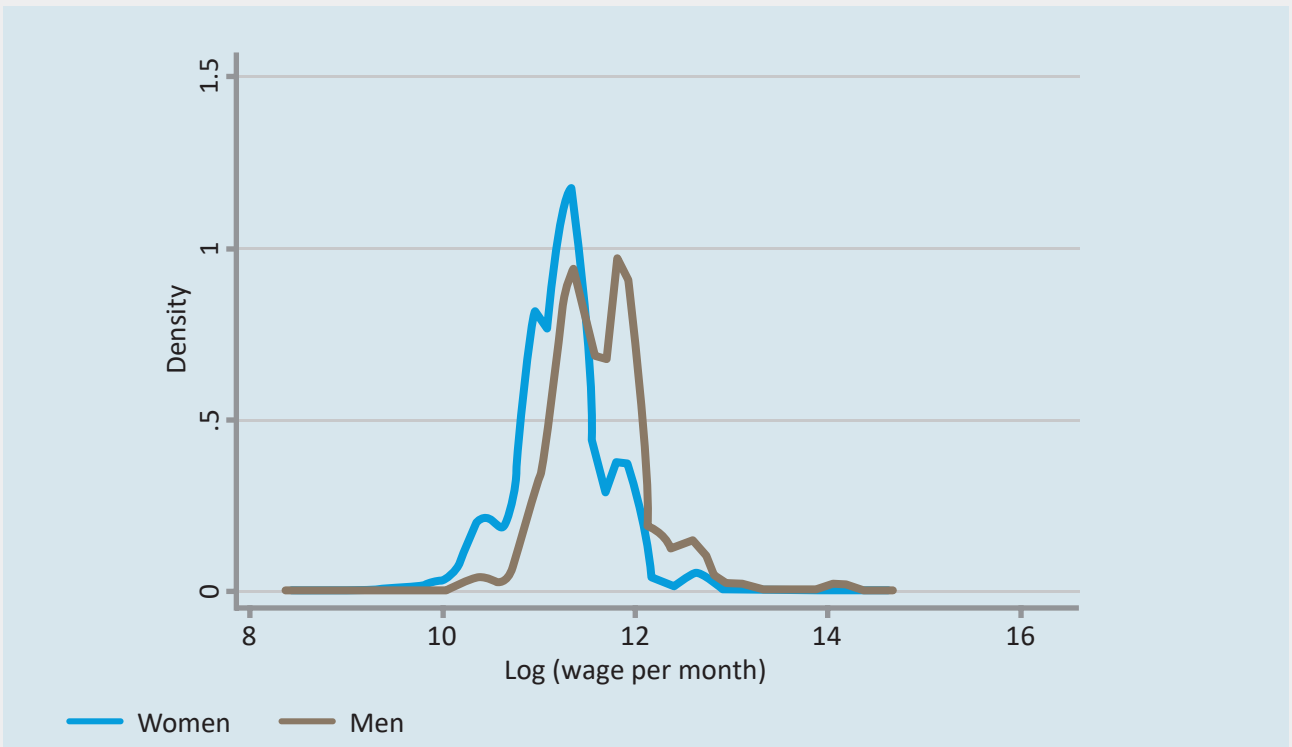
TABLE 7:
Gender pay gap calculated at the monthly level

	Males	Females	Gender gap
Log wages per month	11.62	11.22	-40.0
Hours worked per month	45.20	39.10	-14.3

Source: Author's own calculations based on LFS. Weights used accordingly.
Note: The gap is a simple difference between the logged mean wages per month for each gender.

Still, we present the above statistics based on the monthly wages, to be able to observe the differences. **Figure 4** presents the kernel distribution of monthly wages (the counterpart of **Figure 2**) and suggests that female wages feature to the left of the male wages and potentially with larger gaps than when hourly wages are considered.

FIGURE 4:
Distribution of log monthly wages, by gender



Source: Author's own calculations based on LFS. Weights used accordingly.

The gender pay gap by education (**Table 8**) reveals a picture similar to **Table 4**, with the exception that the gaps amplify.

TABLE 8:
Raw gender Pay Gap (monthly wages), by education

	Males	Females	Gender pay gap
	Log wage per month		%
All	11.62	11.22	-40.0
Lower secondary or below	11.52	11.10	-43.0
Vocational	11.56	10.93	-63.0
Upper secondary	11.55	11.11	-44.0
Tertiary or above	11.80	11.37	-40.0

Source: Author's own calculations based on LFS. Weights used accordingly.
Note: The gap is a simple difference between the logged mean wages per month for each gender.

Likewise, **Table 9** presents the gender pay gaps by sector, with the monthly wages. It reveals expectedly bigger gaps compared to **Table 5**, but the patterns slightly change. Namely, the monthly gender pay gap increases significantly in construction and non-market services, suggesting that the gender hours gap is potentially larger there than in the other sectors.

Table 10 presents the results for the occupations and suggests similar patterns as in **Table 6**, except that the gaps amplify.

TABLE 9:
Raw gender Pay Gap (monthly wages), by sector

	Males	Females	Gender pay gap
	Log wage per month		%
All	11.62	11.22	-40.0
Agriculture	11.48	11.25	-23.0
Manufacturing	11.65	11.31	-34.0
Construction	11.75	11.30	-45.0
Market services	11.60	11.27	-33.0
Non-market services	11.62	11.17	-45.0

Source: Author's own calculations based on LFS. Weights used accordingly.
Note: The gap is a simple difference between the logged mean wages per month for each gender.

TABLE 10:
Raw gender Pay Gap (monthly wages), by occupation

	Males	Females	Gender pay gap
	Log wage per month		%
All	11.62	11.22	-40.0
Managers	11.92	11.67	-25.0
Professionals	11.84	11.36	-48.0
Technicians and associate professionals	11.65	11.18	-47.0
Clerical support workers	11.60	11.20	-40.0
Services and sales workers	11.59	11.15	-44.0
Skilled agricultural, forestry and fishery workers	11.50	11.33	-17.0
Craft and related trades workers	11.55	11.17	-38.0
Plant and machine operators and assemblers	11.60	11.27	-33.0
Elementary occupations	11.38	10.99	-39.0

Source: Author's own calculations based on LFS. Weights used accordingly.
Note: The gap is a simple difference between the logged mean wages per month for each gender.

In conclusion, the consideration of hours in the calculation of the gender pay gap makes an important difference because women work fewer hours, on average, than men. This needs to be borne in mind when pursuing calculations of the gender pay gap.

5.2 Adjusted gender pay gap

We estimate the adjusted gender pay gap in **Table 11**. For comparison, we first provide a regression estimate of the raw pay gap in column (1), which is the same provided in **Table 4**. We add age and its square and education as personal characteristics to explain the gender pay gap (column 2). Work experience is not available in our survey. We consider occupations (reference category: elementary occupations) and sectors (reference category: manufacturing), as well as an indicator of whether or not the person has a permanent or temporary contract, all to reflect labour-market characteristics (columns 3–6). We use marital status as an exclusion restriction in the Heckman-selection equation (columns 7–10).

The adjusted gender pay gap in Armenia is 28.4 per

cent. The adjusted gap is higher than the unadjusted one (23.1 per cent), suggesting that employed women have slightly better labour-market characteristics, though lower pay, than employed men in Armenia, and that some sectoral and/or occupational segregation takes place.

We analyse the rest of the coefficients group by group. Column (2) adds only personal characteristics and suggests that wage grows with age, though concavely. Education offers significant returns, though only with regard to tertiary education, while differences among the other three levels are small or insignificant. Column (3) adds only the sectors and finds that their addition insignificantly increases the adjusted gap. When both personal characteristics and sectors are put together (column 4), the gap inflates but not as much as when education only is added. This potentially suggests an interplay between the observed characteristics (notably education) and sectors, i.e. sectoral segregation of women by education. For example, individuals in agriculture are found to receive a lower wage than those in industry (the reference category, column 3), but the magnitude is then reduced. This is a potential sign that less-educated women are more likely to be found in agriculture. Likewise, the reduction of the coefficient on non-market services may suggest that higher-educated women are more likely to be found in such sectors. Hence, women segregate into particular sectors (most notably agriculture, education, health and social care) based on their education, or vice versa, they choose fields of education that align with traditionally feminine sectors.

Column (5) suggests that almost all occupations have higher wages than elementary occupations and that wages reduce as the skill level declines. Occupations themselves also inflate the gender pay gap. The magnitudes of their coefficients are somehow reduced when occupations are added to personal characteristics and sectors (column 6), while the gender pay gap is generally maintained. Similarly, this suggests some interplay between occupation and education. Also, returns to education more than halve, suggesting that the increase of the adjusted gender pay gap is explained by both education and occupational segregation. Women segregate into particular occupations (most notably as sales, professional and clerical workers) based on their education, or vice versa, they choose fields of education that are linked to feminine occupations.

Overall, it is likely that education has the strongest effect on inflating the adjusted pay gap, i.e. working women in Armenia do have a higher level of education than working men. However, there are also signs of the sectoral and occupational segregation of women correlated with their level and/or field of education.

All findings are largely replicated when potential selectivity is corrected through the Heckman procedure (columns 7–10), whereby the gender wage gap reduces to its pre-adjustment level, i.e. between 22.9 and 23.6 per cent. This suggests that selectivity has some power in explaining part of the gender pay gap in Armenia. The outcome equation suggests that women are less likely to be employed; employment probability grows with age, though concavely; and education is rewarding for employment chances. Towards the bottom of the table, the inverse Mills ratio is provided. It is negative and significant, which suggests that the error terms in the selection and outcome equations are negatively correlated with the coefficient on lambda, which means the [unobserved] factors that make participation more likely tend to be associated with lower reservation wages. In plain words, negative selection suggests that women with worse labour-market characteristics (compared to women who are outside of it) are participating in the labour market in Armenia.

Overall, we find evidence in **Table 11** that the gender pay gap increases after adjusting for the personal and labour-market characteristics of workers, suggesting that working women have better characteristics than working men. Then, the gap declines again to the pre-adjustment level after correcting for selectivity, suggesting that working women have worse characteristics than non-working women.

TABLE 11:
The adjusted gender pay gap

	Unadjusted GPG	Adjusted GPG					Heckman-corrected estimates			
		Personal char. only	Sector only	Personal + sector	Occupation only	All	Outcome equation (personal char. only)	Selection equation (probability of empl.)	Outcome equation (all char.)	Selection equation (probability of empl.)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Gender (Female=1)	-0.231***	-0.277***	-0.246***	-0.267***	-0.306***	-0.284***	-0.229***	-0.473***	-0.239***	-0.471***
	(0.018)	(0.017)	(0.018)	(0.017)	(0.017)	(0.018)	(0.021)	(0.029)	(0.022)	(0.029)
Age (in years)		0.0158***		0.0134***		0.0137***	-0.00271	0.175***	-0.00369	0.176***
		(0.005)		(0.005)		(0.004)	(0.006)	(0.007)	(0.007)	(0.007)
Age squared		-0.0002***		-0.0002***		-0.0002***	3.62E-05	-0.002***	4.02E-05	-0.002***
		(0.000)		(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lower secondary and lower education level		-0.407***		-0.409***		-0.150***	-0.307***	-0.882***	-0.0552	-0.881***
		(0.019)		(0.020)		(0.025)	(0.031)	(0.035)	(0.034)	(0.035)
Vocational education level		-0.405***		-0.415***		-0.163***	-0.339***	-0.610***	-0.100**	-0.610***
		(0.042)		(0.041)		(0.042)	(0.046)	(0.074)	(0.046)	(0.074)
Upper secondary education level		-0.350***		-0.353***		-0.153***	-0.292***	-0.530***	-0.0985***	-0.528***
		(0.021)		(0.021)		(0.025)	(0.024)	(0.041)	(0.027)	(0.041)
Agriculture			-0.188***	-0.149***		-0.140***			-0.141***	
			(0.042)	(0.040)		(0.047)			(0.047)	
Construction			0.0129	0.0227		0.0327			0.0321	
			(0.045)	(0.042)		(0.042)			(0.042)	
Market services			-0.078***	-0.127***		-0.147***			-0.148***	
			(0.025)	(0.024)		(0.024)			(0.024)	
Non-market services			0.0662***	-0.0564***		-0.148***			-0.148***	
			(0.022)	(0.022)		(0.024)			(0.024)	
Managers					0.632***	0.539***			0.540***	
					(0.068)	(0.069)			(0.069)	
Professionals					0.609***	0.506***			0.507***	
					(0.025)	(0.034)			(0.034)	
Technicians and associate professionals					0.292***	0.287***			0.289***	
					(0.025)	(0.029)			(0.029)	
Clerical support workers					0.231***	0.196***			0.196***	
					(0.034)	(0.035)			(0.035)	
Services and sales workers					0.126***	0.150***				
					(0.022)	(0.023)				
Skilled agricultural, forestry and fishery workers					0.110**	0.152***				
					(0.055)	(0.059)				
Craft and related trades workers					0.162***	0.0898***				
					(0.026)	(0.028)				
Plant and machine operators and assemblers					0.160***	0.134***				
					(0.033)	(0.031)				
Permanent job contract						-0.0227				
						(0.027)				
The person is married								-0.223***		-0.228***
								(0.034)		(0.033)
Constant	6.359***	6.281***	6.337***	6.383***	6.113***	6.092***	6.735***	-2.810***	6.515***	-2.819***
	(0.013)	(0.089)	(0.020)	(0.091)	(0.018)	(0.094)	(0.143)	(0.132)	(0.151)	(0.132)
Observations	4,951	4,951	4,951	4,951	4,951	4,951	13,862	13,862	13,862	13,862
R-squared	0.051	0.191	0.066	0.201	0.231	0.255				
Inverse Mills ratio (lambda)							-0.177***		-0.166***	
							(0.0430)		(0.0428)	

Source: Author's own calculations based on LFS.
*Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. Standard errors given in parentheses. Results robust to heteroskedasticity. Weights used accordingly.*

We turn to discussing the results based on repeated imputations, presented in **Table 12**. For convenience, the first column reproduces the OLS estimates of the adjusted gender pay gap. Column (2) reports the estimates with 5 imputations, column (3) with 10, and column (4) with 50. Note that imputations include workers' characteristics and exclude job-related characteristics, as there was no sufficient information for the latter to be imputed.

Before looking at the coefficients of interest, note that below each estimated coefficient there are two pieces of information (besides the usual standard error) given in italics: the first number represents the relative efficiency of the multiple-imputation inference, while the percentage below that number relates to the share of between-imputation variance – i.e. the one due to missing observations – in the total variance. The relative efficiency of the multiple imputation inference is determined by the amount of missing information and the number of imputations. Our results, in general, land some evidence in line with Graham et al. (2007) that increasing the number of imputations increases the relative efficiency, since the numbers increase and approximate unity as we move from 5 to 50 imputations. The between-imputation variation is fairly large for the majority of variables, which is expected given that more than a large part of our sample were individuals who were unemployed or inactive, hence without a wage observation. This prevents the uncertainty due to the missing information in our sample being small.

TABLE 12:
Results after imputation

Variables	No imputations	5 imputations	10 imputations	50 imputations
	Dependent variable: Log of the net hourly wage			
	(1)	(2)	(3)	(4)
Gender (Female=1)	-0.277***	-0.1000***	-0.101***	-0.1000***
	(0.017)	(0.013)	(0.011)	(0.013)
		0.927	0.984	0.992
		29.9%	14.4%	38.4%
Age (in years)	0.0158***	0.004	0.004	0.004
	(0.005)	(0.003)	(0.003)	(0.003)
		0.896	0.970	0.991
		44.2%	27.4%	46.4%
Age squared	-0.000178***	-0.0000493	-0.0000453	-0.0000426
	(0.000)	(0.000)	(0.000)	(0.000)
		0.900	0.972	0.991
		41.4%	25.5%	43.8%
Lower secondary and below	-0.407***	-0.354***	-0.350***	-0.346***
	(0.019)	(0.015)	(0.014)	(0.017)
		0.940	0.985	0.991
		24.3%	13.5%	42.1%
Vocational	-0.405***	-0.360***	-0.351***	-0.347***
	(0.042)	(0.047)	(0.034)	(0.035)
		0.878	0.967	0.993
		53.4%	29.7%	36.1%
Upper secondary	-0.350***	-0.337***	-0.338***	-0.334***
	(0.021)	(0.020)	(0.019)	(0.019)
		0.916	0.960	0.993
		34.7%	36.4%	36.7%
Constant	6.281***	6.426***	6.434***	6.430***
	(0.089)	(0.065)	(0.051)	(0.055)
		0.883	0.961	0.991
		50.3%	35.4%	46.0%
Observations	4,951	13,862	13,862	13,862
R-square	0.051			
Imputations		8,911	8,911	8,911

Source: Author's own calculations.
*Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. Estimates robust to heteroskedasticity. Weights used accordingly.*

Turning to the results of our interest – the gender pay gap – the repeated imputations give a gap that is more than twice smaller than the adjusted-for-workers'-characteristics gap and comparatively smaller than the unadjusted gap. This is the first evidence that the majority of the inflated adjusted-for-characteristics gender pay gap in Armenia is in fact due to the non-random selection of women into employment, not due to gender discrimination. More precisely, the lower pay gaps on imputed rather than actual wage distributions suggest, as expected, that women in Armenia who are outside the labour market do not possess the worst characteristics (recall **Figure 1**, that unemployed women are actually quite better educated than employed women, while inactive ones perform similarly). Our findings in **Table 12**, column (4) suggest that once workers' characteristics and selectivity bias into employment have been taken into consideration, the unexplained gender wage gap reduces to about 10 per cent, which could be labelled as gender pay discrimination against women in Armenia.

5.3 Gender pay gap decomposed

We present the gender pay gap decompositions. We first present the Blinder-Oaxaca decomposition (**Table 13**). However, it decomposes the gap at its mean; from that viewpoint, it is less informative. Then, we pursue decomposition at deciles (**Table 14** and **Figure 5**).

The Blinder-Oaxaca method decomposes the gender pay gap on the explained part (due to differences in workers' personal and job characteristics) and the unexplained part (differences in returns to the same personal characteristics and due to unobservable differences in personal characteristics). **Table 13** concludes what we have concluded in **Table 11**: personal and labour-market characteristics amplify the gap in Armenia, suggesting that employed women likely have better labour-market characteristics than employed men, and therefore, the entire adjusted gap remains unexplained, either due to unobservable characteristics, selection bias or simply discrimination against women. For comparison, **Table 13** provides the decomposition of the monthly gender pay gap (column 2), whereby the work of observable factors is likely blurred by the gender hours gap.

TABLE 13:
Blinder-Oaxaca decomposition of the gender pay gap

	Average log hourly wages	Average log monthly wages
	(1)	(2)
Men	6.359***	11.62***
	(0.013)	(0.012)
Women	6.128***	11.22***
	(0.012)	(0.012)
Difference (Raw wage gap)	0.231***	0.401***
	(0.017)	(0.017)
Explained part by characteristics	-0.0767***	-0.0111
	(0.015)	(0.020)
Unexplained part (Adjusted wage gap)	0.276***	0.396***
	(0.020)	(0.020)
Interaction of the two parts	0.0313*	0.0155
	(0.017)	(0.022)

Source: Author's own calculations.
*Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. Standard errors given in parentheses. Results robust to heteroskedasticity.*

The gap may differ at various points of the wage distribution, which may reveal more important information (like sticky floors or glass ceiling) or may potentially be associated with vertical and horizontal segregation in sectors or occupations. **Table 14** presents the adjusted pay gap through deciles (and the top centile) with two methods: OLS and repeated information. Thus, the latter also takes into account selection. The adjusted-for-char-

acteristics gap (top panel) follows an upward pattern, suggesting that women face comparatively tougher pay conditions than men as they climb the income ladder. Namely, the gap almost doubles between the bottom decile (21.3 per cent) and the top decile (35.9 per cent). The gap for the top 1 per cent of wage earners – 41.8 per cent – is a clear sign of a glass ceiling at the very top. The adjusted-for-characteristics-and-selection gap (bottom panel) follows a flat pattern across all deciles, as it hovers around 10 per cent on average. Then, the glass ceiling is corroborated, i.e. a gender pay gap of 18.8 per cent for the top 1 per cent of paid jobs (almost double the average). This strongly suggests that selection plays an important role at the top of the career ladder since, when accounted for, it reveals a glass ceiling for the top managerial and leadership positions that are associated with the top wages.

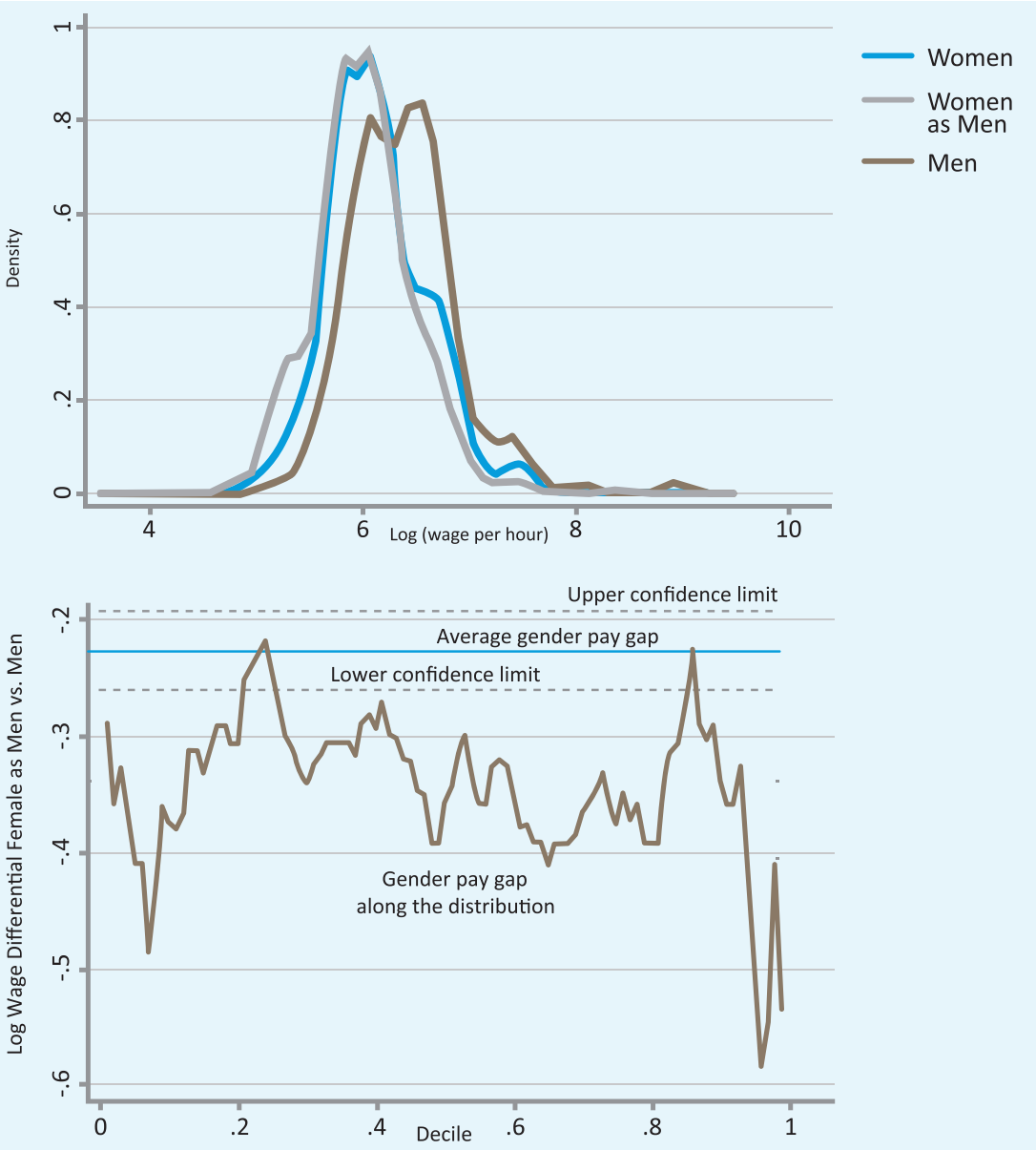
TABLE 14:
Quantile regression decomposition, by decile

Adjusted gender wage gap by OLS										
	10	20	30	40	50	60	70	80	90	99
Gender wage gap	-0.213***	-0.215***	-0.211***	-0.296***	-0.293***	-0.324***	-0.291***	-0.324***	-0.359***	-0.418**
	(0.016)	(0.014)	(0.012)	(0.018)	(0.016)	(0.020)	(0.019)	(0.015)	(0.027)	(0.170)
Age	0.00456	0.00358	0	0.00685	0.0072	0.00858	0.0142***	0.0122**	0.0278***	0.0585
	(0.005)	(0.004)	(0.003)	(0.005)	(0.004)	(0.006)	(0.004)	(0.005)	(0.006)	(0.044)
Age squared	-4.70E-05	-3.71E-05	0.00E+00	-8.15E-05	-9.23e-05*	-9.85E-05	-0.000166***	-0.000128**	-0.000292***	-0.00073
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Lower secondary ed.	-0.259***	-0.280***	-0.377***	-0.342***	-0.388***	-0.426***	-0.423***	-0.492***	-0.558***	-0.867***
	(0.023)	(0.021)	(0.018)	(0.019)	(0.020)	(0.023)	(0.028)	(0.018)	(0.037)	(0.191)
Vocational ed.	-0.317***	-0.341***	-0.393***	-0.418***	-0.411***	-0.430***	-0.437***	-0.485***	-0.464***	-0.770***
	(0.034)	(0.045)	(0.021)	(0.036)	(0.055)	(0.048)	(0.050)	(0.069)	(0.171)	(0.281)
Upper secondary ed.	-0.191***	-0.202***	-0.336***	-0.307***	-0.316***	-0.371***	-0.401***	-0.497***	-0.541***	-0.503
	(0.023)	(0.015)	(0.022)	(0.022)	(0.021)	(0.027)	(0.025)	(0.019)	(0.041)	(0.364)
Constant	5.857***	6.066***	6.330***	6.315***	6.429***	6.551***	6.552***	6.774***	6.669***	7.141***
	(0.097)	(0.087)	(0.060)	(0.098)	(0.086)	(0.116)	(0.083)	(0.109)	(0.127)	(0.796)
Observations	4,951	4,951	4,951	4,951	4,951	4,951	4,951	4,951	4,951	4,951
Adjusted gender wage gap by repeated imputations										
Gender wage gap	-0.0900***	-0.0970***	-0.113***	-0.109***	-0.114***	-0.103***	-0.101***	-0.103***	-0.0862***	-0.188***
	(0.022)	(0.018)	(0.015)	(0.017)	(0.015)	(0.016)	(0.016)	(0.015)	(0.021)	(0.067)
Age	0.00468	0.00462	0.00305	0.00299	0.00248	0.00141	0.0022	0.0018	0.0012	0.0118
	(0.005)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.012)
Age squared	-5.26E-05	-5.15E-05	-3.88E-05	-4.25E-05	-3.59E-05	-2.11E-05	-2.54E-05	-2.03E-05	-1.35E-05	-1.36E-04
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lower secondary ed.	-0.311***	-0.312***	-0.326***	-0.322***	-0.345***	-0.352***	-0.344***	-0.313***	-0.360***	-0.593***
	(0.028)	(0.025)	(0.017)	(0.023)	(0.021)	(0.023)	(0.018)	(0.018)	(0.031)	(0.106)
Vocational ed.	-0.312***	-0.323***	-0.345***	-0.351***	-0.356***	-0.351***	-0.375***	-0.319***	-0.329***	-0.481***
	(0.060)	(0.049)	(0.041)	(0.047)	(0.051)	(0.044)	(0.038)	(0.057)	(0.066)	(0.148)
Upper secondary ed.	-0.277***	-0.283***	-0.307***	-0.304***	-0.340***	-0.355***	-0.355***	-0.321***	-0.365***	-0.548***
	(0.031)	(0.026)	(0.017)	(0.023)	(0.025)	(0.025)	(0.022)	(0.021)	(0.036)	(0.122)
Constant	5.784***	5.991***	6.189***	6.305***	6.455***	6.587***	6.691***	6.819***	7.066***	7.688***
	(0.096)	(0.081)	(0.064)	(0.069)	(0.069)	(0.069)	(0.063)	(0.067)	(0.089)	(0.239)
Observations	13,862	13,862	13,862	13,862	13,862	13,862	13,862	13,862	13,862	13,862

Source: Author's own calculations.
*Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.*
Standard errors given in parentheses. Results robust to heteroskedasticity.

Similar information may be obtained when the reweighting approach is applied. The upper panel of **Figure 5** presents the distribution of the log hourly wage of men (brown line) and of women (blue line): female wages feature to the left of the male wage, which is more pronounced in the left half of the wage distribution. The panels feature a third line – a light-brown one – that is drawn by assigning men's characteristics to women – a reweighting – and then is used for the calculation of the gender pay gap. The light-brown line is not much different than the blue line (and is even insignificantly to the left of the female line), suggesting that women's wages would not significantly change if these women were to obtain men's observable characteristics (like education, age and the like). Then, these women-as-men are compared to men, and the gap is presented in the lower panel. Obviously, by utilizing this method, we estimate that the gender pay gap retains a constant trend through the wage distribution, while deepening only in the far right side, implying a glass ceiling. This analysis shows that the gap is not predominantly a result of different (observable) characteristics, but of different returns to the same characteristics (discrimination) and/or different unobservable characteristics of men and women and/or observed selection patterns.

FIGURE 5:
Decomposition of the gender pay gap by reweighting



Source: Author's own calculations. Weights used accordingly.

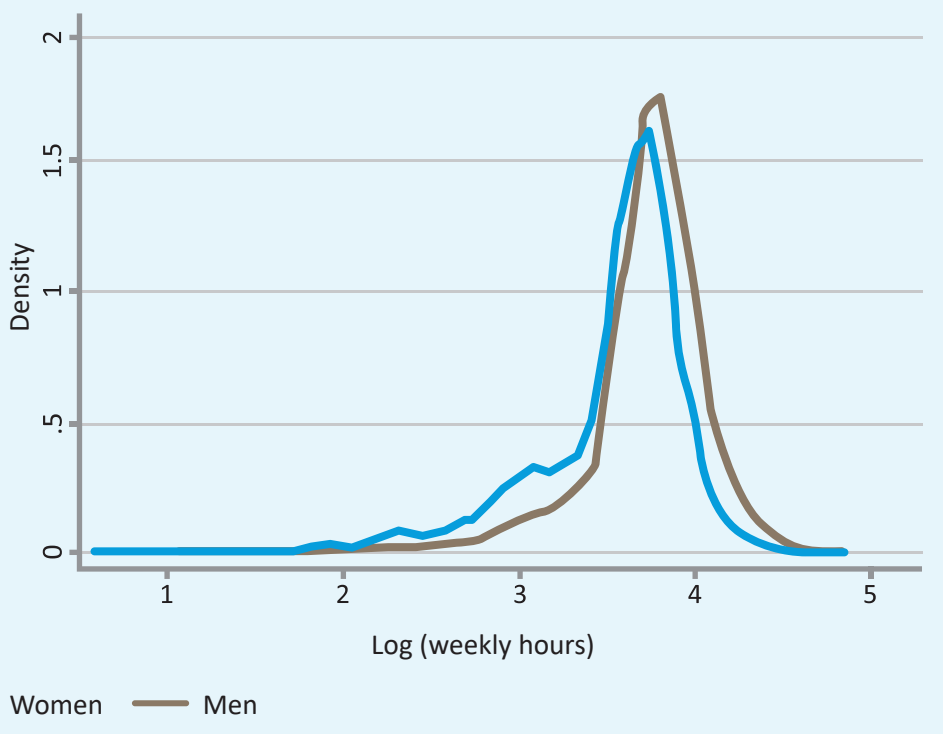
6 OTHER WORK-RELATED GENDER INEQUALITIES IN ARMENIA

This section looks at several other gender inequalities in the Armenian labour market. Given the importance of hours worked between men and women, which we identified in the previous section, we start with further disaggregation of the hours worked. Then, we delve into the gender gaps depending on household structure. Finally, we calculate some segregation indicators.

6.1 Gender differences in hours worked

The analysis of the gender pay gap in Section 5 suggested that women and men in Armenia work different hours, an important reason why the monthly wages exhibit a large gender difference. We will now delve deeper into the issue of hours worked. Figure 6 presents a density distribution of hours worked by men and women and suggests that women work fewer hours than men along the entire distribution, i.e. for both short and long working hours. There is, however, a particularly larger gap to the left of the median that likely resonates with part-time workers, suggesting that women are considerably more prone to work part-time than men, especially when compared to the gap between hours closer to full-time.

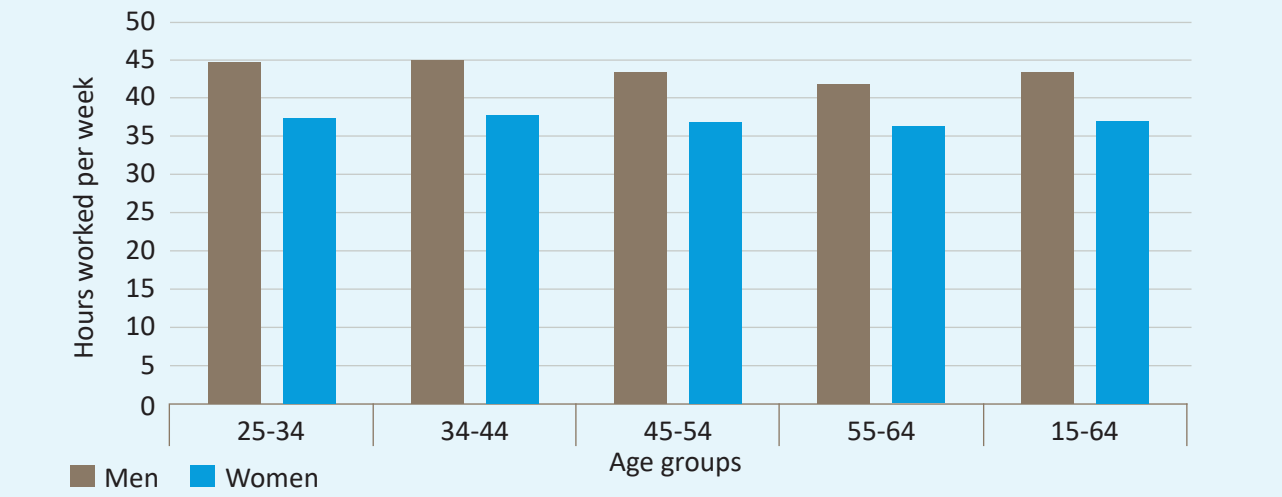
FIGURE 6:
Hours worked by men and women



Source: Author's own calculations. Weights used accordingly.

A similar picture emerges when hours are broken down by age. **Figure 7** suggests that women work fewer hours in any age group, the difference being slightly reduced with age.

FIGURE 7:
Hours worked by men and women, by age



Source: Author's own calculations. Weights used accordingly.

The gender hours gap may have some occupational and labour-market status specifics. **Table 15** suggests that such a gap exists among all occupations, though it is more pronounced in the corners of the skills distribution. Similarly, the hours gap is present among all employment statuses, except for the unpaid family workers. Finally, observed by education level, the gap persists at all levels.

TABLE 15:
Average hours worked across occupation, employment status and education level, by gender

	Men (%)	Women (%)
ALL	45.2	39.1
Occupation		
Armed forces	47.5	42.8
Managers	40.7	33.7
Professionals	43.0	38.3
Technicians and associate professionals	45.4	40.6
Clerical support workers	48.5	45.1
Services and sales workers	36.1	29.5
Skilled agricultural, forestry and fishery workers	45.8	42.7
Craft and related trades workers	46.9	43.9
Plant and machine operators and assemblers	46.6	40.8
Elementary occupations	47.5	42.8
Employment status		
Employee	44.7	38.7
Employer	48.7	42.9
Own account worker	54.0	46.1
Unpaid family worker	14.2	11.0
Education level		
Lower secondary or below	**43.3**	**36.0**
Vocational	**45.3**	**41.3**
Upper secondary	**44.1**	**39.1**
Tertiary or above	**43.7**	**35.9**

Source: Author's own calculations based on LFS. Weights used accordingly.

Overall, the gender hours gap exists among all ages, educational levels, occupations and employment statuses. Women in Armenia work fewer hours than men, in keeping with the time share devoted to unpaid domestic work.

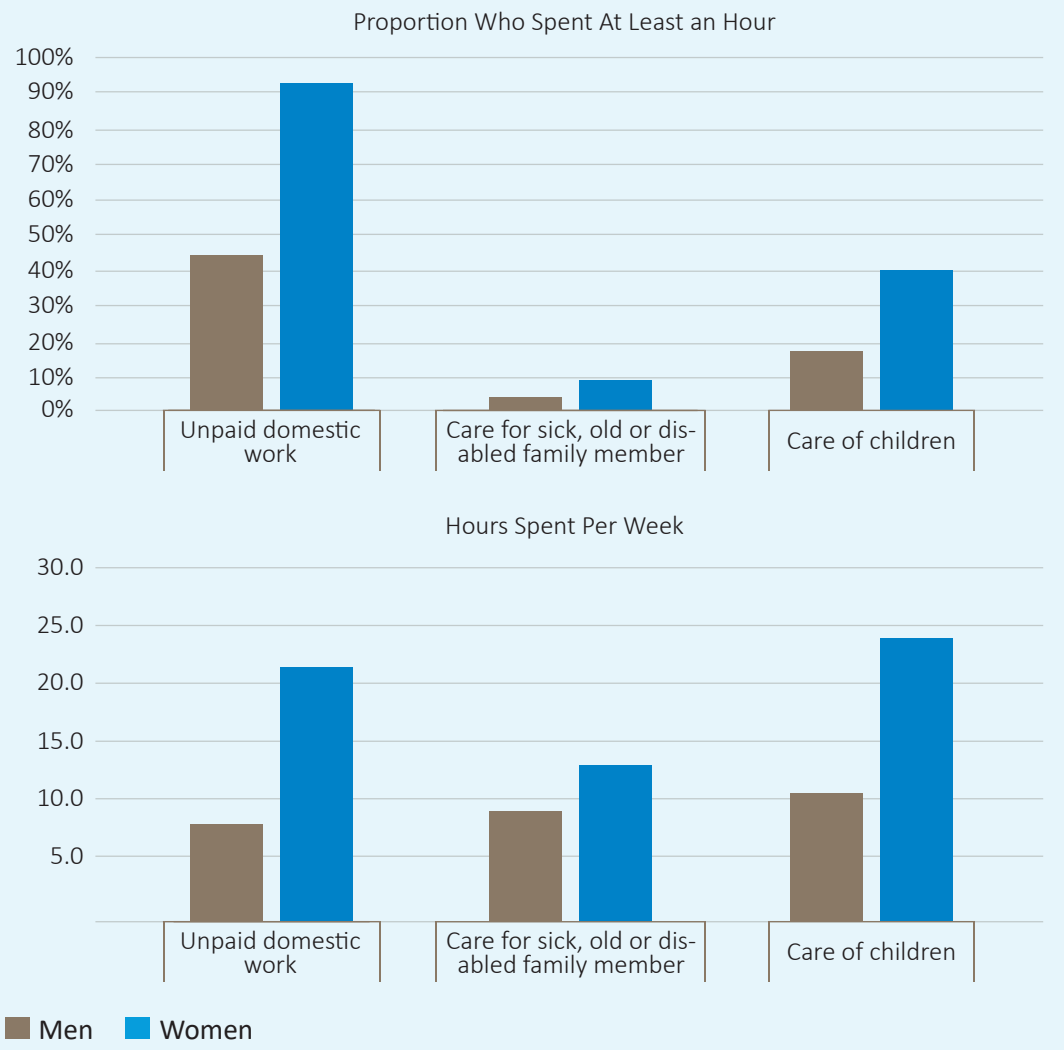
6.2 Gender inequality related to household structure

The relationship between labour-market activity and unpaid domestic work is especially relevant when observed through a gender lens. Women, particularly in patriarchal-minded and pro-conservative societies, are those who are thought of as being mainly responsible for the household and the dependants. Therefore, they spend large amounts of time in doing unpaid domestic work. Indeed, **Figure 8** confirms this. It shows the percentage of men and women (aged 15–64) who spent at least an hour per week on three types of unpaid domestic work: household chores; caring for sick, elderly and disabled family members; and caring for children. In all three categories, women spend comparatively more time than men, with the most pronounced difference evident for household chores.

> Inactive – individual who is neither employed nor unemployed

Then, the gender gap is maintained in the hours spent on these domestic activities. Namely, women spend most of their time on household chores and childcare, indeed more than twice the time men spend. Overall, women spend 58.5 hours weekly on domestic work, while men only spend 28.4 hours.

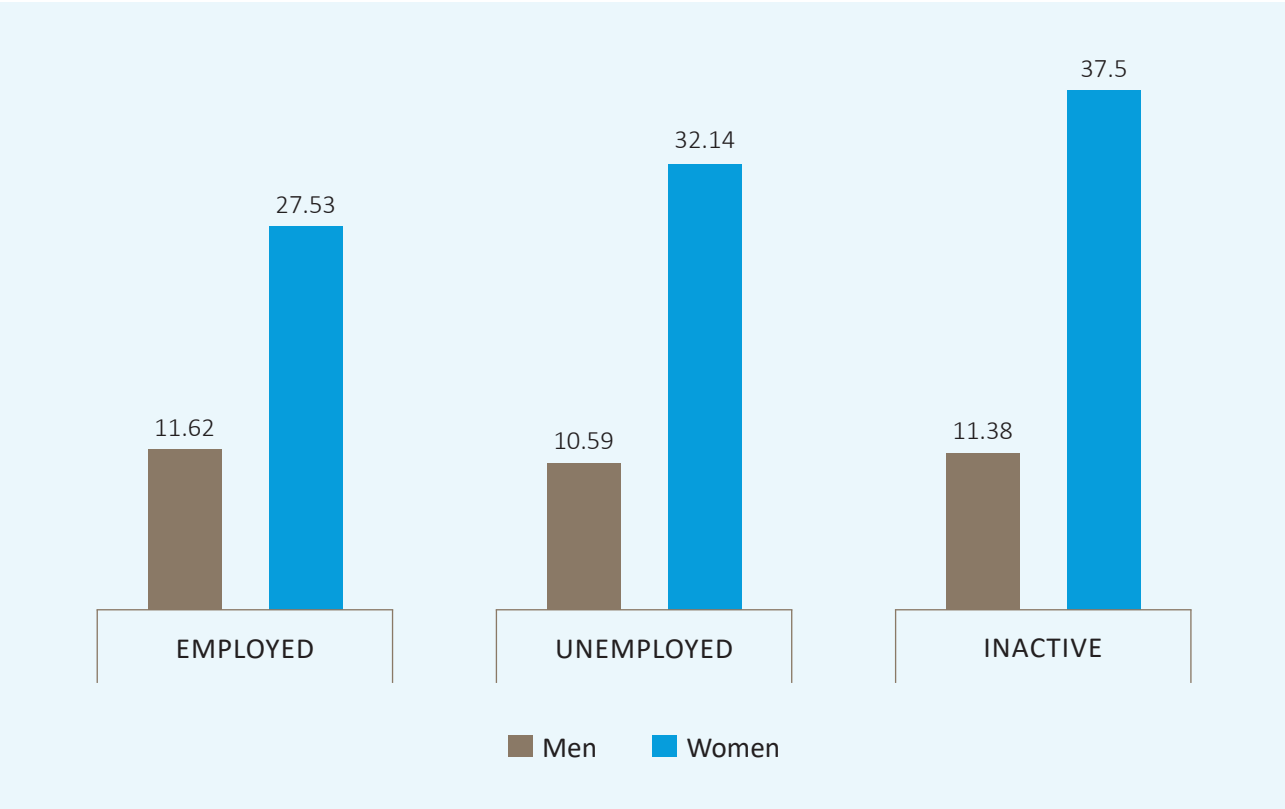
FIGURE 8:
Unpaid domestic work, by type



Source: Author's own calculations. Weights used accordingly.

Interestingly, though, the hours women spend on unpaid domestic work vary across labour-market statuses, but that does not apply to men (**Figure 9**). Employed women spend 27.5 hours weekly on domestic work, while inactive women spend over a third more (37.5 hours). On the other hand, men spend about 11 hours weekly, irrespective of their labour-market status.

FIGURE 9:
Unpaid domestic work, by labour-market status (hours)



Source: Author's own calculations. Weights used accordingly.

We next observe some labour-market characteristics of the labour force in Armenia, given their family structure.[5] Specifically, we observe single individuals, lone parents,[6] couples without children, and couples with children (one, two, and three or more, aged 14 or under). The underlying assumption is that family circumstances, especially the presence of children in the household, affect the labour-market behaviour of the mother, primarily. **Figure 10** presents the labour-market status for these categories, of both men and women. Labour-market activity does not differ for singles but then does move in an unfavourable direction, depending on the "intensity" of the domestic responsibilities. The largest discrepancies appear in couples with children and are further intensified with the number of children. For example, a mother of two children experiences a six-times higher non-participation rate than a father of two.

[5]The family structure was not provided by Armstat, except for the identification variable of the relatives to the household head (i.e. the person responding to the interview). Therefore, we pursued our own identification of families based on that variable. However, it may be the case that in multi-family households, this variable is insufficient to identify to whom the children belong. This is expected to impose some measurement bias in the family structure but is not expect to affect the main conclusions.

[6]Note that the number of lone parents in the sample is very low, so the produced figures should be approached with great caution. At points, estimates were not feasible.

FIGURE 10:
Labour-market status of men and women, by household structure

Source: Author's own calculations. Weights used accordingly.

We continue with disaggregating these numbers by age in **Table 16**, by observing the employment rates. The gender employment gap is present throughout, except among singles and, less so, among couples without children. Within the other family structures, the women in the age group 25–34 are most exposed to lower employment compared to men: the gender employment gap in this age group is a sizeable 47.6 p.p. for couples with one child, 41.6 p.p. with two children and 38.7 p.p. with three children. The latter remains very large even for the age group 35–44, suggesting that the presence and number of children is a significant barrier to women's labour-market activation and employment in Armenia.

TABLE 16:
Employment rates, by gender, age and family status

	Aged 25–34		Aged 35–44		Aged 45–54		Aged 55–64		Total (aged 15–64)	
	M (%)	W (%)	M (%)	W (%)	M (%)	W (%)	M (%)	W (%)	**M (%)**	**W (%)**
Single	52.3	56.5	49.4	55.2	42.8	55.0	37.7	41.3	**34.8**	**38.9**
Lone parent	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	**n/a**	**n/a**
Couple without children	65.1	52.8	55.7	51.3	59.9	50.6	52.3	39.8	**55.1**	**45.5**
Couple with any children (aged ≤ 14)	67.5	24.6	69.1	47.4	63.2	45.1	61.5	37.0	**66.8**	**36.7**
One child	84.1	36.5	62.9	50.8	58.7	45.5	65.9	26.3	**63.8**	**45.4**
Two children	64.8	24.7	71.8	47.6	75.1	33.5	56.1	NA	**69.6**	**33.6**
Three or more children	54.1	15.4	71.9	33.2	70.7	63.9	n/a	n/a	**67.2**	**23.3**
Total	**59.7**	**36.4**	**61.1**	**49.2**	**57.5**	**51.0**	**51.8**	**40.7**	**50.8**	**39.3**

Source: Author's own calculations. Weights used accordingly.

Similar results are observed by education (**Table 17**). The same family structures as before are exposed to the gender employment gap, though the differences are likely more age-specific than education-specific. Namely, the gap in the group "couple with children" exists across all educational levels.

TABLE 17:
Employment rates, by gender, education level and family status

	Lower secondary or below		Vocational		Upper secondary		Tertiary or above		Total (aged 15–64)	
	M (%)	W (%)	M (%)	W (%)	M (%)	W (%)	M (%)	W (%)	**M (%)**	**W (%)**
Single	26.8	23.5	38.2	46.8	41.6	44.0	58.3	64.1	**34.8**	**38.9**
Lone parent	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	**n/a**	**n/a**
Couple without children	53.5	40.5	56.3	37.4	49.3	43.8	65.4	61.9	**55.1**	**45.5**
Couple with any children (aged ≤ 14)	58.7	31.6	78.3	31.7	70.9	33.0	80.6	46.5	**66.8**	**36.7**
One child	56.0	43.9	61.7	22.7	68.9	43.6	80.0	50.6	**63.8**	**45.4**
Two children	59.5	23.3	97.3	39.9	77.7	25.0	79.6	48.2	**69.6**	**33.6**
Three or more children	62.6	22.4	80.2	32.1	55.7	21.0	86.4	26.5	**67.2**	**23.3**
Total	**43.1**	**30.6**	**57.0**	**38.9**	**53.7**	**38.9**	**67.7**	**56.4**	**50.8**	**39.3**

Source: Author's own calculations. Weights used accordingly.

Overall, family structure is likely an important determinant of gender labour-market inequalities in Armenia. In particular, motherhood – of greater numbers of children – is related to higher non-participation and lower employment rates. The gaps especially exist at younger ages, can be related to the age of the children, and are not education-specific.

6.3 Horizontal and vertical gender segregation

We analyse the horizontal gender segregation by calculating the Duncan Segregation Index (Duncan and Duncan, 1955). It is a measure of occupational/sectoral segregation based on gender that gauges whether there is a larger than expected presence of one gender over the other in a given occupation or sector. It shows the share of employed women and men who would need to trade places with one another across industries (occupations) in order for their distribution to become identical (Blau et al. 2002). A Duncan Segregation Index value of 0 indicates perfect gender integration within the workforce, while a value of 1 indicates complete gender segregation.

Since the extent of gender segregation of jobs becomes more obvious when comparing the distribution of men and women across a more detailed job disaggregation, we use the four-digit level of both NACE Rev. 2 for economic sectors and ISCO-88 for occupations. **Table 18** presents the results. The occupational segregation ranges between 0.42 and 0.89, while the sectoral segregation ranges between 0.61 and 0.96. However, with the exception of the segregation of persons with vocational education, horizontal segregation in Armenia is of high magnitude. This means that more than two thirds of women and men employees would need to trade places across sectors and job categories for their distribution to become identical.

Occupational segregation slightly loses power with education (vocational education excepted), while sectoral segregation is more powerful at lower educational levels and then declines for the upper secondary and tertiary levels.

TABLE 18:
Horizontal gender segregation index, by occupation and sector

	All	Education level			
		Lower secondary or below	Vocational	Upper secondary	Tertiary or above
Occupation	0.468	0.891	0.421	0.846	0.797
Sector	0.961	0.943	0.613	0.744	0.799

Source: Author's own calculations. Weights used accordingly.

Table 19 presents the gender share of employment (representation) in top managerial and professional positions, to consider vertical gender segregation. Recall that in **Table 3**, we observed an early sign of the glass ceiling effect, which was then corroborated in **Table 14**. **Table 19** lends support to the presence of vertical gender segregation in the occupational categories of directors and chief executives, production and operations managers and managers of small enterprises, but less so for legislators and senior officials and other specialist managers.

TABLE 19:
Vertical gender segregation

	Men (%)	Women (%)
Legislators and senior officials	51.0	49.0
Directors and chief executives	57.3	42.7
Production and operations managers	67.5	32.5
Other specialist managers	54.1	45.9
Managers of small enterprises	73.2	26.8

Source: Author's own calculations. Weights used accordingly.

Overall, both horizontal and vertical gender segregation in Armenia are potentially sizeable. At least three quarters of women and men employees would need to trade places across job categories for their distribution to become identical. The glass ceiling effect for top managerial positions is well corroborated.

7 CONCLUDING REMARKS

The objective of this study has been to calculate the adjusted gender pay gap in Armenia. We pursued two adjustments: one for personal and labour-market characteristics; the other, for selectivity. We estimated a Mincerian earnings function, whereby wages are a function of education, age, sector and occupation, and certainly gender. The coefficient in front of gender provided us with the size and significance of the gender pay gap. We applied OLS, Heckman's two-step method and repeated imputations. The latter helped us in estimating the gender pay discrimination, i.e. what is left after characteristics and selectivity have been accounted for.

7.1 Summary of findings

The raw (unadjusted) gender pay gap in Armenia is estimated at 23.1 per cent. We raised a note of caution in comparing this gap with the one calculated with monthly wages. Namely, the latter is 40 per cent in Armenia. However, it captures the gender pay gap and the gender gap in hours worked. Specifically, Armenian women were found to work less than men by about 14.3 per cent, which explains a third to half of the gender pay gap when calculated with monthly wages.

The adjusted gender pay gap in Armenia is estimated at 28.4 per cent. It is larger than the unadjusted gender pay gap, suggesting that working women have better labour-market characteristics than men. This also relates to women's potentially more positive selection into the labour market, despite the fact that non-working women (unemployed and inactive) also do possess considerable levels of education. Therefore, qualifications cannot explain the gender pay gap in Armenia; quite the contrary, they amplify it. The addition of sectors and occupations does not affect the resultant gap, suggesting that potential sectoral and/or occupational segregations likewise cannot explain the gap.

The adjusted gender pay gap cleaned for selectivity (e.g. that more-educated women tend to have more opportunities to find a job) in Armenia is estimated at about 10 per cent. It suggests that once we control for characteristics and selectivity, the gap declines at this level. Hence, this is a residual gender pay gap that could be ascribed to labour-market discrimination and the work of unobservable factors.

The distributional analysis showed that the gender pay gap in Armenia does not vary along the wage distribution. However, we identified a potential glass ceiling effect: the top 1 per cent of earners face a gender pay gap of around 19 per cent, which is almost double the average.

The analysis of the other gender inequalities in Armenia suggested that women work fewer hours than men and that such differences are spread among ages, occupations and economic statuses. However, the inequalities are more important given family structure. Mothers in couples are most prone to low employment incidents and large gender employment gaps, especially at a young (childbearing) age. Results find evidence for horizontal gender segregation, as at least three quarters of women and men employees would need to trade places across the job categories for their distribution to become identical. Vertical segregation is quite forceful as well.

7.2 Recommendations

Given the conclusions from this study, we provide the following set of recommendations, addressing both the policy and the technical sides.

Policy recommendations

Work on activation. Given that selection into employment is key to reducing the gender pay gap in Armenia, the Government should encourage more activation of women. Namely, women outside the Armenian labour market do not have the worst labour-market characteristics. Provided this, they may need either encouragement to participate (e.g. through awareness-raising campaigns) or an enabling environment (e.g. more childcare facilities). However, a proper investigation into the determinants of female inactivity in the labour market in Armenia is beyond the scope of this study.

Introduce or redesign policies that may work to reduce the gender pay gap. For example, a properly set binding minimum wage may increase wages in sectors largely populated by women, thereby level-

ling their wages with their male counterparts. Another example is fostering policies for flexible working arrangements as well as family policies that may ensure more work-life balance, especially for women.

Encourage female participation in top managerial positions. A hallmark way to do this is to prescribe gender quotas in corporate boards by law.

Secure supportive institutional set-up. The Government needs to show clear willingness for establishing and supporting institutional arrangements that are gender responsive. For example, the gender perspective should be encouraged in the development of collective agreements and in any type of budgeting, and gender rules should be introduced in the procurement process.

Fight gender-based discrimination in the labour market. Policies (one being the minimum wage) may be effective at combating gender-based discrimination. However, discrimination is also rooted in societal norms, traditions and culture. Awareness-raising campaigns may help in combating discrimination in a soft manner. Establishing or strengthening institutional bodies (e.g. an anti-discrimination agency) to fight discrimination is the harder manner.

Technical recommendations

Consider the distinction between gap based on hourly and on monthly wages. Given that the current practice of Armstat is based on calculating the gender pay gap based on monthly salaries from tax administrative data (since hours are not provided to Armstat by the tax authorities) as well as based on LFS, a confusion among stakeholders may arise: the gender pay gap based on monthly salaries also incorporates the differences in hours worked. Therefore, a switch – both technical and in general understanding – should be encouraged that the gender pay gap should be calculated based on hourly wages. This does not imply that changes in laws from monthly- to hourly-based compensation is needed; rather, it is only a technical way of calculating the gender pay gap.

Wisely choose a referent survey, or choose between survey and administrative data. The current calculation of the gender pay gap in Armenia is based on monthly data from the tax authorities as well from the LFS. Tax authorities have the hours worked but these are presently not supplied to Armstat, while hours worked from LFS are not utilized. Actually, tax authorities should supply Armstat with hours worked and salaries at the individual level, both disaggregated by gender. Then, the most precise gender wage gap will be calculated, while the same calculation based on LFS should be used for complementing the results. Calculating the adjusted gender wage gap, would be more difficult or even impossible if tax authorities do not have data on education, age and related variables for the taxpayers. However, this would be easy with the LFS, as was done in this report. Hence, survey-based and administrative data should be weighed against these caveats.

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ANNEX: GUIDELINES FOR CALCULATING THE GENDER PAY GAP IN STATA

Before starting with the analysis in Stata, it is recommended that one performs an update of it, done through

```
ado update
```

and also install a user-written missing command, through

```
ssc install command-name
```

Secondly, write the command that will specify which data set Stata should upload by writing:

```
use "C:\destination of the data set\the data set"
```

In what follows, we present the commands underlying the calculation of the gender pay gap and of its decomposition.

In its simplest unadjusted form, the gender wage gap could be calculated by using OLS, with the following command:

```
reg lw gender [pw=weight], robust
```

whereby lw stands for the log hourly wage and is regressed on gender, which is defined through a dummy variable taking a value of 1 for women and 0 for men. The command robust corrects for the errors' heteroskedasticity.

Then, to avoid rewriting the list of variables all the way through, we create a list. The command global creates a matrix of a few individual and/or labour-market characteristics. Variables in pers are as follows: education represented through the secondary and tertiary level (the primary level being the reference), age, and age squared. Note that education is specified with the operator i, which tells Stata to consider the levels separately. Variables in lm are the sectors and occupations, both specified through the operator i though also involving a number, e.g. ib2. and ib9., respectively. This operator tells Stata that we would like the second and the ninth category in each of the two variables to be the reference category. If we do not set it in this manner, Stata will drop the first category by default. The list excres represents the exclusion restrictions we are using in the Heckman method.

```
global pers age age2 i.education_levels

global lm ib2.sec_cat ib9.occ

global excres numchild married
```

Then, we regress the logarithmic wage on the vector of individual characteristics, so as to obtain the adjusted-for-characteristics gender wage gap.

```
reg lw gender $pers [pw=weight], robust

reg lw gender $pers $lm [pw=weight], robust

reg lw gender $pers $lm permanent [pw=weight], robust
```

We first introduce only the vector of personal characteristics; then, we add the labour-market characteristics; and finally we introduce the permanency of the working contract.

The Heckman sample-selection method could be coded in the following manner:

```
heckman lw gender $pers [pw=weight], select(gender $pers $excres) robust

heckman lw gender $pers $lm permanent [pw=weight], select(gender $pers $excres) robust
```

The term heckman is the Stata coding term for applying the Heckman sample correction, while select refers to the equation with the variables on which heckman should adjust for the sample correction.

The repeated imputations method could be coded in the following manner.
Firstly, we generate gender-specific medians as the fiftieth percentile of the variable (in this case, of the log wage lw). To make use of the weights in the calculation of the medians, we apply the following steps. First, we divide the subsamples of men and women into halves:

```
xtile halv_m = lw [pw=weight] if gender==0, n(2)

xtile halv_f = lw [pw=weight] if gender==1, n(2)
```

Then, for each half, we take the maximum value; for the first half, this would boil down to the median (while for the second half, the maximum value would be the maximum wage in the sample).

```
bys halv_m: egen median_m_aux = max(lw) if halv_m==1

gen consta = 1

bys consta: egen median_m = max(median_m_aux)


bys halv_f: egen median_f_aux = max(lw) if halv_f==1

bys consta: egen median_f = max(median_f_aux)
```

Then, we create one variable median, which takes one value for men and another for women, so as to create a gender-specific median.

```
gen median = median_m if gender==0

replace median = median_f if gender==1
```

The following code generates another variable named d_median, which is, at the outset, generated as a missing variable (.). The following statement replaces all missing cells with 1 if the logarithmic hourly wage is greater than the median, for all individuals with positive wage. Similarly, the third statement replaces the missing cells with 0 if the logarithmic wage is lower than the median, for all individuals with positive wage. Finally, the last statement drops from the analysis all observations that are missing.

```
gen d_median=.

replace d_median=1 if lw>median & lw>0

replace d_median=0 if lw<median & lw>0

replace d_median=. if lw==.
```

The following two lines run a probit model to predict whether a person belongs below or above the median wage depending on their personal characteristics (i.e. the same variables as in the basic OLS specification), except gender. The yhat is the generated variable that shows the prediction according to the probability that a person without a wage would fall below or above the gender-specific median, had s/he worked.

```
probit d_median $pers [pw=weight]

predict yhat
```

As yhat is continuous, in the next lines, we reduce it to a dummy variable. The first line generates a new variable named d_yhat that is set as missing at the outset. The second replaces this missing variable with 0 if yhat is less than or equal to 0.5, and the third line of command replaces it with 1 if yhat is greater than 0.5.

```
gen d_yhat=.
replace d_yhat=0 if yhat<=0.5
replace d_yhat=1 if yhat>0.5
```

Once this is done, mi set mlong declares a multiple imputation data set. The mlong is a marginal long-style data set where it first marks incomplete observations, then it omits assigned observations that are zeros, and lastly it records an arbitrarily coded observation-identification variable. The mi register imputed registers that lw is the variable needed for analysis and that it should be imputed. The mi describe describes the multiple imputation data where it shows how many are imputed, as well as how many are complete and incomplete.

```
mi set mlong
mi register imputed lw
mi describe
```

The next command sets the initial value of a random-number seed. The option is used to reproduce the same results at any time.

```
set seed 29390
```

The mi impute mvn uses multivariate normal data augmentation to impute missing values of continuous imputation lw where it is equal to d_yhat (above or below the median that we created earlier). The add(50) force means that this should be imputed 50 times (recall, here we use variants of 5 and 10).

```
mi impute mvn lw = d_yhat, rseed(29390) add(50) force
```

Then, the mi estimate computes multiple imputation estimates of coefficients by fitting the estimation command to the multiple imputation data. The following displays the replication dots or the imputed observations where one dot is displayed for each successful replication. Then lw is regressed on all variables (which we previously put in pers).

```
mi estimate, dots post: regress lw gender $pers [pw=weight], vce(robust)
```

The most commonly used decomposition of the gender pay gap is the Blinder-Oaxaca decomposition. The unadjusted gender wage gap can be decomposed with the following commands (for simplicity in the following calculations, we rename the gender variable to female):

```
oaxaca lw female $pers $lm [pw=weight], by(female) vce(robust)
```

The oaxaca command tells Stata to use the Blinder-Oaxaca model to estimate the logarithmic wage on the human capital characteristics; additionally, the by() command tells Stata to analyse the logarithmic wages on the human capital characteristics by gender.

The quantile decomposition approach is another very commonly used approach in decomposing the wage structure. The approach can be coded in the following way:

```
foreach num in 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 0.99 {
  qreg lw female $pers [aw=weight], quantile(`num')
  outreg2 using nnn, append
  }
```

The command qreg denotes quantile regression, whereby the logarithmic wage is regressed on the matrix of human capital characteristics. The quantile() command assigns which quintile the regression should analyse. In our analysis, we have divided the wage structure into deciles, which are provided in the foreach part. This part

is set to tell Stata that qreg should be iterated for each decile of the wage distribution, as well as for the last centile (0.99). As preferred, one could divide the wage structure into two, three, four or five percentile ranges by using the quantile() command.

The quantile decomposition could also be used for decomposition of the imputed data set. In so doing, we first need to tell Stata that it should use the imputed data set (preferably with the biggest number of imputed data sets, in our case, 50). Then, we apply the above procedure as follows:

```
foreach num in 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 0.99 {
mi estimate, dots post: qreg lw female $pers [aw=weight], quantile(`num')
  outreg2 using nnn, append
  }
```

Hence, the set-up is the same as above, with the exception of the setting of the qreg command, which needs to be set along mi estimate so that the programme knows that the repeated imputations should be used instead of the original data set.

The weighting decomposition approach can be coded as follows. We first generate a new dummy variable named male that is first set to 0 and then replaced to 1 when female equals 0.

```
gen male=0
replace male=1 if female==0
```

We save a new (temporary) data set named temp01, to keep the observations if the gender dummy is 1 and to drop the zeros. The following command replaces the data set with temp02 with a gender dummy set on 2. Then, the second temporary file is appended to the first one.

```
save temp01, replace
keep if female==1
replace female=2
save temp2, replace
use temp01, clear
append using temp2
```

The following lines run a probit model to predict a man's wage based on the matrix of human capital characteristics between those that belong to the gender dummy if it is 0 or 1, according to the two data sets. The newly generated variable pmale that shows the predicted probability of being a man is then summed up if the male dummy is equal or close to 1.

```
probit male $pers $lm [pw=weight] if female==0 | female==1
predict pmale
summ pmale if male~=1, detail
```

Then, the pmale variable is replaced with 0.99 if the variable contains data greater than 0.99 and close or equal to 1. We next sum the male dummy if it is less than 2 by using the quietly command, which indicates that Stata should not provide the output of the results of this summation. Once done, we generate a pbar variable to denote the mean, which is restored from the list stored from the r() command.

```
replace pmale=0.99 if pmale>0.99 & male~=1
quietly summ male if male<2
gen pbar=r(mean)
```

Once we create this pbar variable, we generate a new variable phix, which is calculated from the equation be-

low if the gender dummy is 2. The last command line details the summarized results.

```
gen phix=(pmale)/(1-pmale)*((1-pbar)/pbar) if female==2
sum phix, detail
```

We estimate a univariate kernel density estimation through the kdensity command if the gender dummy is 0, 1 and 2, respectively. Since the kernel density produces graphs, we write the nograph command as to not provide a graph in the output at this time. The variables generated are evalm1/evalf1, which represent the log wages of men and women, respectively. The densm1/densf1, accordingly, represent the densities of the wage distribution. The width() sets the width of bins to specify how the data should be aggregated. For the gender dummy that equals 2, the weights estimated from the variable phix are used in the kernel density estimation (as compared to the other two kernels, where we use the original weights).

```
kdensity lw if female==0 [aweight=weight], gen(evalm1 densm1) width(0.10) nograph
kdensity lw if female==1 [aweight=weight], gen(evalf1 densf1) width(0.10) nograph
kdensity lw if female==2 [aweight=phix], gen(evalfm densfm) width(0.10) nograph
```

The next long command line creates a graph that depicts all three kernel densities. The graph twoway command creates graphs, allowing options for the appearance of the graph. First, the kernel density function of women is represented as a short-dashed line; secondly, the kernel density of men is represented as a long-dashed line; and the last is the kernel density estimation when women have been assigned the characteristics of men, represented as a solid line. The commands ytitle and xtitle indicate how the y- and x-axes should be labelled. The command legend() creates a legend in the graph for the represented data. The order command shows which keys appear and in which order. The graph has no default style, so symxsize assigns the width of the key's symbol. Additionally, keygap and textwidth assign the gap between the symbols or text and the text's width.

```
graph twoway (connected densf1 evalf1, m(i) lp(shortdash_dot) lw(medium) lc(black)) (connected densm1 evalm1, m(i) lp(longdash) lw(medium) lc(black)) (connected densfm evalfm, m(i) lp(solid) lw(medium) lc(black)), ytitle("Density") xtitle("Log(wage per hour)") graphregion(color(white)) legend(ring(0) pos(2) col(1) lab(1 "Women") lab(2 "Men") lab(3 "Women as Men") order(1 3 2 4) region(lstyle(none)) symxsize(8) keygap(1) textwidth(25))
```

Finally, we would like to create the gender pay gap along the wage distribution, by comparing men with women had they had the characteristics of men. For the latter, we use the previously generated phix weights. The following commands define the centiles of the wage distribution for each subsample:

```
pctile evalfm2=lw if female==2 [aweight=phix], nq(100)
pctile evalm2=lw if female==0 [aweight=weight], nq(100)
```

and then, the difference between the two is generated.

```
gen qdiff=evalfm2-evalm2 if _n<100
gen qtau=_n/100 if _n<100
```

In the last step, we chart a graph presenting the generated difference qdiff along the wage distribution qtau. The yline command also provides the unadjusted gender pay gap and its confidence interval, to be compared with the new calculation.

```
graph twoway (line qdiff qtau if qtau>0.0 & qtau<1.0, connect(l) m(i) lw(medium) lc(black)), yline(-.1617971, lpattern(solid) lcolor(red)) yline(-.126974 -.1966203, lpattern(dash) lcolor(erose)) xtitle("Decile") ytitle("Log Wage Differential Female as Men vs. Men") graphregion(color(white))
```

GLOSSARY

adjusted gender pay gap

The differences between average men's and women's wages, accounting for their different endowments, most notably education, as well as a range of job characteristics

Blinder-Oaxaca decomposition

A statistical method that explains the difference in the means of a dependent variable (e.g. wages) between two groups (e.g. men and women) by decomposing the gap into a portion that arises because two comparison groups, on average, have different qualifications or credentials (e.g., years of schooling and experience in the labour market) when both groups receive the same treatment (explained component), and a portion that arises because one group is more favourably treated than the other given the same individual characteristics (unexplained component).

career advancement

The upward progression of one's career

discrimination

The unjust or prejudicial treatment of different categories of people, especially on the grounds of race, age, or sex.

Duncan Segregation Index

A measure of occupational segregation based on gender that measures whether there is a larger than expected presence of one gender over the other in a given occupation or labour force by identifying the percentage of employed women (or men) who would have to change occupations for the occupational distribution of men and women to be equal

earnings distribution

The way wages or earnings are distributed among those who receive them, usually observed from the lowest to the highest earnings

economic inequality

The unequal distribution of income and opportunity between different groups in society

employed

Individual who has engaged in work for in-kind or cash payment for at least an hour in the reference week

employer

A person or institution that hires employees

employment rate

The ratio of the number of employed individuals (see 'employed') and the active labour force

endowment

A quality or ability possessed or inherited by someone

Establishment Survey

See 'establishment-level survey'

establishment-level survey

A survey that seeks to measure the behaviour, structure or output of organizations rather than individuals

exclusion restrictions

Instrumental variables are used when an explanatory variable of interest is correlated with the error term,

in which case ordinary least squares gives biased results. A valid instrument induces changes in the explanatory variable but has no independent effect on the dependent variable. If this condition is met, then the instrument is said to satisfy the exclusion restriction.

experience

Experience of employment, usually measured through the number of years spent on particular job(s)

explained gender pay gap

The part of the gender pay gap explained by personal characteristics of workers or by other observable characteristics

gender employment gap

The difference between the employment rates of men and women, usually expressed in percentage points

gender equality

The state of equal ease of access to resources and opportunities regardless of gender, including economic participation and decision-making; and the state of valuing different behaviours, aspirations and needs equally, regardless of gender

gender hours gap

Gender differences in hours worked'

gender inactivity gap

See 'gender participation gap'

gender participation gap

The difference between the labour market participation rates of men and women, usually expressed in percentage points.

gender pay gap

The difference between the average wage of men and women, expressed as a percentage of men's wage.

gender segregation

See 'segregation'

gender stereotypes

Preconceived ideas whereby females and males are arbitrarily assigned characteristics and roles determined and limited by their gender

gender unemployment gap

The difference in the unemployment rates of men and women in the labour market (usually expressed as percentage points)

gender wage gap

See 'gender pay gap'

glass ceiling

An unacknowledged barrier to advancement in a profession, especially affecting women and members of minorities

Heckman selection method

A statistical technique to correct bias from non-randomly selected samples or otherwise incidentally truncated dependent variables. This is achieved by explicitly modelling the individual sampling probability of each observation (the so-called selection equation) together with the conditional expectation of the dependent variable (the so-called outcome equation)

horizontal segregation

Differences in the number of people of each gender present across occupations

human capital

The stock of habits, knowledge and social and personality attributes (including creativity) embodied in the ability to perform labour so as to produce economic value

human capital theory

The stock of habits, knowledge and social and personality attributes (including creativity) embodied in the ability to perform labour so as to produce economic value

inactive

Individual who is neither employed (see 'employed') nor unemployed (see 'unemployed')

labour force

The labour force, or currently active population, comprises all persons who fulfil the requirements for inclusion among the employed or the unemployed

labour market

The market of employment and labour, in terms of supply and demand

maternity protection

Special protection for pregnant women and women workers who recently gave birth or are breastfeeding to prevent harm to their or their infants' health, and at the same time ensure that they will not lose their job simply because of pregnancy or maternity leave

measurement error

The difference between a measured quantity and its true value. It includes random error (naturally occurring errors that are to be expected with any experiment) and systematic error (caused by a miscalibrated instrument that affects all measurements)

median regression

A regression that estimates the median of the dependent variable, conditional on the values of the independent variable

Mincerian earnings function

A single-equation model that explains wage income as a function of schooling and experience

multiple imputation

See 'repeated imputation'

non-response bias

A phenomenon in which the results of a survey become non-representative because the participants disproportionately possess certain traits that affect the outcome, i.e. because respondents are systematically different than non-respondents

on-the-job training

A hands-on method of teaching the skills, knowledge and competencies needed for employees to perform a specific job within the workplace

ordinary least squares

A method that chooses the parameters of a linear function of a set of explanatory variables by minimizing the sum of the squares of the differences between the observed dependent variable (values of the variable being predicted) in the given data set and those predicted by the linear function

own account worker

A worker who, working on his/her own account or with one or more partners, holds the type of job defined as a self-employed job, and has not engaged any employees on a continuous basis to work for him/her during the reference period

patriarchal-minded societies

Systemic societal structures that institutionalize male physical, social and economic power over women

precarious employment

A non-standard employment that is poorly paid, insecure, unprotected and cannot support a household

prejudice

See 'social prejudice'

quantile regression

A method that estimates the conditional median or other quantiles of the response variable given certain values of the predictor variables

raw gender pay gap

See 'unadjusted gender pay gap'

repeated imputation

Imputation is a statistical process used to replace data that are missing from a data set due to item non-response. Repeated imputation is a method for reflecting the added uncertainty due to the fact that imputed values are not actual values, and yet still allow the idea of complete-data methods to analyse each data set completed by imputation

response bias

The tendency of a person to answer questions on a survey untruthfully or misleadingly (also called 'survey bias')

salary

See 'wage'

segregation

The systemic separation of people into groups in daily life, based on particular characteristic like gender, race or ethnicity

selection bias

See 'selectivity bias'

selectivity bias

Selectivity bias is the bias introduced by the selection of individuals, groups or data for analysis in such a way that proper randomization is not achieved, thereby ensuring that the sample obtained is not representative of the population intended to be analyzed.

self-employed

See 'own account worker'

social prejudice

An unjustified or incorrect attitude (usually negative) towards an individual based solely on his/her gender or generally on the individual's membership to a social group

sticky floor

A discriminatory employment or wage pattern that keeps workers, mainly women, in the lower ranks of the job or wage scale, with low mobility and invisible barriers to career advancement

survey data

The resultant data that is collected from a sample of respondents that took a survey

unadjusted gender pay gap

The simple differences between average men's and women's wages, not accounting for their different endowments

underreporting

See 'response bias'

unemployed

Individual who does not have a job for payment in kind or in cash, who is actively seeking a job in the reference week; and who is ready to start work in 15 days if offered a job

unexplained gender pay gap

The part of the gender pay gap that cannot be explained by personal characteristics or other observable factors

unpaid domestic work

Labour that does not receive any direct remuneration and falls outside of the national accounts (i.e. is not reflected in GDP), i.e. occurs inside households for their consumption

unpaid family worker

A person who works without pay in a market-oriented family establishment or in an economic unit managed by a household member

vertical segregation

The situation where people do not get jobs above a particular rank in organizations because of their race, age or sex

wage

A particular amount of money that is paid, usually every month, to an employee.

wage distribution

See 'earnings distribution'

wage employee

An employee who is paid on a salary basis

wage structure

The levels or hierarchy of job and pay ranges, specifically the interrelationship of the levels of pay for different types of employees

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