20 YEARS OF ARMENIAN GENDER PAY GAP:

WHAT HAS CHANGED?

By

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Abstract

In this thesis I analyze the dynamics of Armenian gender pay gap over the last two decades. To do so, I estimate and decompose Armenian pay gap using 2019 Armenian labor force survey data. I find unobservable characteristics are the main contributors to the gap. Using Armenian Population Census 2001 database I then test whether the change in endowments explains the evolution of the gap. I find that only the change in education levels could contribute the decline in the gap. I conclude that the change is mainly driven by a set of unobservable variables. To enable further decrease in the gender pay gap, Armenia must rather focus on correction of social norms.

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1 Introduction

Gender based discrimination is a persistent phenomenon for most developing countries (Jayachandran, 2015). Morrison and Jutting (2005) show clear links between the discrimination and gender-based segregation in labor market. A number of studies show that gender-based discrimination result in significant inefficiencies for countries' economies. Although females form a significant portion in population, countries usually underuse them as a resource. Obviously, underinvested and underused human capital cuts down the country's long-term sustainable development potential. Thus, Mascherini et. al (2016) found that low female labor market participation rate costed 2.8% of GDP for EU in 2013. Pervaiz (et. al 2011) using time series data (1972-2009) claimed that gender inequality negatively affects Pakistani GDP growth. According to Barcena et al (2018), not only does equality lead to full resource utilization in the economy, but also it is necessary for rapid technological growth as it unlocks possibilities for learning, more diverse and innovative thinking.

The problem of "inefficient inequality" was the main topic at the Centre for European Policy Studies' conference (2016) where a number of articles was dedicated to the economic costs caused by inequalities in labor market. They all highlight that the costs of discrimination in labor market are significant and multidimensional. Namely, Bisello (et. al) state that increase in equality also leads to an increase of the population's well-being, as women feel more involved in the social life. Overall, gender-based discrimination in labor market is not only an issue for countries from a moral point of view, but it also causes sizeable economic costs.

The discrimination in labor market can take various forms. Participation discrimination, discrimination in typical occupied positions, gender-based pays are among them.

Gender pay discrimination being one of the most common forms of discrimination in labor market is the topic of many researches. Blau and Kahn (2003) defined gender wage gap as difference between hourly payments between males and females as a percentage of males' wage. This became the commonly used definition of the gender wage gap. It treats males as the reference category. Eurostat uses the term "unadjusted gender pay" when giving the above-mentioned definition[1], to contrast it with the adjusted gap which accounts differences in relevant characteristics. A number of studies show, that gender wage gap has tangible negative impact on economic growth. Thus, Tavares and Cavalcanti (2007) used a macroeconomic growth model to show that an increasing gender wage gap results in decreasing income per capita. They also found that gender-based discrimination in labor market causes a decrease in output per capita directly due to lower female participation and indirectly due to an increase in fertility. Similarly, Cassells' (et. al. 2009) macroeconomic model predicted 0.5% growth of Australian GDP if the pay gap decreased from 17% to 16% and 8.5% GDP growth if the gap was eliminated. Joanna W. (2013) while failing to estimate causality of the gap, using data from 18 OECD countries for the period of (1970-2005) confirmed the negative correlation between gender pay gap and sectoral growth.

Closer to the end of 20th century gender pay gap started to decrease in a number of countries. Ganguli and Terrell (2005) and Pignatti (2012) confirmed the decreasing trends of the gap for Ukraine for periods of (1986-2003) and (2003-2007), respectively. Analogically, Pham and Reilly (2007) and Kecmanovic and Barrett (2011) found similar evidences for Vietnam (1993-2002) and Serbia (2001-2005), respectively. Using PSID microdata (1980-2010) Blau and Kahn (2017) confirmed the decline of the pay gap for the US. Nevertheless, these tendencies are not homogenous across all countries. For instance, as Pastore and Verashchagina (2011)

[1] https://ec.europa.eu/eurostat/web/products-datasets/-/SDG_05_20

and Chi and Li (2008) showed the gap increased in Belarus (1996-2006) and China (1987-2004), respectively.

Although Armenia has experienced significant decline in the gender pay gap, as I will show in the next chapter (Figure 1), the drop stopped around a decade ago. In 2019, the country obtained the significant 20% of unadjusted gap (Table 1). Armenian gender pay gap has been a largely overlooked topic for a long time. Although in recent years, a couple of prominent articles did analyze the pay gap in Armenia, they only covered a year snapshot. Thus, Lourdes et. al. (2018) using Armenian labor force survey (LFS)[2] for the year of 2015 estimated the gender pay gap around 20%. In their analysis, they applied (re-centered influence functions) RIF approach and demonstrated the gap was not a result of characteristics differences between males and females, especially in middle percentiles. On the contrary, the females on average obtained better endowments in Armenia. In 2020, UN Women published another analysis of Armenian gender pay gap based on Armenian LFS 2018 data. Their estimated unadjusted gap equaled around 23%, and the adjusted gap was approximately 28%. In their analysis, they found statistical evidence for such phenomena as low self-selection among women and the presence of glass-ceiling effect in Armenian labor market.

The latter researches shed light on Armenian gender pay gap. Rather less attention, however, has been devoted to the dynamics of the gap. To build a comprehensive understanding of the problem and to build reasonable expectations one needs to look analyze the evolution of the gap. This would also hint how to affect the dynamics itself.

In this paper I reveal the channels that drove the change over the years. I embrace the biggest statistically observable historical interval to analyze whether the major observable

[2] Armenian labor force surveys are published annually by Statistical Committee of the republic of Armenia since 2014 (https://www.armstat.am/en/?nid=212)

characteristics explain the dynamics. In doing so I use the latest and the earliest available personal level data for Armenia (2000 and 2019) years. I first estimate and analyze Armenian gender pay gap for 2019. I then apply decomposition and replacement techniques to analyze the change in the gap.

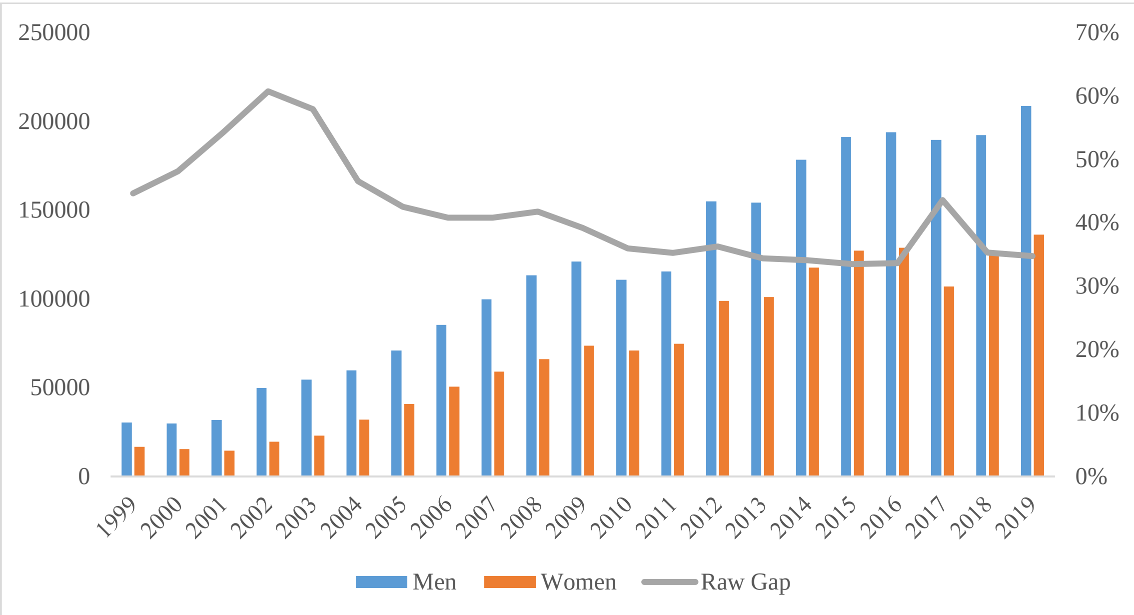
This paper is organized in the following manner: in Chapter II I provide relevant descriptive statistics and perform Armenian 2019 gender pay gap estimation. I then present my methodology in Chapter III. In Chapter IV perform my analysis and obtain the results. I then conclude in Chapter V.

2 Overview of Armenian gender pay gap

2.1 Stylized facts

I first looked at gender wage gap in Armenia over the last two decades. Namely, using annual reports of the average monthly wages by gender and the annual real wage indices by Statistical Committee of the Republic of Armenia (SCRA) I calculated Armenian real monthly wage dynamics and the raw wage gap for the period of 1999-2019 (Figure 1). The picture showed high values of wage differences between men and women at early 2000s, reaching up to 61% at 2002. Over years women's real monthly wages grew at a faster pace, thus lowering the wage gap. However, the gap is still significant and persistent up until the recent years.

Figure 1. Average real monthly wages by gender (AMD) and the raw wage gap (%) 1999-2019

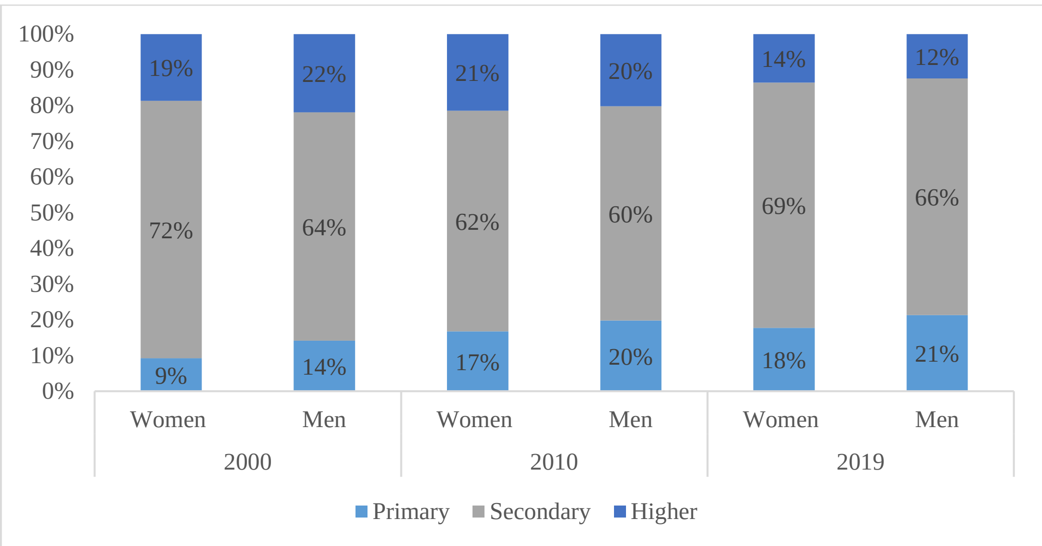


Source: Author's elaboration based on Statistical Committee of the Republic of Armenia (https://armstat.am/file/article/trud_2020_14.pdf)

Note, that above I presented the raw monthly wage gap, meaning it didn't account for variables that typically affect wages. There could be a number of objective and subjective reasons behind the gap. Such as the difference in hours worked per month (different types of contracts), personal characteristics, labor market characteristics, economic and social norms etc. First, I considered the most common suspects and reviewed some stylized facts to build an intuition.

Education level could be a reason why a person gets different wage, as it is usually used as a signal for the person's skill level (Mincer, 1974). Figure 2 showed no significant differences in the quality of education for men and women over the period. Moreover, data showed women in Armenia always had a bigger above-primary education percent. Note, that the difference in the higher education share changed in favor of woman over time. This could possibly explain the decrease in the gender wage gap.

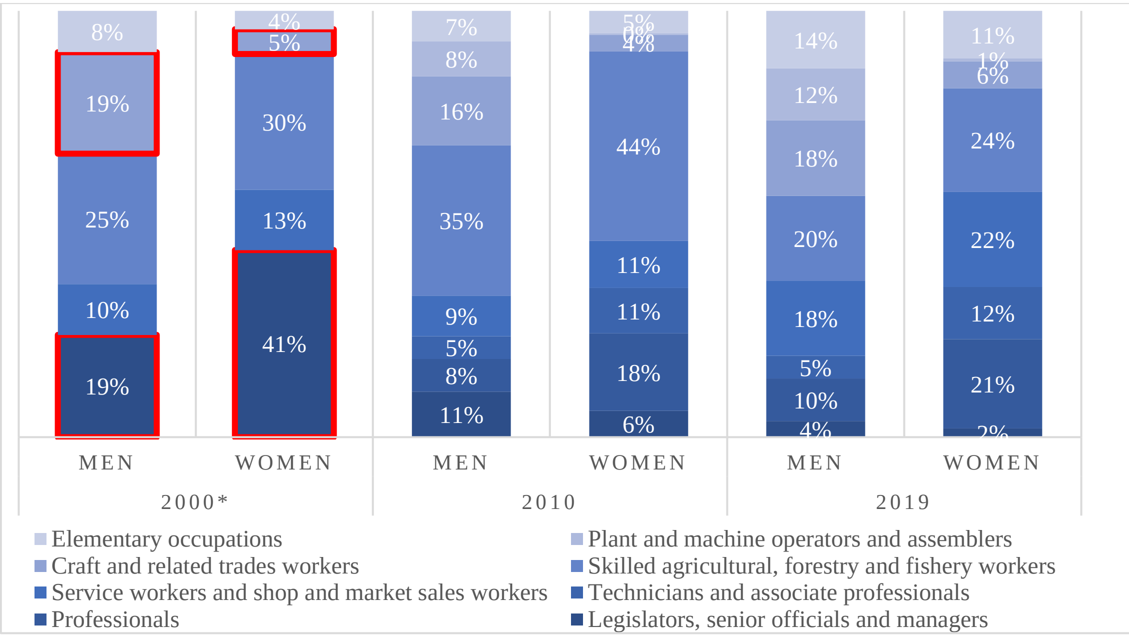
Figure 2. Education structure by gender (2000, 2010, 2019)



Source: Author's elaboration based on Statistical Committee of the Republic of Armenia (Population Census 2001, 2011, Labor Force Survey 2019)

Another factor that usually differences the wage is the position a worker occupies. It turned out women usually had a better occupation structure, always obtaining higher percent for the positions like managers, professional, technicians. On the other hand, men dominated in the highest ranked positions (legislators, senior officials, managers).

Figure 3. Labor force occupation by gender (2000, 2010, 2019)



Source: Author's elaboration based on Statistical Committee of the Republic of Armenia (Population Census 2001, 2011, Labor Force Survey 2019). Note: Census 2001 provides data for managers, professionals, technicians as an aggregated occupation only. This is also the case for craft, operators and assemblers.

To estimate the raw gender gap for 2019 I selected all the individuals in the working age (15-63) in LFS 2019. In the data I found personal level monthly wages under the column "How much wage / income did you receive during the last 4 weeks? In cash (after deductions)". Those individuals who did not want to mention the exact amount of wage could select among given wage intervals. For such cases, I calculated the weighted average monthly wage for the respective intervals using information of the previous column. I then assigned the relevant values to the intervals.

Using the monthly wage data run a simple OLS regression where the log monthly wage is the depended variable and the gender dummy is the only independent variable (Equation 1).

$$ln(mw) = \beta_0 + \beta_1\, gender + \varepsilon \textbf{Error! Bookmark not defined.} \tag{1}$$

Error! Bookmark not defined.where *ln(mw)* is the log monthly wage, *gender* is a dummy variable for males = 0 and females = 1, β_0, β_1 are parameters and ε is the error term. The monthly gender pay gap equaled -0.387 (Table 1, column 1). That is, in 2019 in Armenia females on average got 38.7% less monthly salary than males.

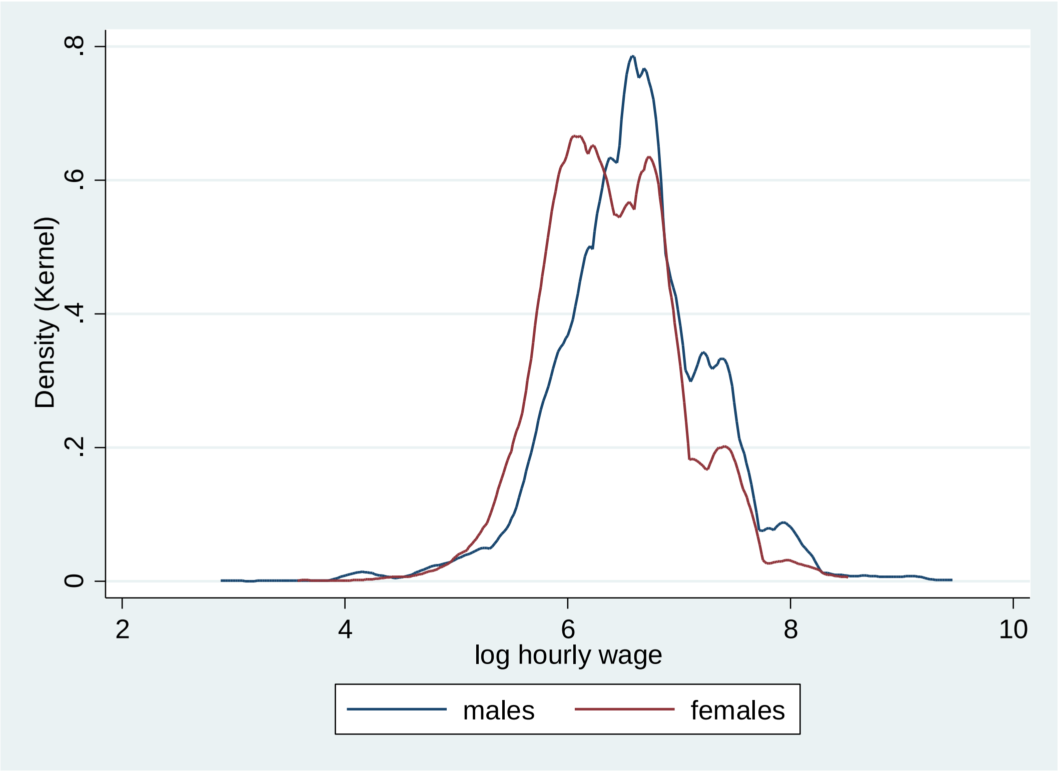
Log monthly wages as include differences in monthly worked hours that could be gender-specific. Thus, I calculated the hourly wages per person. For that used the information from columns “For what period was the wage/income for?” and “How many hours do you usually work per week” in LFS 2019 to calculate hours worked per month. I then combined it with the information about the monthly wages and got hourly wages for the individuals. Using the acquired hourly wages for 2019, I calculated kernel density estimate for log hourly wages by gender (Figure 4). The graph confirmed that males on average earn more than females in Armenia.

I then run an OLS regression with log hourly wages to estimate the new raw gender pay gap (Equation 2). The findings in Table 1 (column 2) confirmed the picture in Figure 1.

$$ln(hw) = \beta_0 + \beta_1\, gender + \varepsilon \tag{2}$$

where *ln(hw)* is the log hourly wage.

Figure 4. Log hourly wage distribution per gender 2019



Source: Author's elaboration based on LFS 2019.

Note: rows with non-empty personal and labor market characteristics (see below) were used. Survey were used accordingly.

Note, that after running the second regression the gender pay gap significantly decreased. This suggested that females indeed had different job contracts, and they worked less hours per month on average.

Table 1. Unadjusted gender pay gap

	log monthly wage	**log hourly wage**
	(1)	**(2)**
Gender (Female = 1)	-0.387***	-0.209***
	(0.0217)	(0.0197)
Constant	12.19***	6.808***
	(0.0335)	(0.0310)
Observations	6,435	6,372
R-squared	0.069	0.026

Source: Author's elaboration based on LFS 2019.

*Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. Standard errors given in parentheses. Results robust to heteroscedasticity. Survey weights were used accordingly.*

2.2 Estimating the adjusted gap

To account for wage-relevant characteristics I first included personal characteristics in the estimation process. In doing so I relied on the famous Mincerian earning function concept (Mincer, 1958). The function in its general form relates the wage at a given point in time to the individual's in-work time (experience) and the level of education. Wages are considered to be a concave function of the relevant job experience.

$$lnW(t) = \beta_0 + \beta_1\, edu + \beta_2 \exp + \beta_3 \exp^2 + \varepsilon \tag{3}$$

where *W(t)* is the wage at time *t, edu* is the level of education.

In the LFS, however, there is no information regarding individuals' job experience. Hence, I replaced the variable by an individual's age. In doing so, I used the concept of age-earning profiles. The idea is that people learn along their life aside direct education and job activity. Thus, ceteris paribus an older person is expected to have more skills and to earn more. I also included the square of age as an independent variable in the wage function to allow for a possible age related non-linearity. An adjusted for personal characteristics gender pay gap is estimated in the following way:

$$\ln(hw) = \beta_0 + \beta_1\, gender + \beta_2\, edu + \beta_3\, \text{age} + \beta_4\, \text{age}^2 + \varepsilon \tag{4}$$

Using 2019 LFS data, I defined *edu* variable by combining different answers from "education level" column. Namely, I defined 4 levels of education[3]:

1. Illiterate, no primary, primary, basic
2. Secondary, high
3. Vocational, secondary specialized
4. Bachelor's degree
5. Certified specialist, Master's degree, post-graduate (Ph.D., doctorate etc...)

In the model I used *edu* as a category variable having the first level as the reference category. Table 2 (column 1) shows the results of the estimation. The gap didn't shrink but increased compared to the unadjusted value. This suggests that working females on average obtain a higher level of education yet are less paid in return. The results also confirm the initial guess that age itself is rewarding, and the return of the age has a concave shape.

In addition to personal characteristics, there is a number of labor market variables that define the expected wage for a worker. Industry and occupation are the most important labor market variable to define the wage gap (Blau and Kahn, 2017). It is common to expect heterogeneity in the expected wages across industries. Analogically, there is typically difference in the

[3] when defining variables, I was keeping them consistent with Population Census 2001 data structure.

expected wage between a manager and a clerk, for instance. Of course, inclusion of occupations contained a risk of having a bad control, as they were somewhat outcomes themselves. Nevertheless, I still had to control for occupations to avoid incompatible comparisons.

I first included workers' occupations from the Armenian 2019 LFS into the OLS regression. I treated it as a category variable and specified the 9^{th} level (the lowest – "Elementary occupations") as the reference category.

The gap again increased compared to the raw gender gap (Table 2, column 2), which meant that women typically had better (higher paid) occupations than men. The results also expectedly confirm that higher positions imply a higher wage for a worker. Hence, by reaching the level of a "professional" a typical worker can significantly improve his wage on average.

I then added a dummy variable which I derived from "which type of contract do you have?" columns of the labor force survey. The variable described whether the worker had a permanent job contract or not (temporary, seasonal, casual). In that case the gap didn't change significantly (Table 2, column 4). Nevertheless, the presence of a permanent contract secured a higher wage on average.

I finally added industries as the last important labor market specific characteristic. The industries from LFS 2019 were reclassified in such a manner so that they are later compatible with 2001 Armenian census industry related data. Here again, the variable was treated as a category variable and the industry of manufacturing was chosen as the reference category. From Table 2 (column 6) one can observe a significant drop in the gender pay gap compared to column (4). This suggested there was an interplay between industries and other characteristics.

Table 2. Adjusted gender pay gap

	Personal	Occupation	Personal and occupation	Pers., occ. and contract	Industry	All	
	(1)	(2)	(3)	(4)	(5)	(6)	
Gender	-0.256***	-0.291***	-0.272***	-0.275***	-0.206***	-0.242***	
(Female = 1)	(0.019)	(0.019)	(0.019)	(0.019)	(0.024)	(0.023)	
Age	0.0115**		0.0131**	0.0130**		0.0145**	Personal characteristics
	(0.006)		(0.005)	(0.005)		(0.006)	
Age sq.	-0.0002***		-0.0002***	-0.0002***		-0.0002***	
	(0.000)		(0.000)	(0.000)		(0.000)	
Secondary, high school	0.058		0.012	0.012		0.018	
	(0.048)		(0.048)	(0.048)		(0.050)	
Vocational education	0.138***		0.021	0.018		0.033	
	(0.049)		(0.049)	(0.050)		(0.052)	
Bachelor's degree	0.455***		0.214***	0.209***		0.227***	
	(0.053)		(0.056)	(0.056)		(0.060)	
Master's and higher	0.570***		0.271***	0.268***		0.297***	
	(0.051)		(0.055)	(0.056)		(0.060)	
Managers and higher		0.730***	0.577***	0.569***		0.572***	Labor market characteristics
		(0.072)	(0.070)	(0.070)		(0.077)	
Professionals		0.632***	0.404***	0.399***		0.449***	
		(0.030)	(0.039)	(0.039)		(0.047)	
Technicians		0.372***	0.295***	0.288***		0.260***	
		(0.033)	(0.034)	(0.034)		(0.040)	
Clerks		0.367***	0.243***	0.236***		0.209***	
		(0.049)	(0.050)	(0.050)		(0.060)	
Service & sales workers		0.163***	0.118***	0.112***		0.0798**	
		(0.028)	(0.028)	(0.028)		(0.035)	

Skilled agric. workers		-0.253***	-0.233***	-0.230***		-0.159**
		(0.040)	(0.040)	(0.040)		(0.067)
Craft workers		0.250***	0.238***	0.233***		0.190***
		(0.031)	(0.031)	(0.031)		(0.038)
Operators & assemblers		0.138***	0.140***	0.134***		0.102**
		(0.037)	(0.037)	(0.037)		(0.041)
Agriculture					-0.490***	-0.120*
					(0.042)	(0.067)
Education					-0.0924**	-0.0873**
					(0.040)	(0.042)
Public administration					0.0980**	0.012
					(0.042)	(0.045)
Trade					0.002	-0.257***
					(0.040)	(0.043)
Other industry					0.0811**	0.032
					(0.033)	(0.033)
Permanent job contract				0.0576**		0.0821***
				(0.025)		(0.030)
Constant	6.507***	6.669***	6.423***	6.330***	6.871***	6.266***
	(0.120)	(0.035)	(0.118)	(0.125)	(0.043)	(0.152)
Observations	6372	6372	6372	6372	6372	6372
R-squared	0.154	0.193	0.214	0.215	0.079	0.194

Source: Author's elaboration based on LFS 2019.

*Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. Standard errors given in parentheses. Results robust to heteroscedasticity. Survey weights were used accordingly.*

Overall, the adjusted gender pay gap was estimated to be bigger than the unadjusted one with the value around -0.24 Thus not only do Armenian women get lower wages on average, they also obtain better characteristics as labor force.

The gap estimate in Table 2 (column 6) might suffer from selection bias problem because in the survey I could observe only those individuals that were active members of the labor market. If there were variables that had impact on both wages and the decisions to participate, then the estimates in Table 2 would be biased.

One way to solve the problem is to use Heckman correction model[4]. The model consists of two equations: the wage equation and the selection equation. Selection equation consists of the standard wage equation variables and additional variables, which can affect a person's decision to participate, but they do not determine the expected wage directly. As a gender specific variable, those could be marriage status, the presence of children etc. Unfortunately, only data on marriage status is available in the LFS. From the respective columns a derived a dummy variable "whether the person is married or not".

I run Heckman model for the raw and the adjusted pay gaps (Table 3). Overall, the gap values were close to the estimates in Table 2, and the pattern across the columns is similar. The main problem of such models is the "quality" of the exclusion restriction.

[4] For more detailed explanation of the model check Marchenko Y., Genton M. (2012)

Table 3. Heckman's selection model for the gender pay gap

	Unadjusted	**Selection eq.**	**Personal char.**	**Selection eq.**	**All**	**Selection eq.**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	
Gender	-0.220***	0.248***	-0.257***	0.171***	-0.236***	0.170***	
(female = 1)	(0.020)	(0.034)	(0.020)	(0.034)	(0.027)	(0.035)	
Age			0.0115**	0.0384***	0.0138**	0.0385***	Personal characteristics
			(0.006)	(0.011)	(0.005)	(0.011)	
Age sq.			-0.0002***	-0.0004***	-0.0002***	-0.0004***	
			(0.000)	(0.000)	(0.000)	(0.000)	
Secondary, high school			0.057	0.162**	0.012	0.161**	
			(0.049)	(0.075)	(0.051)	(0.075)	
Vocational education			0.134**	0.555***	0.028	0.553***	
			(0.053)	(0.078)	(0.070)	(0.079)	
Bachelor's degree			0.451***	0.690***	0.226***	0.690***	
			(0.059)	(0.088)	(0.083)	(0.088)	
Master's and higher			0.566***	0.778***	0.291***	0.779***	
			(0.058)	(0.084)	(0.087)	(0.084)	
Managers and higher					0.570***		Labor market characteristics
					(0.070)		
Professionals					0.448***		
					(0.041)		
Technicians					0.283***		
					(0.035)		
Clerks					0.217***		
					(0.050)		
Service & sales workers					0.107***		
					(0.031)		
Skilled agric. workers					-0.137**		
					(0.062)		

Craft workers					0.197***		
					(0.032)		
Operators & assemblers					0.103***		
					(0.037)		
Agriculture					-0.149***		
					(0.057)		
Education					-0.0688*		
					(0.036)		
Public administration					-0.028		
					(0.036)		
Trade					-0.242***		
					(0.037)		
Other industry					0.023		
					(0.027)		
Marriage status		-0.183***		-0.278***		-0.279***	Excl. var.
(married =1)		(0.037)		(0.043)		(0.043)	
Constant	6.864***	0.530***	6.518***	-0.456**	6.357***	-0.456**	
	(0.052)	(0.087)	(0.141)	(0.203)	(0.207)	(0.203)	
athrho		-0.132		-0.019		0.112	
		(0.110)		(0.130)		(0.308)	
lnsigma		-0.449***		-0.524***	-0.567***	-0.567***	
		(0.015)		(0.013)	(0.020)	(0.020)	
Observations	9044	9044	9044	9044	9044	9044	

Source: Author's elaboration based on LFS 2019.

*Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. Standard errors given in parentheses. Results robust to heteroscedasticity. Survey weights were used accordingly.*

To roll out this issue I used an alternative approach that also accounts for the selection bias. Namely, I applied the so-called multiple imputations technique that is usually used to solve missing data issues. Using bayesian approach the method allows to simulate missing data based on the observed sample data.[5]

After performing multiple (50) imputations procedure on 2019 LFS data, I estimated the raw and adjusted gender pay gaps (Table 4). The gaps showed a familiar pattern: it increased with the addition of characteristics compared to the raw value. Also, the gap was generally lower than the gap calculated with the original data (column 4), meaning there could be a selection bias. Namely, the result meant the women with better characteristics often do not participate in labor market. Nevertheless, the gap never significantly moved away from the value of -0.2. The adjusted gap fluctuated around that value regardless the calculation techniques I used. This meant that the adjusted pay gap estimate was robust trustworthy.

Table 4. Gender pay gap estimate with the imputed data.

	Raw	**Personal**	**Personal and labor market**	**ALL**	
	(1)	**(2)**	**(3)**	**(4)**	
Gender	-0.143***	-0.177***	-0.153***	-0.156***	
(Female = 1)	(0.018)	(0.017)	(0.018)	(0.018)	
Age		0.00753	0.0051	0.00505	Personal characteristics
		(0.005)	(0.005)	(0.005)	
Age sq.		-0.000127**	-0.0001	-0.0001	
		(0.000)	(0.000)	(0.000)	
Secondary, high school		0.042	0.0141	0.0162	
		(0.041)	(0.041)	(0.041)	
Vocational education		0.102**	0.0133	0.0121	
		(0.041)	(0.043)	(0.043)	
		0.439***	0.250***	0.247***	

[5] For a detailed explanation of the technique check Allison P. (1999)

Bachelor's degree		(0.046)	(0.051)	(0.051)	
Master's and higher		0.531***	0.317***	0.316***	
		(0.045)	(0.051)	(0.051)	
Managers and higher			0.397***	0.385***	Labor market characteristics
			(0.062)	(0.062)	
Professionals			0.369***	0.359***	
			(0.039)	(0.039)	
Technicians			0.247***	0.237***	
			(0.035)	(0.035)	
Clerks			0.189***	0.179***	
			(0.050)	(0.050)	
Service & sales workers			0.103***	0.0943***	
			(0.030)	(0.030)	
Skilled agric. workers			0.0526	0.0413	
			(0.054)	(0.054)	
Craft workers			0.151***	0.152***	
			(0.031)	(0.031)	
Operators & assemblers			0.118***	0.110***	
			(0.035)	(0.035)	
Agriculture			-0.122**	-0.0966*	
			(0.055)	(0.056)	
Education			-0.0685*	-0.0657*	
			(0.036)	(0.036)	
Public administration			-0.0133	-0.00344	
			(0.036)	(0.036)	
Trade			-0.237***	-0.228***	
			(0.037)	(0.037)	
Other industry			-0.00995	0.00256	
			(0.027)	(0.027)	
				0.0474**	

Permanent job contract				(0.024)	
Constant	6.669***	6.442***	6.432***	6.352***	
	(0.116)	(0.107)	(0.112)	(0.116)	
Observations	9,044	9,044	9,044	9,044	

Source: Author's elaboration based on LFS 2019.

*Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. Standard errors given in parentheses. Results robust to heteroscedasticity. Weights used accordingly.*

Lastly, I decomposed the gap by different percentiles. Up to this point, I have been looking into the average gap across all income groups. To further explore the nature of the pay gap I performed a quantile decomposition of the gender pay gap and analyzed it for different levels (deciles) of income. Apparently, gender pay gap was not monotonous. Moreover, it showed an upward trend when moving to higher deciles (Table 6). Note, that the last two deciles obtained the highest adjusted pay gap estimates. This suggested that women experience tougher times when moving up to higher income levels.

Table 5. Quantile regression by decile, original data

	0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**0.99**
Gender	-0.196***	-0.227***	-0.292***	-0.289***	-0.282***	-0.302***	-0.286***	-0.265***	-0.345***	-0.395***
	(0.030)	(0.020)	(0.020)	(0.021)	(0.022)	(0.022)	(0.022)	(0.026)	(0.031)	(0.038)
Age	0.00359	0.00935	0.00988*	0.0142**	0.0110*	0.0184***	0.0208***	0.0245***	0.0174*	0.0131
	(0.008)	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.008)	(0.010)	(0.009)
Age sq.	-0.0001	-0.0006**	-0.0006**	-0.0002***	-0.0002**	-0.0003***	-0.0003***	-0.0003***	-0.0004**	-0.0002*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
S/H sch.	0.064	0.120**	0.108**	0.111**	0.103*	0.0587	0.0729	-0.168	-0.0409	-0.0114
	(0.095)	(0.059)	(0.052)	(0.049)	(0.058)	(0.058)	(0.059)	(0.150)	(0.051)	(0.115)
Voc. edu	0.142	0.191***	0.158***	0.188***	0.186***	0.142**	0.173***	-0.0941	-0.0101	0.0154

	(0.095)	(0.058)	(0.053)	(0.052)	(0.059)	(0.060)	(0.060)	(0.151)	(0.052)	(0.116)
Bach dgr	0.460***	0.484***	0.471***	0.477***	0.487***	0.446***	0.480***	0.261*	0.363***	0.532***
	(0.101)	(0.064)	(0.064)	(0.053)	(0.067)	(0.069)	(0.060)	(0.158)	(0.084)	(0.180)
MA +	0.506***	0.551***	0.550***	0.576***	0.596***	0.582***	0.616***	0.400***	0.562***	0.778***
	(0.098)	(0.058)	(0.056)	(0.052)	(0.065)	(0.060)	(0.063)	(0.151)	(0.050)	(0.168)
Const	5.845***	5.990***	6.252***	6.308***	6.475***	6.550***	6.607***	6.943***	7.390***	8.110***
	(0.189)	(0.136)	(0.126)	(0.142)	(0.144)	(0.133)	(0.140)	(0.221)	(0.211)	(0.203)
Observ.	6,372	6,372	6,372	6,372	6,372	6,372	6,372	6,372	6,372	6,372

Source: Author's elaboration based on LFS 2019.

A similar analysis was performed with the imputed data to account for women's self-selection bias. Here again the estimated gaps were slightly lower than those for the original data, the pattern across different deciles, however, was very similar (Table 7). In both cases the adjusted gender pay gap was relatively low for low deciles. Although the gap showed some decline in the upper middle deciles, it ultimately grows for the higher decile. This was a good sign for the so-called "glass ceiling" phenomenon. Apparently, women in Armenia experience tougher when reaching the top of the career ladder.

Table 6. Quantile regression by decile, imputed data

	0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**0.99**
Gender	-0.123***	-0.140***	-0.190***	-0.207***	-0.208***	-0.203***	-0.202***	-0.189***	-0.219***	-0.318***
	(0.029)	(0.022)	(0.022)	(0.019)	(0.020)	(0.023)	(0.022)	(0.025)	(0.036)	(0.052)
Age	0.00102	0.00391	0.00311	0.00657	0.00748	0.0117*	0.0147**	0.0156**	0.0129	-0.00423
	(0.009)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.007)	(0.010)	(0.014)
Age sq.	-0.00004	-0.00007	-0.00007	-0.00011	-0.00012	-0.00018**	-0.0002***	-0.00022**	-0.0002*	0.00004
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
S/H sch.	0.0473	0.0691	0.0736	0.0591	0.0685	0.0646	0.0437	-0.0347	-0.0267	0.0369
	(0.078)	(0.059)	(0.051)	(0.048)	(0.059)	(0.051)	(0.052)	(0.097)	(0.064)	(0.162)

Voc. edu	0.131*	0.140**	0.123**	0.116**	0.120**	0.124**	0.103*	0.00603	-0.00624	0.0708
	(0.079)	(0.061)	(0.051)	(0.050)	(0.061)	(0.051)	(0.054)	(0.097)	(0.064)	(0.165)
Bach dgr	0.465***	0.469***	0.449***	0.449***	0.464***	0.425***	0.414***	0.394***	0.353***	0.540***
	(0.084)	(0.065)	(0.059)	(0.048)	(0.065)	(0.062)	(0.056)	(0.105)	(0.083)	(0.186)
MA +	0.495***	0.518***	0.530***	0.506***	0.518***	0.539***	0.526***	0.514***	0.543***	0.719***
	(0.081)	(0.062)	(0.057)	(0.053)	(0.067)	(0.054)	(0.060)	(0.103)	(0.064)	(0.202)
Const	5.746***	5.941***	6.212***	6.321***	6.462***	6.526***	6.621***	6.847***	7.229***	8.226***
	(0.175)	(0.130)	(0.128)	(0.121)	(0.136)	(0.138)	(0.134)	(0.176)	(0.208)	(0.320)
Observ.	9,044	9,044	9,044	9,044	9,044	9,044	9,044	9,044	9,044	9,044

Source: Author's elaboration based on LFS 2019.

3 Methodology

When estimating the gap, I assumed the coefficients of the covariates were the same for males and females. If I could estimate the gender-specific coefficients using 2019 data I would be able to assess which part of the gap was caused by the differences in mean characteristics and which part of it was determined by differences in returns. Moreover, I would be able to check whether the differences in group characteristics between the years could contribute to the changes in the gap values. A proper decomposition would allow me to assess the role of each the characteristics as a possible channel for the gap change.

Technically at the first stage of my analysis I wanted to perform something similar to Blinder-Oaxaca (BO) decomposition. The method was offered in 1973 by Blinder and Oaxaca in their respective publications. It allows to decompose the difference in mean outcome values for the specified mutually exclusive groups of a sample.

I was particularly interested in applying this technique because of the data limitations. When I looked into the relevant historical data, I found the first Armenian labor force survey was published in 2014. Although the LFS offered highly detailed and consistent data that would allow me to perform an in-depth analysis, the gap was already relatively static back in 2014 (Figure 1). Before that date Armenian National Statistical Service had released two Population Censuses in 2001 and 2011 (for 2000 and 2010, respectively). I managed to get access to the data by requesting it from IPUMS International[6]. Although those were huge individual-level surveys, covering around 10% of Armenian population, the biggest drawback was the absence of personal wages or earnings[7]. Nevertheless, the data contained the individuals' personal and labor market characteristics in compatible formats, mostly. Hence, I could observe the mean

[6] IPUMS International Harmonized Census Data for Social Science and Health Research database (https://international.ipums.org/international/index.shtml)
[7] From now on, I will focus on 2001 census only because the gap became static starting from the year of 2010.

gender pay difference and the mean differences in characteristics for 2000. In those circumstances BO approach was appropriate to apply.

BO decomposition itself has a number of variations, and the general idea is the following. Let us have a linear model $LHW = X'\beta + \varepsilon$ and two mutually exclusive values of a variable (*M* and *F*). Also, let the model of outcomes be separable in observed and unobserved characteristics. Then we define the gap by

$$\Delta\, LHW = Y_M - Y_F \tag{5}$$

where $LHW_i = X_i{}'\beta_i + \varepsilon_i \; and \; E(\varepsilon_i) = 0, i = M, F.$

Using (5) I rewrite:

$$\Delta\overline{LHW} = \bar{X}'_M\hat{\beta}_M - \bar{X}'_F\hat{\beta}_F \tag{6}$$

where $\overline{LHW}$ and $\bar{X}'$ are the respective mean values and $\hat{\beta}$ is the least squares estimator for β. The common BO technique suggests to rewrite (6) in the following manner:

$$\Delta\overline{LHW} = (\bar{X}_M - \bar{X}_F)'\hat{\beta}_F + \bar{X}'_F(\hat{\beta}_M - \hat{\beta}_F) + (\bar{X}_M - \bar{X}_F)'(\hat{\beta}_M - \hat{\beta}_F) \tag{7}$$

In equation (7) $(\bar{X}_M - \bar{X}_F)'\hat{\beta}_F$ is usually called endowments, as it is the part explained by the difference in the respective covariates. $\bar{X}'_F(\hat{\beta}_M - \hat{\beta}_F)$ is the coefficient effect – the part explained by the difference in the respective coefficients. $(\bar{X}_M - \bar{X}_F)'(\hat{\beta}_M - \hat{\beta}_F)$ is the mixed or interaction part accounting for the both coefficient and endowment group differences at the same time. Equation (7) represent the so-called “threefold decomposition”.

Alternatively, to demonstrate how much one is overvalued or undervalued compared to another one, researchers usually use the so-called “twofold decomposition”. In the latter, a reference coefficient vector is introduced, which is usually called as a "non-discriminatory" coefficient vector. A typical twofold decomposition looks like the following:

$$\Delta\bar{Y} = (\bar{X}_M - \bar{X}_F)'\hat{\beta}_R + \bar{X}'_M(\hat{\beta}_M - \hat{\beta}_R) + \bar{X}_F{}'(\hat{\beta}_R - \hat{\beta}_F) \quad (8)$$

where $\hat{\beta}_R$ is the so-called "non-discriminatory" vector.

In equation (8) $(\bar{X}_M - \bar{X}_F)'\hat{\beta}_R$ is the part that is explained by the group differences in the values of covariates – the explained part. $\bar{X}'_M(\hat{\beta}_M - \hat{\beta}_R) + \bar{X}_F{}'(\hat{\beta}_R - \hat{\beta}_F)$ is then the unexplained part and is analogical to the coefficient effect of the threefold decomposition. The unexplained part itself consists of two components: each describes how much each of the groups is under or overvalued. Now, there is a big amount of literature dedicated to the problem of how exactly $\hat{\beta}_R$ should be evaluated. The estimate of $\hat{\beta}_R$ is important because it describes how each of the groups are treated by the society. From the point of view of this paper, I am not interested in the process of evaluation of $\hat{\beta}_R$. The question how much a group is overvalued or undervalued is of lesser importance to me. I am rather interested in the difference itself.

Hence, I decomposed 2019 gender pay gap in the following manner:

$$\Delta\overline{lhw} = (\bar{X}_m - \bar{X}_f)'\hat{\beta}_m + \bar{X}'_f(\hat{\beta}_m - \hat{\beta}_f) \quad (9)$$

where $\Delta\overline{lhw} = \overline{lhw_m} - \overline{lhw_f}$ is the difference in mean log hourly wages by gender; $\bar{X}_i = (1\ ,\ \overline{age_i}\ ,\ \overline{age\ sq._i}\ ,\ \overline{edu_i}\ ,\ \overline{ind_i}\ ,\ \overline{occ_i})$ is the vector of mean covariates (age, square of age, education level, industry and occupation, respectively), *i* = *m*, *f*; $\hat{\beta}_i = \left(\widehat{const}._i\ , \hat{\beta}_{age,i}\ , \hat{\beta}_{age\ sq.,i}\ , \hat{\beta}_{edu,i}\ , \hat{\beta}_{ind,i}\ , \hat{\beta}_{occ,i}\right)$ is the vector of least square estimate of gender-grouped regressions, *i* = *m*, *f* stands for males and females subgroups respectively.

Technically, in equation (9) males were treated as the reference category, which fits the gender gap definition by Blau and Kahn (2003). Conventionally, I called $(\bar{X}_m - \bar{X}_f)'\hat{\beta}_m$ and $\bar{X}'_f(\hat{\beta}_m - \hat{\beta}_f)$ as endowment and coefficient effects, respectively.

Equation (9) is a snapshot for a year. I could write the same equation for the year 2000. I could not estimate coefficients for 2000 because of data limitations, I could obtain mean values for the dependent and independent variables[8]. Consider the following equation:

$$\Delta\overline{lhw}^* = (\bar{X}_m{}^{2000} - \bar{X}_f{}^{2000})'\hat{\beta}_m{}^{2019} + \bar{X}'_f{}^{2000}(\hat{\beta}_m{}^{2019} - \hat{\beta}_f{}^{2019}) \qquad (10)$$

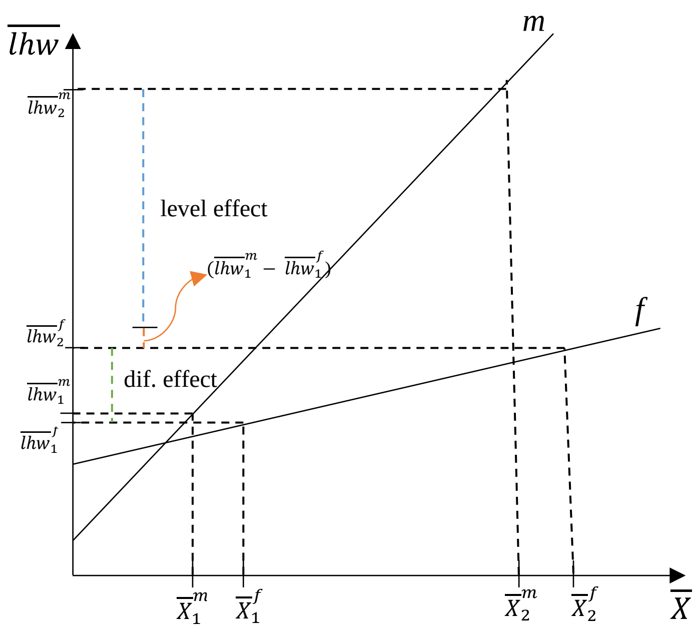
Equation (10) allows to estimate the value of 2000 gap if the characteristics had the same returns as in 2019. I then could compare $\Delta\overline{lhw}^*$ with the actual average log hourly wage gap of 2000 and see if differences in mean characteristics over years could contribute to the evolution of the gap.

I started to replace 2019 mean covariates with the respective values from 2000 one at a time. By doing so I could estimate each characteristic's impact separately first. It is important to note there are two effects that stay behind of any shift in the gap. To illustrate those effects, I depicted the simplest case two-dimensional case in Figure 5. The graph depicts the situation similar to the case in this paper: $\widehat{const.}_f$ > $\widehat{const.}_f$, $\hat{\beta}_m$ > $\hat{\beta}_f$, $\bar{X}_m$ > $\bar{X}_f$. Note that the value of the gap can change both as a result of changes in the mean covariate gap and the change in the levels of the covariates themselves. The same covariate gap results in a bigger pay gap for higher covariate values. Let $(\overline{lhw}_1^m$ - $\overline{lhw}_1^f)$ – $(\overline{lhw}_1^m - \overline{lhw}_2^f)$ be "difference effect" and $(\overline{lhw}_1^m$ - $\overline{lhw}_1^f)$ – $(\overline{lhw}_2^m - \overline{lhw}_2^f)$ be "level effect". Generally, both effects take place as shown in Table 7 (columns 7 - 9). On one hand, the characteristics gap is more in the favor of

[8] For the year of 2000 I could obtain log of the mean wage per gender on the contrary to the mean of the log wages in case of 2019. For 2019

men in 2000, forcing the gap to increase. On the other hand, the levels of the mean values are lower, which in turn shrinks the gap.

Figure 5. Difference and level effects of the replacement



The replacement procedure must be accomplished with the estimation of $\Delta\overline{lhw}^*$. As a result, I could learn whether the change in characteristics were responsible in the decline of the gap, and which of those contributed the most.

4 Decomposition, replacement, results

To evaluate model (9) I separately estimated OLS models for each group of the dependent variables (males and females) for the year of 2019. The results are given in Table 7 (columns 1-6). Although there was around 21% gender pay gap (in favor of males) in 2019, females outperformed their "counterparts" with all listed characteristics (Table 7, column 6). Expectedly, the coefficients had to be in favor of men in such circumstances (Table 7, column 3). Although, females developed their advantages over the years, they outperformed males even in 2000 (Table 7, columns 6 and 9).

Table 7. Mean covariates and betas by gender

	2019 Coefficients			**2019 Mean char. values**			**2000 Mean char. values**		
	Male	Female	Delta	Male	Female	Delta	Male	Female	Delta
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Age	0.0291***	0.0023	0.027	40.59	42.37	-1.78	38.03	39.39	-1.36
	(0.0077)	(0.0078)							
Age sq.	-0.0004***	-0.0001	0.000	1798.73	1945.32	-146.59	1607.71	1681.43	-73.71
	(0.0001)	(0.0001)							
Education	0.0963***	0.123***	-0.027	3.02	3.38	-0.36	2.58	2.73	-0.15
	(0.0128)	(0.0142)							
Industry	0.0626***	0.0137*	0.049	4.07	4.23	-0.16	3.17	3.23	-0.06
	(0.0072)	(0.0082)							
Occupation[9]	0.0510***	0.0421***	0.009	4.44	5.59	-1.15	-	-	-
	(0.0061)	(0.0068)							
Constant	5.371***	5.711***							
	(0.1520)	(0.1670)							

[9] Here I reversed the order of occupation values in LFS to make the results more tractable. In this model the rank increases for the higher values of occupation.

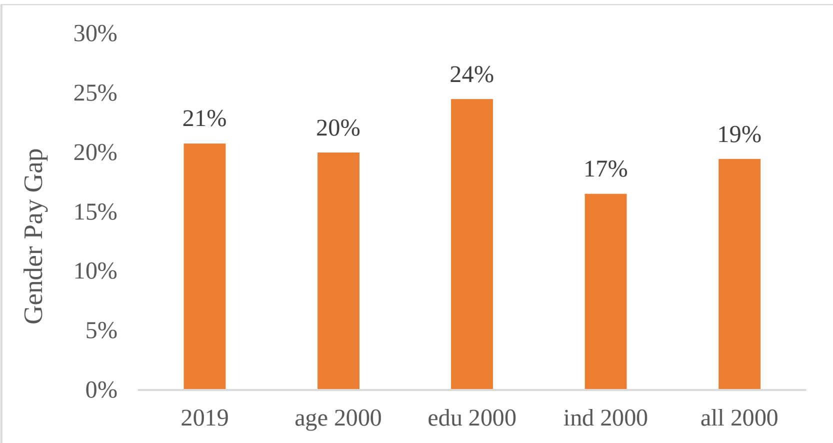
Observations	3512	2860		3512	2860		45664	37540	
R-sq.	0.1660	0.1640							
log h wage[10]				6.60	6.39	0.21	5.11	4.65	0.46
log m wage				11.90	11.46	0.43	10.30	9.65	0.66

Source: Author's elaboration based on LFS 2019 and Census 2001.

*Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. Standard errors given in parentheses. Results robust to heteroscedasticity. All weights were used accordingly.*

Finally, I decomposed 2019 gap as suggested in equation (5). Indeed, none of 2019 gap could be "covered" by the endowment effect and vice versa – the coefficient effect had the biggest impact on 2019 gap (Table 8). I then performed the replacement procedure for each of the covariate separately and estimated the corresponding effects on the pay gap (Figure 6). It turns out that change in education had the most significant effect on the gap change. Namely, by replacing 2019 education mean covariates with their counterparts from 2000, the gap increased by 3 percentage points. For the rest characteristics the picture is the opposite.

Figure 6. Replacement effects on the gender pay gap



Source: Author's elaboration based on LFS 2019 and Census 2001.

[10] I could only observe average monthly wage for the year of 2000. I used 2019 proportions to make a transition from average monthly wages to average hourly wages. Then from average hourly wages I made a transition to average log hourly wages.

Even though the differences in characteristics were more in favor of males back in 2000 compared to 2019, their levels were lower (Table 7). Eventually, the level effect prevailed and the gap decreased when all 2019 characteristics were replaced. The results showed that the coefficient effect failed to catch up, resulting in decrease of the gap, except for the case of education. (Table 9). To allow the gap to increase for the given 2000 endowments, the coefficient gap in 2000 had to be bigger that the one I estimated for 2019 (equation 9).

Table 9. 2000 years' mean covariates impact on 2019 hourly pay gap

	Male	**Female**	**Gap**	**Endow.**	**Coef.**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
$lhw_{2019\ actual}$	6.60	6.39	0.21	-0.10	0.30
lhw_{2019} with 2000 age	6.60	6.40	0.20	-0.11	0.31
lhw_{2019} with 2000 education levels	6.56	6.31	0.24	-0.08	0.32
lhw_{2019} with 2000 industries	6.54	6.38	0.17	-0.09	0.25
lhw_{2019} with 2000 mean covariates[11]	6.50	6.31	0.19	-0.09	0.28
lhw_{2000} actual (estimated)	5.11	4.65	0.46	-	-

Source: Author's elaboration based on LFS 2019 and Census 2001.

In this framework the result hinted, that the evolution of the gap is driven by changes in the return gap between males and females. It is important to note, however, that the results did not necessarily imply that the gap dynamics is only explained by gender-based discrimination in Armenian labor market. The variables were aggregated enough to allow for possible heterogeneities inside themselves. Thus, it is possible that males and females were obtaining different types of education back in 2000s, or they were performing different duties at their workplaces. This could explain the change in the values of betas over years. In addition, there could be a number of unobserved variables, that affected the wages. And last but not least, it is

[11] here 2019 mean covariates of occupations are applied in the calculation, because the respective data for 2000 is not available

possible that the labor market started to treat them more evenly, causing the gap to decrease over time.

5 Conclusion

To conclude, gender pay gap in Armenia significantly dropped since early 2000s. However, the gap somewhat stabilized since a decade ago and is still very significant (20%). The gap cannot be explained by the aggregated personal and labor market characteristics, as females in Armenia outperform males with those. Moreover, the evolution itself cannot be explained by changes in those characteristics. Only difference in education levels could partially cover the declining dynamics. Apparently, social norms and prejudices are the reason why the gap is so persistent in Armenia. Probably, females back in 2000s were more focused in obtaining "feminine" professions and gender-based segregation in workers' duties was larger. A decline in discrimination could also explain the evolution of the gap in Armenia. Most probably, both took place in reality: females are now treated more evenly by the labor market and their choices became more profit-driven. To enable further decrease of the pay gap, Armenian authorities should rather focus on the correction of social norms, because females in Armenia never suffered from limited education access or discrimination in labor force participation.

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