Female Labour Participation, Economic Growth and Pay Inequality: Empirical Evidence for Some OECD Countries

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Abstract

This study examines empirically the relationship between women's labour force participation, economic growth and pay inequality in the 16 OECD member countries with available data for the 2000-2012 period by using macro panel approach. The study applies unit root test under cross sectional dependence, panel cointegration and the Pooled Mean Group Estimation (PMGE). The study finds a long-run co-integrating relationship between growth, women's labour force participation and pay inequality for the OECD countries. The results show that women's labour force participation reduce pay inequality in the OECD counties. The study also suggests that economic growth raises differences between men and women's pay inequality in the labour market.

Keywords: Women's employment, gender wage gap, growth, panel co-integration, PMGE.

JEL Classification: C-23, J-21. J-31, O-50

1. Introduction

In recent years, women's relatively increased participation in the labor market and the resulting impact of growth on income distribution and their impact on wage inequality have been discussed by researchers extensively[2]. "Long-held beliefs that women's entry into waged labour has emancipatory potential may have to be re-evaluated, at least until current labour market conditions, are challenged"(McDowell, 1991:401). At the same time with feminization of works, women begin to fit into conditions required in new male labor markets. Women start to be involved in labor markets owing to economic growth and development both in developed and developing countries. Nevertheless more women increasingly began to work in low quality and low productive jobs. Despite the 1970 Equal Pay Act, "equal pay for equal

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[2] Gender pay gap is used a measure of unequal pay for women compared to men. In the OECD countries, the gender wage gap, defined as the difference between male and female median wages divided by male median wages, is estimated at 16 percent (OECD 2012).

work" without due consideration of social gender, gender pay gaps still persist in almost all OECD countries. In many OECD countries the wage gap between men and women ranges from 10 to 20 percent. The highest gap is 27.7 % in Japan and 18.4% in Germany. It is also higher in USA (18.8%) and UK (18.4%). In eastern European countries like Hungary (6.4%) and Poland (6.2%), there has been a significant decline in wage disparity. Women who are working in the highest wage earners category, in most OECD countries earn 21% less compared to their men counterparts. This condition in which women are being hampered from advancing to their highest earning career is called "glass ceiling". The term "ceiling" at the same time is used to indicate the very low rate of women working in top management positions (OECD, 2012:85). In most of the OECD membership, female employment is deepened in the services sector, which accounts for 80 percent of employed women, compared to 60 percent for men (Elborgh-Woytek and et al.,2013). ILO (2010) finds that women are extreme-densitied in sectors that are qualified by low status and pay.

Feminist economists put forth two integrated hypothesis called "crowding" and "discrimination" in order to explain the wage gap between men and women (Becker, 1971 and Treiman and Hartmann, 1981). Increase in women labor supply due to the limitedness and lack of new jobs, gives rise to gender discrimination towards women. This discrimination largely takes place where women work in secondary positions and the wage discrimination that prevails. Furthermore, movement towards high paying jobs is farfetched. In a study by Berik et al. (2009) and Seguino (1997), one of the reasons for this is because of the patriarchal norms that are embedded in cultural, political, legal and economic institutions. Due to this, in many countries women employment is determined by accepted patriarchal norms regarding women's gender roles. On the other hand, according to socialist feminists participation of women in the labor market are identical to the subsequent expansion of the "surplus population" or "reserve army of the unemployed" as theorized by Marx. And this expansion is able to suppress wages in sectors where women work intensively (İzdeş, 2010:142).

The impact of increase in participation rate of women in the labor market on wage inequality in developed and developing countries shows disparities[3]. It is evident that while higher women's labor force participation increases wage inequality in developing countries, it leads to a reduction in developed countries (Elveren, 2014). If the number of jobs which hire

[3] The labor force participation rate is defined as "the percentage of the working age population who are either working (the employed) or not working but actively searching for work (the unemployed)" (Juhn and Potter, 2006).

women is abundant, on account of the hypothesis of exclusion it leads to increasing wage inequality. Because of competition between women, this condition may result in suppression of wages downward. On the other hand, an increase in participation rate of women in the labor market affects men wages and gives way to equality. However, this trend causes excessive real wages to go down to a lower equilibrium level. In countries where economic growth and development are at a higher level, preference of more educated labor is expected to play the role of alleviating wage inequality. Due to women's high education level, higher female labor force participation would result in more skilled work force and could provide an important rise to growth (Steinberg and Nakane, 2012).

Current studies show that gender wage gap can lead to higher economic growth and investments (Wolszczak-Derlacz, 2013). This study has examined the impact of economic growth and female labour participation on the gender wages gap in 16 OECD countries using a panel cointegration analysis for the 2000-2012 period. The remainder of this paper is presented as follows. Section 2 presents descriptive data and methodolgy. Section 3 lays out panel cointegration test and estimation and section 4 discusses the results of estimation.

2. Data and Methodolgy

In this study, the mutual relationship between female labour participation, economic growth and pay inequality in OECD countries between the years of 2000-2012 was analyzed. To analyze the relationship between gender wage gap, female labour participation and GDP per capita, the question of whether a cross-sectional dependency exists arose. After the cross-sectional dependency tests, unit root tests were used. Then, panel co-integration test was carried out to see whether there was a long-term relationship among the variables. Finally, to test whether there was a causal relationship among the variables, a panel causality test was performed. For panel cointegration analysis equation (1) is our empirical pay inequality.

$$lnGG = \alpha_i + \delta_{it} + \beta_{1i} lnGDP + \beta_{2i} lnLFP + \varepsilon_{it} \tag{1}$$

where $i = 1,2, \dots N$ is the number of countries (N=16), $t = 1,2, \dots T$ is the time series dimension of the data (T=13), α_i are country-specific fixed effects and δ_{it} country-specific time trends[4]. The dependent variable, lnGG, is the gender wage gap as a proxy for the pay inequality, lnGDP variable is GDP per capita at constant US$ 2000 with PPP and lnLFP is

[4] Where appropriate the fixed effects parameter is extended to include deterministic time trends. The inclusion of country-specific fixed-effects and deterministic time trends allow us to capture any country-specific omitted variables assumed to be stable in the long term.

women's labour force participation rate. All the variables were gotten from the OECD Database, and the data of these countries were preferred according to their availability in the database. So, lack of data leads to a balanced panel data for only the 2000-2012 period for 16 countries. ε is the error term, β_1 and β_2 are parameters of interest to be estimated. To estimate equation (1), we have used a balanced dataset consisting of the 16 OECD countries: Australia, Austria, Bel, Can, CZE, DNK, FIN, GER, JPN, KOR, NZL, NOR, SWE, GBR, USA, HUN. Time series graph of variables are reported in Table A1 of Appendix. The data used in the study were as follows:

Table 1 Data Set

lnGG	Gender Wage Gap	OECD database
lnLFP	Female Labour Participation	OECD database
lnGDP	GDP Per Capita	OECD database

3. Panel Cointegration Tests and Estimation

3.1. Slope Homogeneity

The first issue in a panel data analysis is to test whether or not slope cefficients are homogenous in an empirical model. It does not allow us to capture heterogeneity due to country specific characteristics if the slope of homogeneity is assumed without any empirical evidences (Breitung, 2005). The $\tilde{\Delta}$ test was proposed by Pesaran and Yamagata (2008) for testing slope homogeneity in large panels. Under the null hypothesis of slope homogeneity with the condition of (N,T)→∞, so long as $\sqrt{N/T} \rightarrow \infty$ and the error terms are normally distributed, the $\tilde{\Delta}$ statistic follows an asymptotic standard normal distribution. The small sample properties of $\tilde{\Delta}$ statistic can be improved under the normally distributed errors by using a bias adjusted statistic (adj $\tilde{\Delta}$) suggested by Pesaran and Yamagata (2008).

Table 2 reports the results from the slope homogeneity tests of Pesaran and Yamagata (2008). Two different test statistics ($\tilde{\Delta}$, $\tilde{\Delta}_{adj}$) are -0.883 and -1.045, respectively, which also suggest a strong evidence to reject the null hypothesis of the slope homogeneity at 1% significance level.

Tablo 2. The Results of Slope Homogeneity

	Test Ststistics	P-value
$\hat{\Delta}$	-0.883	0.811
$\hat{\Delta}_{adj}$	-1.045	0.852

3.2. Panel Unit Root Test with Cross-section Dependence

Cointegration reflects a long term relationship between nonstationary data. Thus, we must first establish whether the pay inequality, GDP per capita and women's labour force participation rate are nonstationary, that is, integrated at least of order one. Before implementing the unit root tests, firstly we determined the cross-sectional dependence between variables. Panel studies that do not control for cross-sectional dependence among the countries can result in biased panel cointegration test results (Cerra and Saxena,2008). Cross-sectional dependency can be explained as a situation in which a shock occurs in units forming panels in terms of economics, then the other units of the panel are also affected by this shock. Pesaran (2007) finds that when cross-sectional dependence is high, the first-generation panel unit root tests tend to over-reject the null. In terms of econometrics, units forming panels are related to error terms in the panel data model, which is given in equation (2).

$$y_{it} = \propto_i + \beta_i x_{it} + \varepsilon_{it} \tag{2}$$

$$Cov(\varepsilon_i, \varepsilon_{ij}) \neq 0$$

There are various tests that analyze cross-sectional dependence in panel data. In this study, tests developed by Pesaran (2004), CD_{LM}, was used. Pesaran proposed a simple alternative test which is based on the pair-wise correlation coefficients when N is large (Pesaran, 2004:5).

The CD_{LM} test, which is to examine cross-sectional dependence, is calculated with the formula mentioned below:

$$CD_{LM} = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \rightarrow N(0,1) \tag{3}$$

CD statistic of Pesaran has mean zero for fixed values of T and N, where N indicates cross section dimension, T is time dimension of panel, $\hat{\rho}_{ij}$ represents the sample estimate of the cross- sectional correlations among residuals. This test, which is asymptotically standard normal distribution, is used when T>N and N>T. The null and alternative hypothesis of this test is similar to CD_{LM1} and LM_{LM2} test.

Under the null hypothesis defined by,

$H_0: \rho_{ij} = \rho_{ji} = cor(\varepsilon_{it}, \varepsilon_{jt}) = 0, i \neq j$ (there is no cross-section dependence)

(4)

$H_1: \rho_{ij} = \rho_{ji} \neq 0, i \neq j$ (there is a cross-section dependence)

Table 2 presents the results for the CD_{LM} test. We can reject the null hypothesis of cross-sectional independence at %5 level. We conclude that, for any reason, if there is any shock related with gender wage gap, GDP per capita and labour female participation rate in any country, then the other countries will be affected.

Table 2. Result of Pesaran (2004) Cross-section Dependence Test

	CD_{LM}	*Absolute Correlation*
lnGG	18.46***	0.500
lnGDP	35.14***	0.890
lnLFP	12.60***	0.628

The null hypothesis of CD test is cross section independence, CD ~ N(0.1). *** denotes significant at 1 per cent level.

Therefore, it is required to use the second generation unit root test and panel co-integration analysis which take the cross sectional dependence into consideraion. Otherwise, the results will be biased. The Cross-sectionally Augmented Dickey-Fuller (CADF) test of Pesaran (2007) can be used as a unit root test under the cross-section dependence. The null hypothesis assumes that all series are non-stationary. The null and alternative hypothesis of the CADF test are presented below:

$H_0: \beta_j = 0$

(5)

$H_1: \beta_j < 0 \quad j = 1,2, \dots N_1; \ \beta_j = 0, j = N_1 + 1, N_1 + 2, \dots N$

where N indicates number of cross sections. CADF regression is shown below Pesaran(2007):

$$\Delta Y_{it} = a_i + b_i Y_{i,t-1} + c\bar{Y}_{i,t-1} + d_i \Delta \bar{Y}_t + \varepsilon_{it} \qquad (6)$$

where $\bar{Y}_t = \frac{1}{N} \sum_{i=1}^{N} Y_{i,t}$, $\Delta \bar{Y}_t = \frac{1}{N} \sum_{i=1}^{N} \Delta Y_{i,t}$, and $\varepsilon_{i,t}$ is the regression error. The computed test statistics needs to be compared with Pesaran (2007:280-281) table values (table IIb and Table IIc). Regression (6) above is a standard Dickey Fuller regression augmented with the lagged level and the first difference of the cross-section average of the individual time series. Adding one lag, the above test regression (6) is modified as follows (see equation (54), Pesaran, 2007, p. 283):

$$\Delta y_{it} = a_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + \sum_{j=0}^{p} d_i \,\Delta \bar{y}_{t-j} + \sum_{j=1}^{p} \delta_{ij} \Delta y_{i,t-j} + \varepsilon_{it} \qquad (7)$$

This is the CADF regression including one lag. The unit root null hypothesis is as above. From equation (6) or (7), we obtain the individual CADF statistics and calculate their simple average, thus obtaining the CIPS (cross-sectionally augmented IPS) statistic. This statistic is a modification to the t-bar (IPS) statistic proposed by Im et al. (2003) being calculated as a simple average of the individual CADF statistics.

The Pesaran statistic, cross-sectionally augmented IPS (CIPS) is given by,

$$CIPS(N,T) = \frac{1}{N}\sum_{i=1}^{q} t_i\,(N,T)$$

where t_i constitutes statistics coming from each CADF model for each individual i of the panel. The exact critical values of the statistic are given by Pesaran (2007).

The results of the Pesaran (2007) panel unit root test with and without trend are both presented in Table 3 using three lag orders. For all three variables, the null hypothesis of the unit roots can not be rejected in level, except for lnLFP variable where the lag order is (0). These results indicate that the variables in level are non-stationary and stationary in first differences, with the exception of all variables with trend, with a lag order 1 and 2.

Table 3. Pesaran (2007) Panel Unit Root Test (CIPS) Results

Variable	Model without Trend			Model with Trend		
	$q = 0$	$q = 1$	$q = 2$	$q = 0$	$q = 1$	$q = 2$
Level						
lnGG	0.770	2.120	2.203	-1.056	0.673	-0.275
lnGDP	0.799	1.749	1.200	2.453	3.121	0.684
lnLFP	-3.589 ***	-1.635*	-0.073	-3.020***	-1.588*	-0.667
First difference						
lnGG	-3.529***	-2.114*	-2.330**	-3.346***	-1.883	1.700
lnGDP	-2.362**	-1.198	-1.700	-2.532	-1.216	1.700
lnLFP	-3.768***	-2.613***	-1.959	-3.969***	-2.554	1.700

Notes: ***; ** and * denote rejection of the null hypothesis of non-stationary at 1%, 5% and 10% levels of significance. The critical values are taken from Table II(b) and Table II(c) on page 280-281 in Pesaran (2007).

3.3.Westerlund Panel CointegrationTest

Westerlund (2007) developed four test statistics ($G_{\tau,}\ G_{\alpha}, P_{\tau} and\ P_{\propto}$) that are based on structural dynamics. A test was carried out to determine whether the null of no error correction can be rejected. If the null can be rejected, there is evidence in favor of cointegration. While two of the four panel tests are cointegrated ($H_A^P\colon \propto_i = \propto < 0\ for\ all\ i$), the other two tests are group-mean tests which test against the alternative hypothesis, that for at least one cross-section unit there is evidence of cointegration ($H_A^G\colon \propto_i < 0\ for\ at\ least\ one\ i$). For the group-mean test statistics, the error correction coefficient is estimated for each cross-section unit individually, and then two average satatistics (denoted G_t, respectively $G_\propto$) are calculated.

As indicated in Table 4, for the lnGG and lnGDP, the estimated values of the Westerlund (2007) panel cointegration test result shows that, the null hypothesis of no cointegration is strongly rejected for all the test statistics at 1% level. But the result of panel cointegration test between lnGG and lnLFP shows that only G_τ test statistics rejects the null hypothesis of no cointegration at 1% level, the rest of the test statistics fail to reject the null hypothesis with the asymptotic p-values (see Table 4). Nonetheless, we can say that lnGG and lnGDP and lnGG and lnLFP are cointegrated in OECD countries.

Table 4. Westerlund panel cointegration tests between lnGG and lnGDP

A. Statistic	Value	Z-Value	P-Value
G_t	-32.152	-148.403	0.000
G_a	-16.610	-2.833	0.002
P_t	-25.949	-20.380	0.000
P_a	-27.670	-12.533	0.000
Westerlund panel cointegration tests between lnGG and lnLFP			
B. Statistic	**Value**	**Z-Value**	**P-Value**
G_t	-15.363	-64.782	0.000
G_a	-12.640	-0.447	0.328
P_t	-6.331	2.470	0.993
P_a	-6.872	1.394	0.918

Notes: The Westerlund (2007) tests are implemented with lnGG as the dependent variables. The test regression is fitted with a constant and trend. The lag and lead lengths are selected as AIC due to small datasets and we set the width of the Barlett kernel to 2. In small datasets, the may be sensitive to the specific choice of parameters. The tests are performed using the Stata 13 with the "xtwest" command (Persyn and Westerlund, 2008).

3.4. Panel Cointegration Estimation: PMGE and MGE

The most widely used dynamic model for panel data is the first-order autoregressive distributed lag model (ARDL) with only a lagged dependent variable capturing the impact of current and lagged explanatory variables. The Pooled Mean Group Estimation (PMGE) and Mean Group Estiamation (MGE) methods calculate both long and short run parameters. MGE method proposed by Pesaran and Smith (1995) derives the long-run parameters for the panel from averages of the long-run parameters of ARDL models for individual unit. The PMGE method proposed by Pesaran et al. (1999) shows an intermediate estimator that allows the short-term parameters to differ between groups while imposing equality of the long-term coefficients between countries. The PMGE can allow the short-run dynamic specification to differ from country to country while making the long-run coefficients constrained to be the same. Pesaran et al. (1999) proposed an estimation of the following autoregressive distributed lag (ARDL) model of order (p_i,q_i):

$$\Delta y_{it} = \emptyset y_{it-1} + \beta_i x_{it} + \sum_{j=1}^{p_i-1} \delta_{ij}\, \Delta_{\mathrm{it-j}} + \sum_{\mathrm{j=0}}^{\mathrm{q_i-1}} \gamma_{\mathrm{ij}} \Delta \mathrm{x_{it-j}} + \alpha_{\mathrm{i}} + \varphi_{\mathrm{i}} \mathrm{t} + \varepsilon_{\mathrm{it}}$$

where y_{it} is the dependent variable, is a $m\,x1$ vector of explanatory variables, $\propto_i$ *and* φ_i represents the country-specific intercepts and time trend parameters respectively, δ_i *and* γ_i include the country-specific coefficients of the short-term dynamics, ε_{it} is a white noise error term. The long-run coefficients β are defined to be the same across countries. If $\emptyset_i$ is significantly negative, there exists a long-run relationship between y_{it} *and* x_{it}. The equation is then estimated using the maximum likelihood procedure to get the PMGE. This regression can also be estimated with individual specific β_i which are then averaged over N to obtain a MGE which is the natural background to test for the presence of slope homogeneity based on the Hausman test.

In Table 5, the prediction of the panel error correction with PMGE and MGE predictors is shown. The Hausman test statistic for choosing between the PMGE and MGE is equal to 0.31, indicating that PMGE is prefered as being more efficient under the null that the long-run coefficients are homogenous and do not cahnge according to the country. Table 5 shows that the PMGE long-run coefficients are in fact statistically significant at panel level for both labour female participation and GDP per capita. According to the PMGE resuls, the error correction coefficient is meaningful negative. This confirms the existence of a long term relationship between gender wage gap, labour female participation rate and GDP per capita.

Table 5 report for the OECD countries that the effect of economic growth on pay inequality is highly significant and the sign of the coefficient is positive. The finding shows that while rising GDP per capita causes higher pay inequality, rising labour female participation rate causes a decrease in pay inequality. A gender wage gap represent differences in productivity. In generally, women are significantly concentrated in occupations with low pay, such as those found in the service, commercial, healthcare and social care sectors. Wages in this occupations are low because these jobs are female dominated and these occupatios themselves are low-productive. The finding that rising national income causes higher pay inequality is a further input for a large body of literature that yields inconclusive results.

Table 5. Panel Cointegration Estimation: PMGE and MG

Long run results	**PMGE**	**MGE**
lnGDP	0.071*** [0.020]	-0.984 [1.102]
lnLFP	-1.567*** [0.142]	1.624 [3.237]
Error Correction Parameters	**-0.5063361*** [0.151]**	**-0.698*** [0.155]**
Short run result		
ΔlnGDP	-0.444 [0.558]	0.149 [0.574]
ΔlnLFP	2.090* [1.104]	0.534 [2.66]
Diagnostic tests		
Log-likellihood	303.5363	
Hausman Test	0.31 (0.8573)	

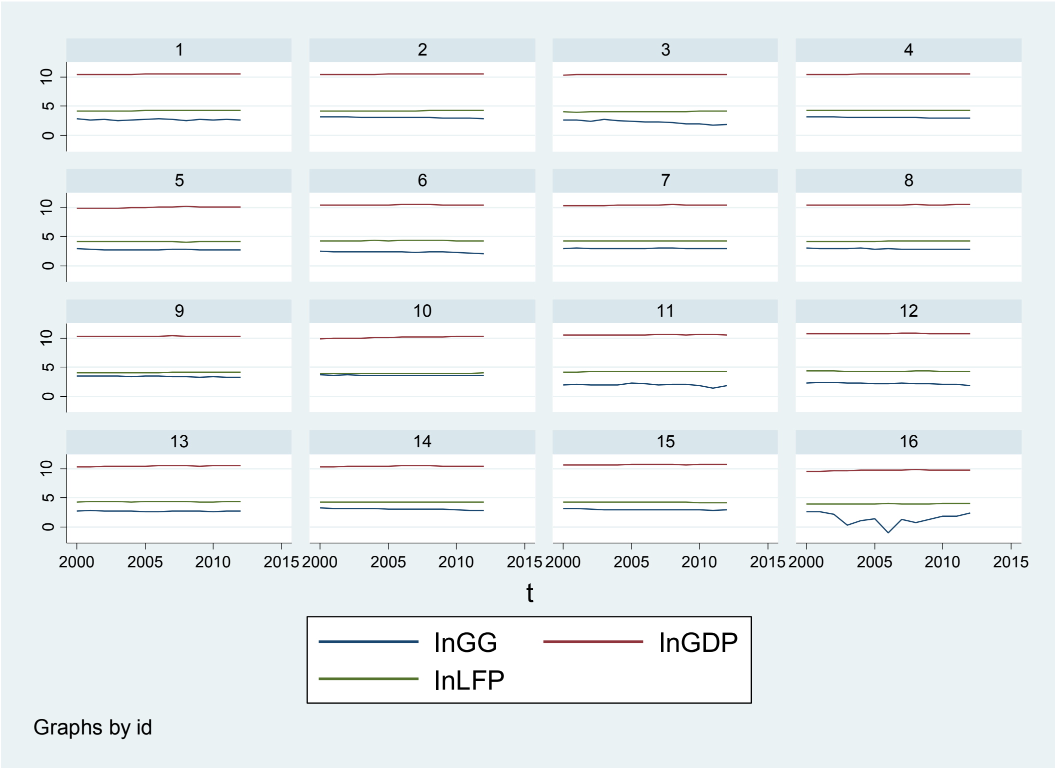
Notes: The values in the brackets denotes the standard error. For the Hausman Test, the p-values are reported in parenthesis. *** and * indicates significance at 1% and 10% level. Hausman test statistics; $H = \widehat{\beta}'\left[var(\widehat{\beta})\right]^{-1}\widehat{\beta} \sim X^2(n)$; $\widehat{\beta} = \beta_{PMG} - \beta_{MGE}$, here, is the difference vector between MG and PMG.

4. Conclusion

This study has examined the impact of economic growth and female labour participation on the gender wage gap in 16 OECD countries. Theoretical and empirical analysis failed in giving clear answers to the kind of relationship existing between these variables. This study tends to contribute more to this unexplored matter with an indication that women's labour force participation is an important determinant in reducing the male-female wage gap. The rate of increase in the number of female labour participation has helped stem the rise in inequality. Using sixteen OECD countries data sets covering 2000-2012, we found that economic growth raises differences between men and women pay inequality in the labour market. It means that gender pay inequality has persisted despite economic growth. The commentary for this differences between women and men are more of a consequence of patriarchal norms, traditions, family perceptions, discrimination, structures and legistation than of economic growth. These factors contribute to a traumatic level of economic inequality between women and men. The gender pay gap remains the most devastating norm of economic inequality for women today. As a result, women's freedom and increasing income cannot help the OECD countries narrow the gender pay gap.

APPENDIX

Table A1. Time series graph of variables (lnGG, lnLFP, lnGDP)



lnGG:Gender wage gap

lnLFP:Labour female participation rate

lnGDP: GDP per capita

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