



ACHIEVING GENDER EQUALITY IN LABOR FORCE PARTICIPATION RATES: WHAT OPTIONS DO POLICY MAKERS HAVE? LESSONS FROM USA, FINLAND AND SWEDEN

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Abstract: *The aim of the study is to develop a pool of policy variables (potential indicators) that can be used by policy makers to eliminate the gender gaps in labor force participation rates (LFPR) for the 15-64 age group (formal age group). Granger-causality was used to investigate the predictive power of selected macroeconomic policy variables on one hand and gender disaggregated LFPRs on the other using data from USA, Finland and Sweden. The variables investigated include: employment by sector and by gender, age/sex disaggregated total employment variables, total employment by group and overall total employment, total unemployment by age, unemployment for total and by gender with advanced, intermediate and basic education, monetary, foreign direct investment, savings, international trade, compensation by sector, health expenditure, government expenditure/revenue, gender wage gap for self-employment/total employment. The results showed that all the variables investigated have potential predictive power for gender disaggregated LFPR, therefore they all present potential*



entry points for addressing gender gaps in LFPRs for the 15-64 age groups. Policy interventions influencing these variables can be used to target desired changes in gender disaggregated LFPR. However, the causal relationships differ by country, specific variable considered, and whether causality is investigated for formal male or female LFPRs. These results imply that: i) policy measures for increasing the male LFPR may differ from those required for increasing the female LFPR; ii) the effect of gender dis-aggregated LFPRs on the policy variables may differ by gender and by country; and iii) that although all the variables investigated have the potential to predict gender disaggregated LFPR, no general theory can be developed regarding causal relationship between these variables and gender disaggregated LFPRs. It signals the need for practitioners/researchers investigating issues involving LFPR to: always establish the underlying causal relationships between LFPR and other variables to determine whether to use dynamic or non-dynamic approaches for their investigations; and to come up with appropriate policy intervention.

JEL classification: E23, C13, C39, E23, J01, J16, J21, L38

Key words: Granger causality relationships, gender disaggregated LFPR, macroeconomic policy variables, developed countries, indicator variables, endogeneity, exogeneity, predictive power

1. INTRODUCTION

The labor force participation rate (LFPR) measures the proportion of the adult population that is in the labor force, including those who are either working or looking for work. The LFPR for females (males) indicates the extent to which females (males) participate in economic activity. Labor force participation rates for women, the world over have been below those of men. Empirical studies have indicated that though female labor force participation rates (FLFPR) have increased over the years, they are still below those of their male (MLFPR) counterparts (Yakubu, 2010, OECD/ILO/IMF/World Bank Group report, 2014). This is still persistent in many economies even in the face of declining trends in male labor force participation rates. According to the OECD/ILO/IMF/World Bank Group report (2014), the global rate of female labor force



participation rose by over 2 percentage points while the male rate fell by nearly 5 percentage points since 1980, but with the female rate of 52% still lagging behind that of their male counterparts of about 77%.

While it is necessary to increase the labor force participation rates of women, it is also necessary to ensure that those for men do not fall below desirable levels. Women's economic activity should be increased to ensure their well-being as well as that of their off-springs, while that for men should be maintained to avoid the reversal of the discrimination towards the men. Both female and male labor should be used efficiently in the production process.

In a bid to attain gender equality in the labor market, several countries have adopted several policy variables that have been categorized by OECD/ILO/IMF/World Bank Group report (2014) into four categories including measures to: eliminate unequal treatment of men and women in the labor market; promote an enabling environment for gender equality in the labor market (good quality education, availability of part-time jobs, among others); make work pay, improve job quality and reduce informality; and to promote entrepreneurship. In reality, there are many variables that influence gender disaggregated LFPR and could be targeted to stimulate each category, thereby stimulating aggregate LFPR, thus the economic activity of both men and women and the wellbeing of the entire world. Many such potential policy variables exist yet their causal relationships with gender disaggregated LFPRs have hardly been studied, thus have not been targeted by policy makers. It is important to identify these potential variables which can be used by policy makers to achieve the desired increase in both female and male LFPR. These issues gave rise to the following research questions:

- i. What factors (mainly macroeconomic policy variables) predict aggregate/gender disaggregated labor force participation rates for the formal gender disaggregated employment (15-64 age group) categories and what are the causal relationships, are they uni-directional or bi-directional?
- ii. What lessons can other countries, including developing countries derive regarding the predictability power of macroeconomic policy variables over gender-disaggregated



LFPRs? And how can they be used as potential indicators for enhancing gender disaggregated LFPR.

Specifically, the study set out to determine the causal relationships between specific potential policy variables on one hand and gender disaggregated labor force participation rates for the formal employment groups on the other hand for three developed countries including USA, Finland and Sweden and to draw lessons from the findings.

Several hypotheses were tested including:

- i. The causal relationships for a specific policy variable differ for formal male and female LFPRs, and they may differ by country, implying no standard causal relationship for a specific policy variable with either formal female LFPRs and/or formal male LFPRs across countries. As a result, policy measures for increasing the male LFPR may differ from those required for increasing the female LFPR and the effect of gender disaggregated LFPRs on the policy variables may differ by gender and by country.
- ii. Aggregation of intervention variables and LFPRs may obscure key policy interventions required for addressing gender inequalities in the economic empowerment (measured by LFPR).
- iii. The total/sex disaggregated employment proportions as well as the corresponding compensations in the different sectors including the agricultural, service and industry sectors are potential indicators (may have potential predictive power) over both formal male and female LFPR but it may differ for each.

2. LITERATURE REVIEW

Researchers such as Darian (1976), Lahoti and Swamilathan (2016), Thamma-Apiroa (2016), among others, have revealed that LFPR can be influenced by the nature of employment, the age distribution of the entire population, age distribution of women, the education level, the wage rate, average family size, the income level, cost of living, the level of economic growth, marital status, the number of single parents, technology advancement, marital status, the amount of child



care in the economy- proportion of population below 18 years, dependency ratio, proportion of population 65+; unemployment rate, divorce rate, access to public health services which may be proxied by expectancy rate, death rate or infant mortality; mobility of the employee, population, sectoral decomposition of GDP, employment creation in the different sectors, among other factors.

Apart from GDP, there are several macroeconomic variables that influence and/or are influenced by aggregate and/or sex/age disaggregated LFPRs, but while these are potential policy variables that can be used to predict movements in LFPRs, this linkage is hardly covered in literature. This study intends to fill this gap and provide policy makers with potential entry points for enhancing LFPRs for both females and males.

3. METHODOLOGY/METHODS

The study applied the Granger-causality methodology (Granger, 1969, 1977) whereby a specific time series X Granger- causes another times series Y if the patterns in time series X can be used to forecast the behavior of Y after some time. This implies that past values of X can be used to predict future values of Y, since Y is expected to exhibit patterns similar to those in X after a time lag. Although the Granger-causality test should not be used to determine ‘true causality’ which is a philosophical “cause-effect” relationship, it can be used to determine “predictive causality” or alternatively referred to as “precedence” or “temporally related” relationships (see also Diebold, 2001). Thus, Granger causality is not used to test whether “X philosophically causes Y” but whether “X forecasts Y”, implying that prior values of X can be used to predict future patterns of Y. Precedence in this case means that the cause precedes the effects but cannot be applied to the contemporaneous values of X and Y and it was relevant since the test was originally not designed to test relationship between contemporaneous values since it uses prior values in one series to forecast future values in another time series, although new developments of the theory may cater these instantaneous effects in addition to non-linear causal relationships and latent confounding effects (Eichler, 2012).



For the purpose of this study, Granger-causality will be based on the original definition and will imply that “X causes Y” and/or vice versa whereby the term “causes” or “causality” will imply predictive or forecast power, thus “X predicts Y (or “X forecasts Y” and or vice versa). Several researchers have used this methodology, including but not limited to Foresti, 2006, Erdil and Yetkiner, 2009, Götz, Hecq and Smeekes, 2016, Gao et al., 2018).

The ability of X to forecast patterns in Y makes it a good candidate for policy intervention aimed at implementing changes in Y. This can be achieved by undertaking policy measures affecting the pattern in X in manner that mirrors the desired change in the pattern of Y. The pattern in Y is expected to change following the change in the pattern in X after a time lag. This makes Granger-causality testing a very useful tool for identifying policy variables (indicators) that can be used to achieve desired changes in particular variables of interest. Specifically, if variable X can be used to forecast changes in Y, the policy interventions can be implemented on X, with a prediction of the change that will occur on Y. Prediction and forecasting are usually used synonymously, however, forecasting is a sub-set of prediction. Prediction involves determining future outcomes or occurrence with or without data but forecasting involves determining future occurrences based on historical data. Therefore, implementing a policy intervention on X, will have future effects on Y because of its forecast ability but since the policy intervention is a new occurrence, its effects on Y would have to be predicted (no historical data with policy intervention) taking into account the forecast ability of X on Y. Forecasting, therefore necessarily means prediction but prediction does necessarily mean forecasting.

Granger causality can be tested using a series of t-tests and F-tests on a model with Y as the dependent variable on lagged values of Y and with lagged values of X, assuming that those X values provide statistically significant information about future values of Y. In other words, a time series variable X Granger-causes another time series variable Y if predictions of the value of Y based on its own past values and on the past values of X are better than predictions of Y based only on its own past values. The test is performed on stationary processes, therefore if a unit root exists in a given time series being investigated, the test is performed using the first (or higher)



differences. The number of lags included is determined using various information criteria including but not limited to the Akaike Information Criterion(AIC) or the Schwarz Information Criterion (SIC). A lag value is retained in the test equation if it has a significant t-value and if it, together with the other lagged values of the variable jointly improve the explanatory power, measured using the F-test.

The Granger-causality test can be applied in a binary, multivariate or Vector Auto Regressive empirical settings (Leamer, 1985). This study used the binary approach to identify the variables that have predictive power (potential indicator variables) that policy makers can use to achieve gender equality in the labor with specific focus on c gender (age/sex) disaggregated labor force participation rates. The binary test has the advantage of being able to identify variables *a priori* for more advanced analysis. For example, suppose X and Y cause each other but are also caused by a third variable Z, binary causality will identify these causal relationships and form the basis for a multivariate setting.

The Granger causality test based on the F –test is implemented by estimating two equations: that is Y on its lagged values as the restricted equation (equation 1) and Y on its lagged values and lagged values of X as the unrestricted one (equation 2).

$$\text{Restricted equation: } Y_t = \alpha + \sum_{i=1}^m \beta_i Y_{t-i} + \nu_t \quad (1)$$

$$\text{Unrestricted equation: } Y_t = \alpha + \sum_{i=1}^m \beta_i Y_{t-i} + \sum_{j=1}^n \phi_j X_{t-j} + \mu_t \quad (2)$$

The null hypothesis for the Granger causality test is that “X does not Granger cause Y” and the alternative is that “X Granger causes Y”. The null hypothesis is rejected if the equation with lagged values of both Y and X (Unrestricted) is superior to the one with only lagged values of Y (Restricted) in terms of its explanatory power captured in the F-test. The statistics is defined as



$$F = \frac{\left[\frac{(SSR_r - SSR_u)}{n} \right]}{\left[\frac{SSR_u}{T - (m + n + 1)} \right]} \quad (3)$$

where

SSR_r = Sum of squared residuals from the restricted equation, (eq. 1)

SSR_u = sums of squared residuals from the unrestricted equation (eq.2)

The elements that form the degrees of freedom are:

T = the number of observations

n = the number of lags for X, the explanatory variable in the unrestricted equation (eq.2).

m = the number of lags for Y, (lagged dependent variable) in the unrestricted equation (eq.2).

The same procedure is used in order to test for the inverse Granger-causality relation in equation 2.

For the binary approach, assuming two variables, X and Y, the two unrestricted equations to be estimated are:

$$Y_t = \alpha + \sum_{i=1}^m \beta_i Y_{t-i} + \sum_{j=1}^n \phi_j X_{t-j} + \mu_t \quad (4)$$

$$X_t = \theta + \sum_{i=1}^p \sigma_i X_{t-i} + \sum_{j=1}^q \tau_j Y_{t-j} + \varepsilon_t \quad (5)$$

Based on the estimated OLS coefficients for the equations (1) and (2) four different hypotheses about the relationship between X and Y variables can be formulated:

- i. Unidirectional Granger-causality from X to Y, whereby X increases the prediction of Y but not vice versa. In this case, $\sum_{j=1}^n \phi_j \neq 0$ and $\sum_{j=1}^q \tau_j = 0$. This implies that X exogenously 'causes' or 'predicts' Y. A single equation approach can be used to



- study the effect of X on Y. NB: Granger-causality provides the necessary (but not sufficient) condition for strong exogeneity which exists if current and lagged values of Y do not explain X and if weak exogeneity exist. Granger-causality does not establish weak exogeneity which is a sufficient condition for strong exogeneity. Weak exogeneity exists if parameters of a model regressing Y_t on X_t can be estimated efficiently without specifying the process that generated the X_t values. Super exogeneity occurs when weak exogeneity exists and the resulting parameters are stable regardless of changes in the values of X. Suffice to say, that weak exogeneity is necessary for estimation and testing; strong exogeneity is necessary for forecasting, while super exogeneity is necessary for policy analysis (For further reading on the forms of exogeneity, and their usefulness, see Nymoen (2017)).
- ii. Unidirectional Granger-causality from Y to X, whereby Y increases the prediction of X but not vice versa. In this case, $\sum_{j=1}^n \phi_j = 0$ and $\sum_{j=1}^q \tau_j \neq 0$. This implies that Y exogenously ‘causes’ or ‘predicts’ X. A single equation model can be used to study the effect of Y on X.
- iii. Bi-directional (or feedback or dual causality or bilateral causality) causality, whereby X increases the prediction of the Y and vice versa. In this case, $\sum_{j=1}^n \phi_j \neq 0$ and $\sum_{j=1}^q \tau_j \neq 0$ which implies that X and Y are endogenously determined, thus X ‘causes’ or ‘predicts’ Y and Y ‘causes’ or ‘predicts’ X. This implies that a feedback relationship exists. For empirical purposes, equations involving these two variables would require a simultaneous approach.
- iv. Independence between X and Y, whereby there is no causality in any direction. In this case, $\sum_{j=1}^n \phi_j = 0$ and $\sum_{j=1}^q \tau_j = 0$, thus there is no need for including either as an explanatory variable for the other.



These hypotheses about the nature of causality were used to determine the causality relationship (endogenous, exogenous or no causal) between gender disaggregated labor force participation rates for the labor force in the formal age group of 15-64 years, hereafter formal LFPR, either for males or females on one hand and other variables. All real variables are measured in 2010 prices, unless otherwise indicated.

3.1. Testing for Stationarity: Unit Root Tests

Granger causality requires that the series have to be covariance stationary. To test for stationarity, the Augmented Dickey Fuller (ADF) (Dickey and Fuller, 1979, 1981) and Phillip Peron (PP) (Phillips and Peron, 1988) were applied. For all of the series, the null hypothesis H_0 of a unit root (non-stationarity) was tested against the alternative of no unit root (stationarity). A series was assumed to be stationary and suitable to be used for the Granger causality test, if the null hypothesis was rejected at the 10% level of significance. The maximum number of lags for the ADF was 10 lags and the optimal lag length was determined using the Schwarz Information Criteria (SIC). The ADF and PP tests are strong tests against unit roots and have been used widely (Foresti, 2006, Arltová and Fedorová, 2016, Kim and Choi, 2017, among others). For further discussions on these tests, see Choi (2015).

3.2. Granger Causality Test Procedure

This is a two-step procedure that involves estimating the restricted and unrestricted equations, computing the restricted and unrestricted sum of squares and performing the F-test. The test was performed using the E-views package and the probabilities for the F-test examined for significance. In each case, 1 up to 10 lags were included wherever data allowed and where the test was applicable. Ten lags were the norm however, for few exceptions, less than 10 lags were used due insufficient data points for the ten lags (details on the exception can be obtained from the author by request).



3.3. Data Sources/

The study focused on three developed countries including Finland, Sweden and United States of America, with data on wide range of variables. The data was obtained from various secondary data bases: OECD (2017, 2018), OECD Statistics- LFS (2017), WDI (2017) and IMF World Data (2017). It was obtained for 123, 127 and 127 variables for USA, Finland and Sweden, respectively. Details on the source of individual variables can be obtained from the author by request.

4. EMPIRICAL RESULTS

4.1 Unit Root Test Results

The ADF and PP tests were used to test for stationarity at the levels and at the first difference. A variable was assumed to be stationary if the ADF and/or PP tests indicated stationarity at the 10% level of significance. Stationarity tests were conducted for both the levels and first differences. Variables whose first difference was stationarity at significance levels greater than 10% but less than 25% were also used for further analysis but with precaution. Emphasis was laid on the stationarity of the first difference since most the variables were I(1) and their first differences are stationary. The test result for the first differences are summarized below for each country. In a few exceptions (indicated in the results section), the levels which were stationary were used for the analysis.

4.1.1 Finland unit root test results

ADF test results

Two variables were dropped from the unit root test including unemployment total for females 65+ and that for males 65+. The first difference of all the variables included were stationary at the 10% level of significance with the exception of average wages which was stationary at 17%, gross domestic spending on research and development (R&D), labor compensation per hour worked Total index 2010, and employment total for the 55-64 group which were stationary at 17%, 14%, 14%, and 11%, respectively; and real foreign direct investment inflow which was not stationary at the difference level.



Phillip Peron Test results

The first difference of all the variables were stationary at the 10% level of significance except: average wages which was significant at 20%, gross domestic spending on R&D which was significant at 14%, labor compensation per hour worked total index 2010, unemployment total for formal group and middle group which were stationary at the 18 percent level of significance.

Conclusion: These results imply that the first differences for all the variables included could be used for Granger causality while average wages, gross domestic spending on R&D, labor compensation per hour worked total index 2010 should be used with caution since they are stationary at levels higher than 10%, but less than 25.

4.1.2 USA unit root test results

The nominal exchange rate (ER) was not applicable for the USA while there was no data for Gini, gender disaggregated data for unemployment with basic and intermediate

ADF test results

The first differences of all the variables included were stationary at the 10% level of significance with the exception of: employment for the female and male old groups, which were significant at 13% and 19 %, respectively; employee compensation in industry, which was significant at the 18% level of significance; as well as the employment total for the old group, and tax revenue which was not significant.

Phillip Peron Test results

The first difference of all the variables were stationary at the 10% level of significance except: employment (logs) for the female and male old groups, which were significant at 15% and 21%, respectively; employee compensation in industry, which was significant at the 21% level of significance and employee compensation in services, which was not significant.

Conclusion: These results imply that the first differences for the variables included can be used for Granger causality although employment (logs) for the female and male old groups; and employee compensation in industry, should be used with caution since they are stationary at levels higher that 10%, but less than 25 %.



4.1.3 Sweden unit root test results

ADF test results

The first differences of the variables included were stationary at the 10% level of significance with the exception of: gender wage gap for self-employment, unemployment with basic education, male (% of male labor force with basic education), unemployment with basic education, male (% of male labor force with basic education) and unemployment with intermediate education, male (% of male labor force with intermediate education) which were significant at 19%, 12%, 23%, 25% and 18%, respectively; employment (logs) for the male old group and that for the total old group which were not significant.

Phillip Peron Test results

The first difference of all the variables included were stationary at the 10% level of significance except unemployment with basic education, male (% of male labor force with basic education), unemployment with intermediate education, female (% of female labor force with intermediate education) unemployment with intermediate education, female (% of female labor force with intermediate education) and unemployment with intermediate education, male (% of male labor force with intermediate education) which were significant at 12%, 23% and 24%, respectively; unemployment with advanced education (% of total labor force with advanced education), unemployment with advanced education, female (% of female labor force with advanced education), and unemployment with intermediate education (% of total labor force with intermediate education), employment (logs) for the male old groups and that for the total old group which were not significant.

Conclusion: These results imply that the first differences for the included variables could be used for Granger causality tests; unemployment with basic education, male (% of male labor force with basic education), unemployment with intermediate education (% of total labor force with intermediate education), unemployment with intermediate education, female (% of female labor force with intermediate education) and unemployment with intermediate education, male (% of male labor force with intermediate education) should be used with caution since they were significant at levels higher than 10% but less than 25% while employment (logs) for the male old



groups and that for the total old group should not be used since they were not stationary at the 10% and not even at the 25% level of significance based on both the ADF and PP tests.

4.2 Granger-Causality Results

4.2.1 Employment by sector and by gender variables

Agricultural sector: The formal female LFPR uni-directionally Granger causes the proportions of both total and sex disaggregated employment in the agriculture sector in the USA but is uni-directionally Granger caused by the former in the Sweden. In Finland, it is endogenously determined with the total employment, exogenously determined by the proportion of female employment in the sector; and it exogenously causes the proportion of male employment in the sector. The formal male LFPR is exogenously Granger caused by the proportions of both total and sex disaggregated employment in the sector in Sweden; exogenously causes the proportions of the total and male employment but has no causality with the proportion of female employment in the sector; while in USA, it exogenously causes the proportion of female employment in the sector, it is exogenously caused by the proportion of male employment in the sector but has no causality with the total proportion of employment. These results indicate that:

Industry sector: The formal female LFPR is uni-directionally Granger caused by the proportions of both total and sex disaggregated employment in the industry sector in the USA and by the proportion of total employment in the Finland and Sweden, implying that policies influencing the former group can potentially influence the later. It uni-directionally Granger causes those for the sex-disaggregated employments in Finland, implying that policies influencing formal female LFPR in the sector have a potential to influence the proportion of sex-disaggregated employments and not vice versa. It has no causality with those for the sex-disaggregated employments in Sweden. The formal male LFPR are endogenously determined with the proportions of both total and sex disaggregated employment in the sector in USA and Finland, implying that policies influencing the former have a potential to influence the later and vice versa. It is exogenously caused by the proportion of total employment in the sector but has no causality with those for the sex disaggregated employment, implying only policies influencing



the proportion of total employment in the sector have a potential to influence formal male LFPR and not vice versa.

Service sector: Formal female LFPR is uni-directionally Granger caused by the proportions of both total and male employment in the service sector in the USA and is endogenously determined with that for female employment in the sector. It is exogenously caused by the proportion of total and female employment in the sector but with no causality with that for male employment in Finland. It is endogenously caused the proportion of male employment in the service sector implying policies that policies influencing both variables potentially influence each other; is uni-directionally Granger caused by total employments but with no causality with that for female employment in Sweden. The formal male LFPR are endogenously determined with the proportions of both female and male employment in the sector in USA, those for total and male employment in Finland, and that for total employment in Sweden, implying that policies influencing the formal male LFPR have the potential to influence these variables and vice versa. It is exogenously caused by the proportion of total employment in the sector in USA and Sweden, exogenously causes the proportion of female employment in Finland but has no causality with the proportion of female in the sector in Sweden

4.2.5 Age/sex disaggregated total employment

Formal Female LFPR: In the USA, formal female LFPRs have a feedback (implying bi-directional predictive power) relationship with the total employment of females as well as the total employment of the middle and old female groups as well as male youth, old and elderly groups; has uni-directional predictive power for that for the female elder group; is uni-directionally predicted by that for female youth, as well as male formal and middle groups. In Finland, formal female LFPR uni-directionally predicts the total employment of the formal and old groups; is uni-directionally predicted by that for the formal, youth and elderly female groups as well as the youth, middle and elderly male groups; and has no causality with that for middle and old female groups. In Sweden, formal female LFPR has a feedback relationship with the total employment of formal and elderly female groups as well as that for the middle male group;



uni-directionally predicts that for the middle and old female groups; and is uni-directionally predicted by that for youth female group and the formal, elderly and youth male groups. No causality tests were conducted for the old male group due non-stationarity of the first difference.

Formal male LFPR: In USA, formal male LFPR has a feedback relationship with total employment for all the groups considered except that for the formal and elderly male groups which uni-directionally predict it. In Finland, formal male LFPR has a feedback relationship with the total employment for the old female group and the formal and elderly male groups; uni-directionally predicts formal, youth and middle female groups and youth male group; and is uni-directionally predicted by that for the middle and old male groups; and has no causality with that for the elderly male group. In Sweden, formal male LFPR has a feedback relationship with the total employment for the formal and elderly female groups as well as the middle male group; uni-directionally predicts that for the middle and old female groups; is uni-directionally predicted by that for the youth female group as well as that for the formal, youth and elderly male groups. No causality tests were conducted for the old male group due non-stationarity of the first difference.

4.2.6 Total employment by age group

In USA, formal female LFPR has a feedback relationship with total employment for the elderly; uni-directionally predicts that for old group; and is uni-directionally predicted by those for the youth, middle and formal groups as well as the overall employment (ages 15-65+). In Finland, it uni-directionally predicts that for middle, and old groups; and is uni-directionally predicted by that for the youth, elderly and formal groups but has no causality with the overall total employment. In Sweden, formal female LFPR has a feedback relationship with total employment for the formal, youth, elderly groups; and uni-directionally predicts that for the middle group but has no causality with that for the overall employment. No causality tests were conducted for the total old group due non-stationarity of the first difference.



In USA, formal male LFPR has a feedback relationship with total employment for the middle and old groups; is uni-directionally predicted by those for all the other categories considered. In Finland, it has a feedback relationship with that for the formal, middle, and old groups; uni-directionally predicts that for the youth and overall employment; and is uni-directionally predicted by that for the elderly. In Sweden, formal LFPR has a feedback relationship with total employment for the formal, youth, and elderly groups; uni-directionally predicts that for the middle group but has no causality with that for the overall employment. No causality tests were conducted for the total old group due non-stationarity of the first difference.

The causal relationship for LFPR with total employment by groups are similar for both female LFPR and male LFPR in Sweden with the exception of that for the old group (no causality test conducted) but are not necessarily the same for Finland and the USA.

4.2.9 Unemployment by sex/age category

In the USA, formal female LFPR are influenced by the unemployment rates for all groups as well as the gender disaggregated group categories (both male and female categories), implying that the unemployment rates have predictive power over the LFPR of women but the reverse is not true, with the exception of that for the elderly female group where the reverse also holds, thus dual predictive power/dual causality. Formal male LFPR have predictive power for unemployment totals for all groups as well as all gender disaggregated categories and the reverse is true with the exception of that for youth female group, and those for the totals for the middle and elderly male groups, which are uni-directionally influenced by the formal male LFPR. This implies that the levels of unemployment in USA regardless of the group and sex category uni-directionally influence the labor force decisions of women while for men, causality runs in both directions with only a few exceptions.

In the Sweden, formal female LFPR have predictive power over the unemployment totals for all group as well as the gender disaggregated group categories (both male and female categories), as in the but the reverse is not true as in the USA, with the exception of that for the old female



group where no causality exists. The opposite is true for formal male LFPR with exception of total unemployment for youth female group where bi-directional causality exists, that for formal female group where no causality exists and that for the youth group (total unemployment for 15-24 age group) which uni-directionally causes (has influence) formal male LFPR. One key finding in this case is that formal male LFPR does not influence and is not influenced by the unemployment of the female of the formal employment age and vice versa. This may refute the argument that Labor force participation decision of men may lead to greater unemployment of females in the working group and vice versa. However, this does not seem to be the case in USA, where bi-directional causality occurs between the two and Finland, where the unemployment total of female of formal working age (15-64) influences the formal male LFPR. Generally speaking, the LFPR of males 15-64 has predictive power over the unemployment of the different categories while unemployment of the different categories has predictive power over the LFPR of females, with only a few exceptions.

In Finland, formal LFPR for both females and males are uni-directionally influenced by the unemployment rates of the both male and female youth and middle groups but not vice versa; the LFPR for males is also uni-directionally influenced by those for the old female group while that for females is also uni-directionally influenced by that for the old male group but the reverse is not true. Also, the LFPR for males is influenced by and influences the total unemployment rate of the female youth and formal male groups while LFPR for females is also influenced by and influences the total unemployment for the female youth group and it influences the total unemployment of the elderly females. In all other cases, there is no causality. These results show that where causality exists in Finland, it runs from unemployment of the different categories to LFPR for both males and females, with only four in the opposite direction.

Overall unemployment of the total and gender disaggregated categories has potential to influence the total and gender disaggregated LFPRs. The causality relationships differ by country and by age/sex group categories.



4.2.10 Unemployment by gender/education category

Formal female LFPR: In USA, formal female LFPR has dual causality with unemployment rate of the labor force with basic education; and uni-directionally influences that for the total, female and male labor force with advanced education and that for the total labor force with intermediate education. The gender disaggregated unemployment rate variables for the intermediate and basic education were dropped from the analysis.

In Finland, formal female LFPR uni-directionally influences the unemployment rate of females with advanced education, intermediate education; is uni-directionally influenced by that for females with basic education, males with intermediate education but has no causality with those for the other categories.

In Sweden, formal female LFPR is influences (has predictive power over) the unemployment of the rate of the total labor force with advanced education and the that for females with basic education and has no causality with the unemployment rates for both males and female with advanced education, the total labor force with basic education and intermediate education as well as that for males with basic education and intermediate education.

Formal male LFPR: In USA, formal male LFPR are uni-directionally predicted by unemployment rate of females with advanced education; uni-directionally predicts that for the total labor force with basic education and; and has no causality with that for the total labor force with intermediate education, male labor force with advanced education and total labor force with advanced education. The gender disaggregated unemployment rate variables for the intermediate and basic education were dropped from the analysis.

In Sweden, formal male LFPR uni-directionally predicts the unemployment rate of the total labor force with advanced and basic education, female labor force with advanced and basic education and that for the male labor force with basic and intermediate education but the reverse is not true;



while it has no causality with the male labor force with advanced education as well as those for the total and female labor forces with intermediate education.

In Finland, formal male LFPR uni-directionally predicts the unemployment rates for the total labor force for all three education categories (advanced, intermediate and basic), female labor force with advanced education and male labor force with basic education; is uni-directionally predicted by those for the female labor force with basic education and that for the male labor force with basic education; has a feedback relationship with that for females with intermediate education. These results show that formal male LFPR has dual causality with only the unemployment rate of females with intermediate education in Finland, in all other cases either uni-directional causality exists or no causality.

Overall these results indicate that the dynamics between gender disaggregated LFPR and unemployment rates by gender/education category can be endogenous, but have in most cases been uni-directional, with more situations where causality runs from: LFPR to unemployment rates by education category (19 out of 46 cases); from unemployment rates by education category to LFPR (6 out of 46 cases); dual causality (2 out of 46 cases). The remaining were no causality situations (19 out of 46 cases). Situation of either bi-directional causality or uni-directional causality from unemployment rates by education category to LFPR would imply that educational levels do influence gender disaggregated LFPR and unemployment thus need to be investigated further in order to design policies that can lead to gender equality in LFPR and reduce unemployment in a gender sensitive manner. These results underscore the need to design a comprehensive package of policies aimed at addressing the education, LFPR and unemployment gender gaps.

4.2.11 Monetary variables

Nominal exchange rates have no causality with formal female LFPR (no predictive power) but are endogenously determined formal male LFPR in Sweden and Finland, implying predictive power over male LFPR but not for female LFPR. This may reflect the fact that men more often



are engaged in tradables/international trade businesses compared to women and have greater command over financial resources. This may imply that women are more engaged in salaried jobs which may have less or no direct links to exchange rates. This may be case if women are engaged in jobs that have similarities with unpaid care work that occurs either in the homes or outside the home, such as nursing, baby-sitting, among others.

Nominal effective exchange rates (NEER) has a feedback relationship with formal female LFPR in Finland; is exogenously predicted by the former in Sweden but has no causality with the former in USA. It is exogenously predicted by formal male LFPR in Finland and Sweden but has no causality with the former in USA.

Long term interest rates exogenously predict formal female LFPR in Finland but is exogenously predicted the former in Sweden and USA. It has a feedback relationship with formal male LFPR and it exogenously predicts the former in USA and Finland.

Short term interest rates have a feedback relationship with formal female LFPR in Finland; exogenously predicts the former in USA and is exogenously predicted by the former in Sweden. It exogenously predicts formal male LFPR in Finland but is exogenously predicted by the former in the USA and Sweden. These results show that Interest rates may have differing effects on male and female LFPRs.

Financial development index has a feedback relationship with formal female LFPR in the Finland and Sweden but is exogenously predicted by the former in the USA. It exogenously predicts formal male LFPR in USA and Finland and is exogenously predicted by the former in Sweden. These results show that female LFPR predicts financial development in all three countries but the reverse is only true in Finland and Sweden; and that efforts to increase financial development may have gender disaggregated effects on LFPR while enhancing the LFPR females may have changes in financial sector performance which ultimately will be desirable for



economic development. The relationship between financial development and LFPR differs by gender category. Evidence shows potential feedback relation with female LFPR.

National wealth, measured by broad money as % of GDP influences (has predictive power) formal female LFPR in USA but the reverse is not true and it is predicted by formal female LFPR in Sweden but it does not predict it. It influences and is influenced by formal male LFPR in USA but has no causality in Sweden. In Finland, there was no data for this variable. These results show that national wealth has the potential to influence and to be influenced by both male and female LFPR, but this may not be the case in reality. Policy makers should identify and target the factors which prevent this dual causality relationship to exist. It is expected that the greater the wealth, the greater will be the total and gender disaggregated LFPs and vice versa.

4.2.12 Foreign direct investment variables

Foreign direct investment, net inflows (% of GDP) exogenously predicts formal female LFPR and has a feedback relationship with formal male LFPR in Sweden but has no causality with both formal male and formal female LFPR in USA and Finland.

Foreign direct investment, net outflows (% of GDP) exogenously predicts formal female LFPR in Sweden but has no causality with the former in USA and Finland. It exogenously predicts formal male LFPR in USA but has a feedback relationship with the former in Finland and Sweden.

Real foreign direct investment, net inflows exogenously predicts formal female LFPR in Sweden but has no causality with the former in Finland and USA. It has a feedback relationship with formal male LFPR in Finland; exogenously predicts the former in USA but is exogenously predicted by the former in Sweden.



Real foreign direct investment, outflows exogenously predicts formal female LFPRs in Finland and Sweden but has no causality with the former in USA. It is exogenously predicted by formal male LFPRs in all three countries. These results show that LFPR of females may be or not influenced by FDI outflows while male LFPRs influence FDI outflows.

Overall: Foreign direct investment variables have no causality with formal female LFPR in USA and Finland with the exception of real foreign direct investment outflows which exogenously predicts the later in Finland. In Sweden, all the FDI inflow and outflow as well as their growth rates exogenously predict formal female LFPR. This shows that formal female LFPR have no predictive power over the FDI variables. FDI variables have the potential to predict formal male LFPR and/or vice versa, with only few cases of no causality.

4.2.13 Savings variables

Gross domestic savings (% of GDP) exogenously predicts formal female LFPR in Finland and Sweden but has no causality with the former in USA. It has a feedback relationship with formal male LFPRs in USA and Sweden but is exogenously predicted by the former in Finland.

Gross savings (% of GDP) exogenously predicts formal female LFPR in Finland and Sweden but has no causality with the former in USA. It has a feedback relationship with formal male LFPRs in USA and Finland but is exogenously predicted by the former in Sweden.

Gross savings (% of GNI) exogenously predicts formal female LFPR in Finland and Sweden but has no causality with the former in USA. It has a feedback relationship with formal male LFPRs in USA and Finland but has no causality with the former in Sweden.

Real gross saving (logs) has a feedback relationship with formal female LFPR in Finland and Sweden but it exogenously predicts it in the USA. It exogenously predicts formal male LFPR in USA and Finland but is exogenously predicted by the former in Sweden.



4.2.14 International trade variables

Real exports of goods and services (constant 2010 US\$)-logs exogenously predicts formal female LFPR in USA and Sweden but has no causality with the former in Finland. It exogenously predicts formal male LFPR in Finland and Sweden but has no causality with the former in USA. These results indicate that real exports may predict gender disaggregated LFPRs but show no evidence for the reverse.

Imports of goods and services (constant 2010 US\$)-logs exogenously predicts formal female LFPR but has no causality with the formal male LFPR in USA. It has a feedback relationship with formal female LFPR but has no causality with formal male LFPR in Finland. It is exogenously predicted by formal LFPR for both males and females in Sweden.

Real openness (constant 2010 US\$)-logs exogenously predicts formal female LFPR in USA and Finland but has no causality with the former in Sweden. It has a feedback relationship with formal male LFPRs in USA but has no causality with the former in Finland and Sweden. These results show that formal female LFPRs do not predict the level of openness of the economy in all three countries but is predicted by the former in USA and Finland while causality only exist between openness and formal male LFPR (feedback) only in the USA.

4.2.15 Labor/employee compensation, sectoral and total for all sectors

Employee compensation in agriculture (including forestry and fishing) exogenously predicts formal female LFPR in Sweden but has no causality with the former in USA and Finland. It is exogenously predicted by formal male LFPR in all three countries. This implies that formal male LFPRs influence the compensation rates in the agricultural sector in the three countries while the formal LFPR of females does not influence it.

Employee compensation in industry has a feedback relationship with formal female LFPR in USA; exogenously predicts it in Finland and is exogenously predicted by the former in Sweden.



It has feedback relationship with formal male LFPR in Finland but has no causality with the former in USA and Finland.

Employee compensation in services has a feedback relationship with formal female LFPR in Finland; exogenously predicts it in USA and is exogenously predicted by the former in Sweden. It has feedback relationship with formal male LFPR in USA and Finland but has no causality with the former Sweden.

In USA and Finland, compensation in industry and service sectors influences formal female LFPRs, but that for the agricultural sector does not. In Sweden, compensation in the agricultural sector influences formal female LFPR but those for the industry and services do not. Formal male LFPRs are only influenced by the compensation in the service sector in USA; influenced by compensation in both the industry and service sectors in Finland but is not influenced by the compensation in any of the sectors in Sweden.

Total employee compensation for all sectors had a feedback relationship with formal female LFPR in all three countries. It had a feedback relationship with formal male LFPR in Finland; was exogenously predicted by the former in Sweden but had no causality with the former in USA. This implies that unlike the formal female LFPR which were influenced by the total compensation for all sectors, formal male LFPR was only influenced by the former in Finland.

The annual growth rate in labor compensation per hour worked exogenously predicts formal female LFPR but is exogenously predicted by formal male LFPR in Finland. It has no causality with the either male or female formal LFPR in USA and Sweden.

Labor compensation per hour worked, Total index 2010 exogenously predicts formal female LFPR in USA and Finland but is exogenously predicted by the former in Sweden. It exogenously predicts formal male LFPR in USA; has a feedback relationship with the former in Finland but is exogenously predicted by the former in Sweden.



Average wages (log) exogenously predicts formal female LFPR in USA; is exogenously predicted by the former in Sweden but has no causality with the former in Finland. It exogenously predicts formal male LFPR in USA; and is exogenously predicted by the former in Sweden and Finland.

4.2.16 Health spending, government and non-government

Government spending and compulsory health insurance has a feedback relationship with formal female LFPR in Finland but exogenously predicts it in USA and Sweden. It has feedback relationship with formal male LFPR in Finland but has no causality with the former in USA and Sweden. These results show that government spending and compulsory health insurance influences formal female LFPR in all three countries but it only influences formal male LFPR in Finland.

Out-of pocket health expenditure has a feedback relationship with formal female LFPR in Finland but it exogenously predicts the former in USA and Sweden. It exogenously predicts formal male LFPR in USA; has no causality with the former in Finland; and is exogenously predicted by the former in Sweden.

Total health expenditure has a feedback relationship with formal female LFPR in Finland; it exogenously predicts the former in USA and is exogenously predicted by the former in Sweden. It has a feedback relationship with formal male LFPR in USA and Finland but has no causality with the former in Sweden.

4.2.17 Selected government spending and revenue variables

Gross domestic spending on R&D exogenously predicted by formal female LFPR in USA and Finland but not vice versa. It has a feedback relationship with formal male LFPR in USA but no causality in Finland. It is predicted by formal female LFPR but it predicts formal male LFPR.



General government spending exogenously predicts formal female LFPR in all three countries; and has a feedback relationship with formal male LFPR in USA and Finland but has no causality with the former in Sweden. These results show that the size of government has the potential to influence LFPR with the differing effect for female LFPR and for male LFPR.

General government net lending exogenously predicts formal female LFPR in all three countries; and has a feedback relationship with formal male LFPR in USA and Finland but has no causality with the former in Sweden.

General government revenue exogenously predicts formal female LFPR in USA and Finland but has no causality in Sweden. It **exogenously** predicts formal male LFPR in Finland and Sweden but has no causality with the former in USA.

Tax revenues exogenously predicts formal female LFPR in USA; is exogenously predicted by the former in Sweden but has no causality with the former in Finland. It has a feedback relationship with formal male LFPR in USA but has no causality with the former in Finland and Sweden. (*Also see Government expenditure on health under section on health expenditure*).

4.2.18 Gender inequality measures

The gender wage gap for self-employment is exogenously predicted by both male and female LFPR in the USA; has a feedback relationship with formal LFPR but no causality relationship with formal male LFPR in Finland; while in Sweden, it has no causality with formal LFPR for both males and females.

The gender wage gap for total employment exogenously predicts female LFPR but has no causality with the formal male LFPR in the USA; has no causality relationship with both formal male and female LFPR in Finland; while in Sweden, it has a feedback relationship formal female LFPR but it exogenously predicts formal male LFPR.



5. CONCLUSIONS

5.1 Lesson Drawn from the Study

Various lessons can be drawn from the finding of the study. These include but are not limited to those high-lighted below:

- 1) The total and sex disaggregated employment proportions in the different sectors including the agricultural, service and industry sectors have potential predictive power over both formal male and female LFPR, therefore policies targeting these variables can be used to target desirable changes in gender disaggregated LFPR. Sector specifics are important for understanding aggregate/gender disaggregated labor force participation rates nexus. This implies that sector specific policy interventions are required to address the inherent gender inequalities, and thereby stimulate economic growth.
- 2) Policies that influence total employment by group may have sex disaggregated effects on LFPR and vice versa. Policies that influence sex disaggregated LFPR may have influence on the total employment of the sex and age disaggregated categories. The causal relations differ by age/sex category and by country. Aggregation may obscure important causal relationships which may have significant implications for policy interventions as well as their impacts on LFPR.
- 3) Policies targeting unemployment of the total and gender disaggregated categories have the potential to influence the total and gender disaggregated LFPRs since unemployment rates have predictive power over gender disaggregated LFPR. The causality relationships differ by country and by age/sex group categories.
- 4) The dynamics between gender disaggregated LFPR and unemployment rates by gender/education category can be endogenous, but have in most cases been uni-directional, from unemployment rates by education category to LFPR.
- 5) Unemployment rates by education category have the potential to predict gender disaggregated LFPR and should therefore be investigated further in order to design policies that can increase LFPR and reduce unemployment in a gender sensitive manner. The results of the study underscore the need to design a comprehensive package of



policies aimed at addressing the education, LFPR and unemployment gender gaps. For example, reducing the education gender gap without addressing the factors influencing the unemployment gender gaps for the different levels of education might fail to lead to increased total LFPR and failure to address the LFPR gender gap that has persisted over the years, world-wide regardless the level of development of the economy in question.

- 6) Other macroeconomic variables that have the potential to predict gender disaggregated LFPR, include:
- i. Monetary variables: nominal exchange rate -local currency per dollar (ER), nominal effective exchange rates, long term interest rates, short term interest rates, Financial development and the country's wealth measured by broad money (% of GDP).
 - ii. Foreign direct investment variables: foreign direct investment, net inflows (% of GDP), foreign direct investment, net outflows (% of GDP), real foreign direct investment, net inflows/ outflows.
 - iii. Savings variables: gross domestic savings (% of GDP), gross savings (% of GDP) and gross savings (% of GNI) and real gross saving
 - iv. International trade variables: real exports of goods and services Imports of goods and services and real openness
 - v. Compensation variables: Employee compensation in the different sectors agriculture, service and industry, total employee compensation for all sectors, labor compensation per hour worked in annual growth rates, labor compensation per hour worked and average wages
 - vi. Health expenditure variables: government spending and compulsory health insurance, out-of pocket health expenditure and total health expenditure
 - vii. Government expenditure/revenue variables: Gross domestic spending on research and development, general government spending or size of government, general government net lending, general government revenue and tax revenues.
 - viii. Gender inequality variables: gender wage gap for self-employment and gender wage gap for total employment



5.2. Overall Conclusion

The causal relationships between LFPR and the variables investigated differ by country, specific variable considered, and whether causality is investigated for formal male or female LFPRs. This implies that no general theory can be developed regarding causal relationship between these variables and gender disaggregated LFPRs. It signals the need for researchers investigating issues involving LFPR to always determine the underlying relationships between LFPR and other variables to determine whether to use dynamic or non-dynamic approaches for their investigations. It is also necessary for policy makers to carefully investigate the causal and other empirical relationships between the above variables on one hand and gender disaggregated LFPR on the other in order to come up with interventions that can lead to desirable changes in gender disaggregated LFPR.

CONFLICTS OF INTEREST AND PLAGIARISM: I declare that there is no conflict of interest and plagiarism.

REFERENCES

1. Arltová, M. and Fedorová, D. (2016). Selection of Unit Root Test on the Basis of Length of the Time Series and Value of AR(1) Parameter. *Statistika*, 96(3):47-64. [Online] <https://www.czso.cz/documents/10180/32912822/32019716q3047.pdf/09710b90-e1d0-4bb1-816e-5b83faad686b?version=1.0> (May 19, 2020)
2. Choi, I. (2015). *Almost All about Unit Roots: Foundations, Developments, and Applications*. New York: Cambridge University Press.
3. Darian J. C. (1976). Factors Influencing the Rising Labor Force Participation Rates of Married Women with Per-School Children. *Social Science Quarterly*, Vol. 56. No. 4 (MARCH, 1976):614-630. Available at: <https://www.jstor.org/stable/pdf/42860415.pdf?refreqid=excelsior%3A8257f7f406521286b0a95d6d2b4d1578> (30-06-2017).
4. Dickey, D. A. and Fuller, W. A. (1979). Distribution of the Estimators for Autoregressive Time Series with a Unit Root. *Journal of the American Statistical Association*, 74; 427-431.



5. Dickey, D A. and Fuller W. A. (1981). Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root. *Econometrica*, 49(4):1057-1072.
6. Diebold, F. X. (2001). *Elements of Forecasting*. South Western Publishing, 2d ed. p.254.
7. Eichler, M. (2012). Causal Inference in Time Series Analysis (PDF). In Berzuini, Carlo (ed.), *Causality: Statistical Perspectives and Applications (3rd ed.)*. Hoboken, N.J.: Wiley. pp. 327–352. ISBN 978-0470665565.
8. Erdil, E. and Yetkiner I. H. (2009). The Granger-causality between Healthcare Expenditure and Output: A Panel Data Approach. *Applied Economics*, 41: 511-8. [Online] <https://www.tandfonline.com/doi/abs/10.1080/00036840601019083>
<https://www.tandfonline.com/doi/pdf/10.1080/00036840601019083?needAccess=true>
(November 21, 2018)
9. IMF, (International Monetary Fund) (2017). Financial Development Data. [Online] https://data.world/imf/financial-development-fd/workspace/file?filename=FD_03-21-2017+10-22-16-34_timeSeries.csv (Sept 06, 2018); <http://data.imf.org/?sk=388DFA60-1D26-4ADE-B505-A05A558D9A42&sId=1479329132326MoreSections>
10. Foresti, P. (2006). Testing for Granger Causality between Stock Prices and Economic Growth. Munich Personal RePEc Archive (MPRA) Paper No. 2962, posted 26 Apr 2007 UTC. [Online] <https://mpra.ub.uni-muenchen.de/2962/> (May 11, 2020)
11. Gao, X. Huang, S. Sun, X. Hao, X and An, X. (2018). Modeling Cointegration and Granger Causality Network to Detect Long-term Equilibrium and Diffusion Paths in the Financial System. [Online] <https://royalsocietypublishing.org/doi/10.1098/rsos.172092> (June 25, 2020)
12. Götz, T. Heq A. and Smeekes, S. (2016). Testing for Granger Causality in Large Mixed-Frequency VARs. *Bundesbank Discussion Paper No. 45/2015*. [Online] https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2797070 (June 25, 2020)
13. Granger C. J. (1969). Investigating Causal Relationships by Econometrics Models and Cross Spectral Methods. *Econometrica*, 37:425-435.
14. Granger, C. W. J. and Newbold, P (1977). *Forecasting Economic Time Series*. New York: Academic Press. p. 225. ISBN 0122951506.



15. Kim, J. H. and Choi, I. (2017). Unit Roots in Economic and Financial Time Series: A Re-Evaluation at the Decision-Based Significance Levels. *Journal of Econometrics* 2017, 5(41): 1-23. Multidisciplinary Digital Publishing Institute (MDPI) Publishers. [Online] <https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&ved=2ahUKEwi56bq1p3qAhXix4UKHQVdDV8QFjAGegQIBxAB&url=https%3A%2F%2Fwww.mdpi.com%2F2225-1146%2F5%2F3%2F41%2Fpdf&usq=AOvVaw3pqC2cLQQrwHka9ne-ZAQQ> (June 25, 2020)
16. Lahoti, R. and Swaminathan, H. (2016). Economic Development and Women's Labor Force participation in India. *Feminist Economics*, 22(2): 168-195. DOI:10.1080/13545701.2015.1066022 Link: <https://doi.org/10.1080/13545701.2015.1066022>, [online] <https://www.tandfonline.com/doi/pdf/10.1080/13545701.2015.1066022> (November 07, 2018)
17. Leamer, E. E. (1985). Vector Autoregressions for Causal Inference? Carnegie-Rochester Conference Series on Public Policy. **22**: 283 – via Elsevier Science Direct
18. Nymoén, R. (2017). Lecture 6- Exogeneity in Stationary Time Series Models, ECON 4160, Autumn Semester 2017. Department of Economics. [Online] <https://www.uio.no/studier/emner/sv/oekonomi/ECON4160/h17/undervisningsmateriale/lect6h17.pdf> (June 25, 2020).
19. OECD (Organisation for Economic Co-operation and Development) Data- Labor Force Statistics (LSF) by sex and age - OECD. Stat. [Online] <https://stats.oecd.org/Index.aspx?DataSetCode=LFS_D# (February 13, 2017)
20. OECD Data. [Online]: <https://data.oecd.org/>
21. OECD (2017), "OECD Economic Outlook No. 101 (Edition 2017/1)", *OECD Economic Outlook: Statistics and Projections* (database), [Online] <https://doi.org/10.1787/639d73ee-en> (07 September 2018).
22. OECD (2018), OECD Economic Outlook Annex Tables-1 – [Online] <http://www.oecd.org/economy/outlook/economic-outlook-annex-tables.htm>)
23. OECD STAT. (2018). Economic Outlook No 103 - May 2018. (Data are reported over the



- period 1960-2019). [Online] <https://stats.oecd.org/Index.aspx?DataSetCode=EO%20>
(October 30, 2018)
24. OECD-Stat- Metadata. [Online]
https://stats.oecd.org/OECDStat_Metadata/ShowMetadata.ashx?Dataset=LFS_D&ShowOnWeb=true&Lang=en
25. OECD/ILO/IMF/World Bank Group report (Aug 2014). Achieving Stronger Growth by promoting a more gender balanced economy. [Online]
<https://www.oecd.org/g20/topics/employment-and-social-policy/ILO-IMF-OECD-WBG-Achieving-stronger-growth-by-promoting-a-more-gender-balanced-economy-G20.pdf> (July 18, 2017).
26. Phillips, P. C. B. and Perron, P. (1988). Testing for a Unit Root in Time Series Regression. (PDF). *Biometrika*. 75 (2): 335–346. [doi:10.1093/biomet/75.2.335](https://doi.org/10.1093/biomet/75.2.335).
27. Thamma-Apiroam, R.(2016). Factors Influencing the Labor Force Participation of Married Women in the United States. [Online]
<http://www.ccsenet.org/journal/index.php/ass/article/download/53161/30699> (June 06, 2017)
28. WDI, (World Development Indicators) Data (2017). [Online]
<http://data.worldbank.org/data-catalog/world-development-indicators> (February 13,
29. Yakubu, A. (2010). Factors Influencing Female Labor Force Participation in South Africa in 2008. *The African Statistical Journal*, 11:85-104. [Online]
<https://www.google.com/search?q=Yakubu%2CA.+Yakubu+%282011%29.++Factors+influencing+Female+Labor+Force+Participation+in+South+Africa+in+2008.The+African+Statistical+Journal%2C+Volume+11%2C+November+2010%2C+pp.+85-104.&ie=utf-8&oe=utf-8&client=firefox-b-ab>(November 07, 2018)