The Mediating Role of Labour Supply in the Relationship between Wage and Fertility for Ghanaian Women. A Marginal Mediation Analysis Approach.

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Abstract
This study explored the effect of wage on fertility rate for Ghanaian women with labour supply as a mediating variable. Using data from GLSS 6, it employed the Marginal Mediation Analysis, which combined average marginal effect and appropriate estimation techniques, to decompose the total effect into direct and indirect effects. Endogeneity was inherent in the mediation model and therefore respondents' belongingness to a trade union was used as an instrument for wage to correct for the anomaly. Two different instrumental variable estimation methods, namely the two stage least squares (2SLS) and the two stage residual inclusion (2SRI), were used after which the average marginal effects of the estimated coefficients were computed. The 2SLS was appropriate for the equation which had labour supply (hours of work) as its dependent variable because the regressand is a continuous variable. In contrast, the equations whose dependent variable was number of children were estimated by the 2SRI due to the nonlinearity of their measured variable. It was revealed that a percentage increase in wage directly reduces the number of children per woman by 0.85. Also, a percentage rise in wage decreases the number of children per woman by 0.016 through labour supply. Thus empowering women in terms of both their earnings and job opportunities on the labour market is effective in combating high fertility rate among Ghanaian women. The more lucrative the job market is, the greater the opportunity cost of home production activities and hence fertility rate will drop.

Keywords: wage, fertility rate, Marginal Mediation Analysis, direct effect, indirect effect, total effect
JEL Classification Code: C5, D1, D6, D9, J2, J3

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1. Introduction

The use of economic variables and tools to analyse fertility rate was first postulated by Thomas Robert Malthus. In his famous book, *Essay on the Principle of Population,* Malthus posited that economic growth results in an exponential rise in population as against the arithmetic boost in food production (Malthus, 1798). The Malthusian paradigm, therefore, predicted a nosedive in the output per capita unless there was an adequate implementation of positive checks and appropriate preventive measures. With heavy criticism against the theory over the empirical validity of the two ratios (exponential and arithmetic) and without an appropriate model to analyse fertility choice, issues of fertility were not accorded the needed attention in economics literature for almost two centuries. However, the extension of economics discourse to incorporate theories of human capital as well as time allocation between market and non-market activities have rejuvenated economic modeling of fertility decisions using a unified theoretic framework (Willis, 1973).

Becker (1960) used the theory of consumer behavior to investigate the number of children per family. His quantity-quality trade-off model asserted that children serve as either consumptive goods and/or investments for their families. In the case where they are regarded as consumptive goods, economic theories of consumer behavior can explore the number of children per family. According to his theory, children provide satisfaction for the families and therefore together with other goods constitute the family's utility function represented by an indifference curve. The constituents of the budget constraint of the family, given the indifferent curve, include the income of the family, prices of goods and services the family buys as well as the cost of the quality of lives families want to give to their children.

Becker concluded that at equilibrium, income has a positive effect on both the quality of lives families want for their children and the fertility rate of households. However, because children are special type of normal goods and parents are also interested in their human capital development, a rise in the income level will cause a family to substitute better education, proper housing, food, clothing etc. for a lower number of children. This, to Becker, accounts for the declining rate of fertility amidst the high economic growth across countries.

Mincer (1963) extended Becker's model by including variations in the total cost of child bearing in determining the fertility rate of families. Mincer's assumption, which is based on role specialization, posited that family utility is maximized when men focus primarily on the provision of income while women divide their time between production at home and on the labour market. Thus, in addition to the monetary budget that the family faces, time available to women, unlike men, is constrained by the hours they spend in the job market and those spent at home. Wage serves as the price or the implicit (opportunity) cost of the time women spent in undertaking home production including child bearing (Matysiak and Vignoli, 2013). As rational economic agents, as the wage on the labour market rises, women sacrifice more home hours which include time needed to raise their children for working hours and hence will prefer to have fewer children. Contrary to men, hours of work features prominently in the effect of wage on fertility decision for women. Therefore, apart from the direct effect of wage on fertility decision for women, the mediating role of labour hours cannot be overlooked.

The quantity-quality trade-off by Becker explains the direct effect while the opportunity (implicit) cost theory by Mincer (1963) explores the indirect effect. Despite this, only a few studies have empirically examined the transmission mechanism through which wage affect fertility decision of women via labour supply. An insight into this trajectory is crucial as it will aid policy makers to know whether labour supply partially or fully mediate the effect of wage on fertility.

A major reason why there are only a few empirical studies on the mediation role of labour supply in the relationship between wage and fertility is the limitedness of appropriate methodologies. In mediation analysis, the indirect effect of the explanatory variable on the outcome variable is obtained by the product of two estimated coefficients from two different equations. Computing this product is straightforward when both equations have continuous variables as their dependent variables. This is so because with such equations both estimated coefficients have additive properties and therefore, the indirect effect can be easily computed by multiplying the coefficients of interest. However, with our mediation analysis, one equation has fertility as its dependent variable whereas labour supply is the dependent variable for the other. Fertility rate (usually measured by number of children) is a count variable and as such a poisson or negative binomial regression is the appropriate tool for estimating the equation that has the fertility as its dependent variable. In contrast, an Ordinary Least Square (OLS) can generate parameter estimates for the other which has labour supply as its outcome variable because labour supply (measured by hours of work per day/week/month) is a continuous variable. Estimated coefficients from a poisson or negative binomial estimation have multiplicative properties whiles those from OLS have additive properties. The estimated coefficients of the two equations are of different measurement metrics and as a result cannot be multiplied to obtain the indirect effect (Barrett, 2018).

This is where Marginal Mediation Analysis (MMA) comes in handy. Formulated by Barrett (2018), this technique transforms parameter estimates of different measurement metrics to a uniform metric so that the indirect effect can be computed. This study employs the MMA to the mediation analysis of labour supply of women in the relationship between wage and fertility in Ghana.

Even though fertility rate in Ghana has seen a drastic decline making it one of the lowest in sub-Saharan Africa, the average number of children per woman as at 2016 stood at 4.0 which is still higher than the global average rate of 2.5 per woman. Also, this rate far exceeds the 2.1 replacement rate stipulated as the average number of children a woman would need to have in order to sustain the population level of a nation. A major threat posed by this high rate of fertility vis-à-vis the replacement rate is food insecurity as well as the nation's inability to imbibe into its growing population the adequate human capital capacity for economic growth (Searchinger, et al., 2013). There is therefore the need to investigate factors that influence fertility rate in Ghana with special focus on whether labour supply fully or partially mediated the effect of wage on number of children per woman.

The remainder of this study is organized as follows. Section 2 reviews the literature. Section 3 spells out the methodology. Section 4 describe the sources of data. Section 5 gives an analysis of the data. While section 6 discusses the results, section 7 concludes.

2. Literature Review

Economic determinants of child bearing decisions continue to remain pivotal to economics as a discipline. The enormous literature on this subject matter can be grouped into macro and micro studies. Two dominant economic variables used in analyzing fertility decisions at the macro level are economic growth/per capita income and business cycle. Studies on the nexus between economic growth and fertility rate has revealed mixed results. For instance, Zuluaga, Jaramillo, and Gamboa (2017) used Gross Domestic Product (GDP) growth at both national and regional as well as unemployment to explore the effect of economic status on birth interval in Colombia. Using the Cox hazard proportional method, the paper ascertained that in general, strengthening the economic status of individuals reduces the spacing between births and consequently increases the number of children per woman. Jemna (2015) also found a positive relationship between economic growth and fertility in Romania. The granger causality technique employed in the study showed that there was a positive bi-directional link between the two variables. The same direction of relationship was detected by Frini and Muller (2012) and Hondroyiannis and Papapetrou (2005) who empirically tested the impact of economic growth on certain socioeconomic variable such as fertility and education in Tunisia. Results from the co-integration analysis indicated that there is a long run positive relationship between per capita income and fertility rate.

Other studies that have investigated the effect of economic growth on fertility rate found a complex link between the two variables. One of those studies was conducted by Luci-Greulich and Thévenon (2014) who observed a rebound in fertility rate in Organization for Economic Cooperation and Development (OECD) countries after a period of decline and examined the economic determinants of this phenomenon. With a panel data of 30 OECD countries spanning over the period from 1960 to 2007, the OLS and fixed effect estimations divulged that though the initial stages of economic development is associated with low fertility, a continuous sprout of income per person will stimulate the number of children per family. Hafner and Mayer-Foulkes (2013) on the other hand found out that while fertility rate and income are negatively related in advanced economies, a rise in income level is accompanied by more children per woman in developing countries.

Studies that explored the influence of business cycle on fertility, generally, show a positive relationship between two variables. For instance, Jones and Schoonbroodt (2016) used a calibrated simulation model to analyse fertility response to shocks in economic growth (business cycle). The quantitative experiment model uncovered that 58 percent of the sharp decline in total fertility rate during the 1930s in the US was attributable to the Great Depression. The model further unveiled that 77 percent of the baby boom in the 1950s is as a result of the slight economic enhancement in the 1950s and early 1960s. A similar finding was unearthed by Davalos and Morales (2017) who investigated how economic cycles affect the child bearing choice of families in Columbia. The regression estimated that periods of economic downturn adversely affected the fertility rate. Explicitly, the fertility rate in the country dwindled by 0.002 children per woman during economic slump.

Most researchers who have studied the relationship between economic advancement and fertility at the micro level used wage as a proxy for economic growth. Most of the studies revealed that a rise in wage rate dwindles the rate of fertility. Alam and Pörtner (2018) explored the effect of crop losses/wage cut on the incidence of pregnancy and fertility among women who are farmers in Kagera region in Tanzania. The OLS, individual and community fixed effect estimations all pointed to the fact that there is a negative link between loss in crop (wage/income) and the probability of conceiving and giving birth. In express terms, it was unearthed that crop loss resulted in a 10 percent decline in the chance of getting pregnant and 17 percent probability of giving birth. Similar results were ascertained by Bono, Weber and Winter-Ebmer (2015), Kamaruddin and Khalili (2015) and Schultz (2005) who all found that a rise in wage causes a nosedive in the rate of fertility.

3. Methodology

a. Estimation model and process

This study aims at investigating the mediating role labour supply (hours of work) plays in how wage influences fertility rate. Thus in the model, wage serves as the predictor or treatment variable while hours of work and number of children per woman are the mediating/intervening and outcome variables respectively. The empirical specification used in the study, which follows the standard mediation model, is therefore stipulated as follows:

$$F_i = \beta_1 + \beta_2 W_i + \vartheta_i^T X_i + \varepsilon_F \tag{1}$$

$$LS_i = \theta + \gamma W_i + \vartheta_i^T X_i + \varepsilon_{LS} \tag{2}$$

$$F_i = \omega_1 + \phi_2 W_i + \delta LS_i + \vartheta_i^T X_i + \varepsilon_F \tag{3}$$

where F_i, LS_i, W_i and X_i are number of children per woman, labour supply/hours of work, wage and covariates respectively. β_i, ϑ, θ, γ, ω and ϕ are coefficients in their respective equations. ε_F and ε_{LS} are also error terms in their respective equations.

A major issue encountered when exploring causal analysis in studies that do not use randomized experiment is endogeneity and the mediation model above is not an exception (Antonakis et al. 2010). The rest of this section, therefore, explores the causes of the endogeneity inherent in the model as well as its remedy. In addition, it discusses Marginal Mediation Analysis (MMA) which is used to estimate the direct (DE), indirect (IE) and total effects (TE) of the variables of interest. The last part of the section will be used to elucidate Iacobucci's Z-mediation which will be used to analyzed the significance of the IE (Iacobucci, 2012).

b. Causes and remedy of endogeneity

Endogeneity arises when the error term of a model correlates with any of the explanatory variables $(E[\varepsilon_i \mid X_i] \neq 0)$ .This problem constitutes a serious violation of the Gauss-Markov theorem of exogeneity and hence renders causal analysis biased, inaccurate and uninterpretable (Antonakis, et al., 2010; Antonakis, et al., 2014). The source of endogeneity includes simultaneity, measurement error, omitted confounding variable(s), selection biased, common-method variance and model misspecification (Antonakis, et al., 2010; Zaefarian, et al., 2017).

The mediation model specified in equations (1) – (3) suffers from a number of the causes of endogeneity. First of all, there exist simultaneity between wage (the price of labour) and hours of work (supply of labour). This is so because there is a reverse causality between the two variables, thus wage influences hours of work and vice versa. In a simple labour market, workers adjust their supply of labour to changes in wages. In the same way, the wages workers earned is greatly influenced by the amount of labour supply available on the market. Estimations from the model will therefore be spurious if this problem is not addressed.

Another root of endogeneity in the model is omitted confounding variables (OCM). There is OCM when a variable that influences both the outcome and explanatory variable(s) is not included in the model. The omission of such variable can overestimate or underestimate the effects of the included predictor variables on the outcome and thus makes them (the effects) biased. Since the study used observational data, there are a number of household factors that influence wage, hours of work and fertility which have not be included in the model because some are difficult to measure.

The reasons outlined above demonstrate that the mediation model is plagued with endogeneity and therefore the estimation of the direct, indirect and total effects without an appropriate remedy will lead to inaccurate results. The use of instrumental variable(s) is one of the accepted solution to the problem (Antonakis, et al., 2010; Wooldridge, 2013). An instrumental variable (IV) or instrument is a variable that influences an explanatory variable (preferably the variable of interest) but does not correlate with the error term. What an instrument does it that, it curves out the part of the explanatory variable that does not relate to the error term and uses it to estimate the model.

The study uses respondent's association to a trade union as the instrument for wage. This choice is suitable because it is appropriate both theoretically and practically. Labour market theorists posit that wage is one of the factors that influences wage (Card, 2007). The wages of workers in Ghana is greatly influenced by one's association to a trade union or not. The wage in Ghana is determined by the National Tripartite Committee which comprises of the trade union congress (the umbrella body of the workers' union), the government and the employers' association (Ghana Labour Act, 2003). As a result, workers who are not members of these labour unions tend to be disadvantaged compared to unionized workers. However, the number of hours workers supply on the labour market is not influenced by whether a worker is unionized or not. This makes one's association to a trade union a good candidate as an instrument for wage. The number of children per woman, in the same vein, has no direct relation with whether a female worker is part of a trade union or not. Belongingness to a trade union was measured as a binary variable in the data. A code of 1 was assigned to women who are members of a trade union and 0 if otherwise.

The two-stage-least-squares (2SLS) approach, which is the instrumental variable (IV) estimation for linear regression, is used for the mediating equation. This is appropriate because the outcome variable for the mediating equation, that is equation (2), is labour supply which is continuous. In theory, wage is regressed on one's association to a trade union and the covariates in the labour supply's equation. The estimated coefficients are used to compute estimated values of wage which is then used in place of the original wage variable in that equation. However, this process cannot be done manually as it will yield incorrect standard errors though the coefficient estimates will be accurate (Wooldridge, 2013). Therefore, the 2SLS estimation is done by Stata using the '***ivregress'*** command.

The outcome variable for the fertility model is a count variable which is nonlinear and as a result there are two competing IV estimation approaches for it. They are the two-stage-predictor-substitution (2SPS) and the two-stage-residual-inclusion (2SRI) methods. The 2SPS is the same as the 2SLS for linear regression in every respect. The technique of 2SRI is however different. The first stage of the 2SRI is the same as the 2SPS, in that they both regress the endogenous variable on the instrument(s) and other covariates in the model. Howbeit, they diverge at the second stage.

In the 2SPS, the original endogenous variable is replaced by its predicted values computed from the estimated coefficients in the first stage. The 2SRI, on the other hand, maintains the original value of the endogenous variable in the second stage and also includes the estimated residuals generated from the first stage estimation. Terza, et al. (2008) argued that the application of the 2SPS on nonlinear model leads to a substantial bias and recommended the use of 2SRI for such models. The study will therefore employ the 2SRI in estimating the fertility models (equations 1 and 3).

c. Marginal Mediation Analysis

Mediation analysis in cases where all equations in the model can be estimated by OLS is pretty straightforward. Assuming fertility rate and hours of work in equations (1) - (3) were all continuous and as such are estimated separately by OLS, then the total and direct effects of wage on fertility would have been simply β_2 from equation (1) and ϕ from equation (3) respectively. The indirect (mediated) effect, on the other hand, would have the product of γ equation (2) and δ equation (3). More so, the summation of the direct (ϕ) and the indirect effects ($\gamma * \delta$) would be equal to the total effect (β_2). This is possible because each coefficient of OLS is additive, thus can be interpreted as an X (the value of the coefficient) unit change in the dependent variable due to a unit change in the predictor variable. The additive property of estimated coefficients of OLS makes it easy to combine them with other coefficients of the same characteristics in a meaningful manner. Furthermore, these coefficients have intuitive interpretations and can be easily understood.

However, the situation gets complex when the model involves non-normal distributions such as when any of the equations has binary or count outcome/dependent variables. These equations are best estimated using Generalised Least Model (GLM) such as logistic, probit, poisson, negative binomial regressions etc. Estimated coefficients of GLM are multiplicative and require much effort to understand. For instance, it is difficult to interpret the log-odds which are the coefficient estimates of logistic regressions. The odd ratio, which is an exponentiation of the log-odd is multiplicative. By multiplicative, the odd ratio is interpreted as a unit change in the explanatory variable leads to an X (value of the odd ratio) times change in the outcome variable. The multiplicative property of estimates of GLMs makes combining them with other coefficients to generate indirect effect quite impossible (Barrett, 2018).

To overcome this challenge among GLM estimates, Barrett (2018) has proposed the merging of the average marginal effect (AME) with mediation analysis into a new framework called the Marginal Mediation Analysis (MMA). AMEs compute the marginal effects at all observed values of the explanatory variables and then calculates the average. Thus the AME of an explanatory variable depends on all level of each control variables as well as the estimated coefficients in the model. This approach makes AME additive and put it in the same category as the estimated coefficients of OLS. In fact, Williams (2018) argued that the AMEs of an OLS regression are the same as its estimated coefficients. With the additive property, AMEs of GLMs can be easily combined with themselves or coefficients of OLS to compute indirect effects.

To summarize the estimation process, equation (2) which has a continuous outcome variable is estimated by the 2SLS approach to deal with endogeneity. Equations (1) and (3), on the other hand, is estimated separately using the 2SRI method because their dependent variable, which is number of children per woman, is a count variable. AMEs for wage and hours of work in equations (1) and

(3) is then generated using Stata command '***margins, dydx(*)'*** . The AME for hours of work in equation (3) is multiplied by the OLS estimated coefficient of wage in equation (2) to compute the indirect effect. The total and direct effects, on the other hand, are the AMEs of wage in equations (1) and (3) respectively.

d. Test of significance

The Sobel's z-test is the dominant test used to evaluate the significance of the indirect effect where all the models are estimated via OLS. Using the coefficients in equations (1) – (3), this z-value is computed by the mathematical expression below:

$$z = \frac{\gamma * \delta}{\sigma_{\gamma\delta}} = \frac{\gamma * \delta}{\sqrt{\gamma^2 s_\delta^2 + \delta^2 s_\gamma^2}} \qquad (4)$$

where s_γ^2 and s_δ^2 are the variances of γ and δ respectively. The computed z-value is then compared to the critical value of the standard normal distribution (z-critical) with a given α, usually 0.05 or 0.01, to ascertain the significance of the indirect effect.

However, the Sobel's test is limited to when the outcome variables in equations (2) – (3) are all continuous. As a result, Iacobucci (2012) has proposed the Z-mediation test. Despite the fact that the author applied the test to categorical outcome variables, it can be extended to all non-normal distributed variables. Z mediation uses the standardized coefficients of γ and δ in equations (2) and (3) respectively to calculate its value. Though γ and δ are of different metrics due to their different estimation techniques, their standardized coefficients are of the same scale and hence can be combined in a sensible manner to compute the value of Z mediation. The Z mediation formula as given by Iacobucci (2012) is as follows:

$$z = \frac{z_\gamma * z_\delta}{\sqrt{z_\gamma^2 + z_\delta^2 + 1}} \qquad (5)$$

where z_γ and z_δ are the standardized coefficients of γ and δ respectively.

Aroian (1947) posited that the product of two normally distributed estimates is asymptotically normal and as a result Iacobucci (2012) suggested the use the standard normal distribution to test the significance of the value of the Z mediation. The significance of the direct and total effects, on the other hand, is based on their p > |z| values obtained from the poisson or negative binomial estimation of equations (1) and (3).

4. Source of Data

The data set used for the analysis of this study is the sixth round of the Ghana Living Standard Survey (GLSS 6). GLSS 6 is a secondary data which concentrates on the household as the main socio-economic unit. The Ghana Statistical Service (GSS) that conducted the survey employed a two stage stratification procedure in selecting the households. First of all, the country was stratified into ten groups in accordance with the number of regions. After that, the households in each region is divided into urban and rural dwellers. The data covers demographic characteristics of the household members. These include the health profile, educational attainment, housing and the household income. The study included all the working female respondents who are within the fertility age (12 to 49 years) and have no missing value for any of the variables. As a result, 791 women were used in the analysis. The total number of children per woman is used for fertility rate. Wage per week, on the other hand, was used as the explanatory variable. Specifically, we controlled for educational status, age at first marriage, use of contraceptive, religion, location and migration status. Table 1 provides descriptions of the variables used in the mediation model.

Table 1: Description of Variables

Variable	Description
Fertility rate	Number of children ever born to the respondent
Wage	Weekly wage rate
Education	Respondent's highest educational attainment [0 = No formal education, 4 = tertiary]
Age at first marriage	Age of respondent at her first marriage
Religion	Respondent's religious affiliation [0 = No religion, 5 = traditional religion]
Location	Place of residence of respondent [0 = Rural, 1 = Urban]
Migration	Migration status of the respondent [0 = Non-migrant, 1 = Migrant]
Association to trade Union	Respondent's belongingness to a trade union [1= Unionized, 0 = otherwise]

5. Analysis of Data

a. Descriptive Statistics

The descriptive statistics of the continuous and categorical variables are demonstrated in tables 2 and 3 respectively. Table 2 revealed that the average number of children per woman in the study stood at 4.4 with a standard deviation of 2.3. The means of the log of weekly wage, hours of work, non labour income figured around US$ 0.70, 3.45 hours and US$ 1.20 respectively. Their respective standard deviations are 1.51, 0.65 and 3.70. The average age at first marriage for the respondents is 20.38 with a standard deviation of 3.70.

Table 2: Descriptive Statistics of continuous variables

Variable	Mean	Std. Dev.	Min	Max
Total number of children	4.46	2.33	0	11
Log(wage)	4.00	1.51	0.69	8.76
Log(Hours of work)	3.45	0.65	0	4.76
Log(non labour income)	5.28	1.35	1.61	9.57
Age at first marriage	20.38	3.70	13	34

As shown on the table 3, respondents who have only primary education dominated the educational category accounting for almost 90%. The remaining percentage was distributed among the rest with those who have secondary, tertiary and no education attaining 7.08%, 1.90% and 1.26% respectively. An overwhelming majority of the respondents were Protestants figuring around 75.73%. This was followed by Catholics (15.8%) and Moslems (4.93%). The percentages for those with no religion and traditionalists were 2.15% and 1.39% respectively. Most of the respondents were rural dwellers (62.20%). The ratio of non-migrants to migrants almost stood at 7:3. The proportion of people who did not use contraceptive (60.56%) far outstripped their counterparts who use such birth control method (39.44%). Lastly, with regards to the instrumental variable, almost two-third of the respondents were found out to be members of a trade union.

Table 3: Descriptive Statistics of categorical variables

Variable	Categories	N (%)
Educational Status	No education	10 (1.26)
	Basic	710 (89.76)
	Secondary	56 (7.08)
	Tertiary	15 (1.90)
Religious Status	No religion	17 (2.15)
	Catholicism	125 (15.8)
	Protestantism	599 (75.73)
	Islam	39 (4.93)
	Traditional	11 (1.39)
Residence	Urban	299 (37.80)
	Rural	492 (62.20)
Contraceptive use	Yes	312 (39.44)
	No	479 (60.56)
Migration Status	Migrants	262 (33.12)
	Non-migrants	529 (66.88)
Association to trade union	Unionized	545 (68.9)
	Non-unionized	246 (31.1)

b. Significance of instrumental variable

As it has been stated earlier, the mediation model in equations (1) – (3) suffers from endogeneity and hence association to a trade union is used as an instrument for wage. To know whether the instrument is strong and valid, it must satisfy two condition. First, it must be uncorrelated with the error term(s) and secondly it must correlate with wage. The first condition cannot be tested because the error terms are unobserved. The test for the second condition can be conducted by regressing wage on the instrument together with all the other covariates in the equations and then checking the significance of the instrument (Wooldridge, 2013).

As revealed by table 4 (in the appendix), the study conducted the test for the second condition and found out the association to a trade union increases wage at significance level of 5%. It can be concluded that the instrument is valid and is fit to resolve the biasedness due to the endogeneity.

c. Estimating Total (TE), Direct (DE) and Indirect effects (IE)

Equations (1) and (3) are estimated by 2SRI using poisson regression, then after the average marginal effects (AMEs) for wage and hours of work in the equations are computed. But before deciding on a poisson regression, a negative binomial regression was estimated to know whether the mean and the variance in the equations are the same or not. The test failed to reject the null hypothesis that alpha is zero, implying there is no statistical difference between the mean and the variance. The poisson regression is therefore the best estimation technique for the two equations. The 2SRI-Poisson regression estimation for equations 1 and 3 are displayed in tables 5 and 6 respectively while the 2SLS estimation of equation 2 is shown in table 7 below.

Table 5: 2SRI-Poisson regression estimation of equation 1
Dependent variable: Fertility (Number of Children)

Variables	Coefficient	Std. Error	Z	P > |z|
Log of wage	-0.199	0.043	-4.61	0.000
Log of non-Lab Income	-0.055	0.013	-4.09	0.000
Education				
Basic	-0.172	0.151	-1.14	0.254
Secondary	-0.770	0.173	-4.45	0.000
Tertiary	-1.261	0.240	-5.25	0.000
Religious Affiliation				
Catholicism	-0.004	0.119	-0.03	0.976
Protestantism	0.012	0.113	0.10	0.917
Islam	0.421	0.130	3.24	0.001
Traditional	-0.113	0.189	-0.60	0.550
Age of first marriage	-0.015	0.005	-2.96	0.003
Contraceptive use	0.038	0.036	1.05	0.293
Migrants	-0.136	0.038	-3.61	0.000
Urban	-0.071	0.037	-1.91	0.057
Residual	-0.173	0.021	-8.25	0.000
Constant	0.832	0.257	3.23	0.001
No of Obs.	791			
LR Chi2 (15)	210.63			
Prob > Chi2	0.000			
Pseudo R2	0.0596			

Table 6: 2SRI-Poisson regression estimation of equation 3
Dependent variable: Fertility (Number of Children)

Variables	Coefficient	Std. Error	Z	P > |z|
Log of wage	-0.191	0.041	-4.68	0.000
Log of Hours of work	0.473	0.029	1.62	0.105
Log of non-Lab Income	-0.054	0.014	-4.02	0.000
Education				
Basic	-0.186	0.151	-1.23	0.217
Secondary	-0.765	0.173	-4.42	0.000
Tertiary	-1.288	0.241	-5.34	0.000
Religious Affiliation				
Catholicism	-0.002	0.119	-0.02	0.986
Protestantism	0.019	0.113	0.17	0.868
Islam	0.415	0.130	3.19	0.001
Traditional	-0.068	0.191	-0.35	0.723
Age of first marriage	-0.015	0.005	-2.95	0.003
Contraceptive use	0.031	0.036	0.85	0.393
Migrants	-0.133	0.038	-3.54	0.000
Urban	-0.082	0.038	-2.17	0.030
Residual	-0.177	0.021	-8.38	0.000
Constant	0.634	0.285	2.22	0.026
No of Obs.	791			
LR Chi2 (15)	213.28			
Prob > Chi2	0.000			
Pseudo R2	0.0603			

Table 7: 2SLS estimation of equation 2
Dependent variable: Log of Hours of work

Variables	Coefficient	Std. Error	Z	P > |z|
Log of wage	1.504	0.325	4.63	0.000
Log of non-Lab Income	-0.074	0.053	-1.38	0.167
Experience	-1.480	0.664	-2.23	0.025
Education				
Basic	-0.698	1.404	-0.50	0.619
Secondary	-3.165	0.816	-3.88	0.000
Tertiary	-4.089	1.007	-4.06	0.000
Age Cohort				
20 – 24	-0.603	0.545	-1.11	0.269
25 – 29	-0.108	0.317	-0.34	0.734
30 – 34	0.045	0.307	0.15	0.883
35 – 39	-1.197	0.532	-2.25	0.024
40 – 44	-0.231	0.361	-0.64	0.522
45 – 49	-0.068	0.382	-0.18	0.858
Migrants	-0.032	0.117	-0.27	0.785
Urban	0.262	0.127	2.07	0.038
Constant	2.086	2.803	0.74	0.457
No of Obs.	791			
F(14, 776)	8.64			
Prob > F	0.000			
R-squared	0.127			
Adj. R-squared	0.111			

Tables 5 – 7 above are the estimation results of the three equations in the mediation model. However, as stated earlier, the average marginal effects (AME), a post-estimation technique, were computed in order to calculate the direct and indirect effects due to the different measurement metrics of the estimated coefficients. The AME for the variables of interest in equation (1) and equation (3) are exhibited in tables 8 and 9 respectively.

Table 8: Average Marginal Effect for log of wage in equation 1

	dy/dx	Delta-method Std. Error	Z	P > |z|
Log of wage	-0.863	0.181	-4.76	0.000

Table 9: Average Marginal Effects for logs of wage and hours of work in equation 3

	dy/dx	Delta-method Std. Error	Z	P > |z|
Log of wage	-0.850	0.183	-4.64	0.000
Log of Hours of work	-0.011	0.005	-2.23	0.01

The AMEs for wage in tables 8 and 9 are the estimated total (TE) and direct (DE) effects respectively. The TE in the model is therefore -0.863 whiles the DE is -0.85.

The indirect effect of wage on fertility in the model is the product of the AME of hours of work in table 9 and the OLS estimated coefficient of log of wage in equation 2. As displayed in table 7 above, which is the result of the 2SLS estimation of hours of work, the estimated coefficient of log of wage is 1.504. The AME of hours of work, on the other hand, is -0.011. The indirect effect in the model is therefore equal to -0.016.

Even though there is a discrepancy between the summation of the IE and DE (-0.866), on one hand, and the TE (-0.863) on the other, Barrett (2018) posited that results generated from Marginal Mediation Analysis are consistent as the difference disappears with large sample size.

d. Significance of IE, TE and DE

The significance of the indirect effect (IE) is tested using the Z-mediation. Recall that the value of z using Z-mediation is computed by;

$$z = \frac{z_\gamma * z_\delta}{\sqrt{z_\gamma^2 + z_\delta^2 + 1}} \tag{6}$$

z_γ is the z value of log of wage in equation (2). z_δ, on the other hand, is the z value for the AME of hours of work in equation (3). Hence, z_γ and z_δ are 4.63 and -2.20 respectively. Substituting the figures in the formula above yields a z value of -1.972. The null hypothesis that the indirect effect is insignificant is rejected at a significance level of 5 percent. Thus it can be concluded the negative effect of wage on fertility through hours of work is significant.

The significance of the total (TE) and direct (DE) effects is evaluated using the p values of the AMEs for log of wage in equations (1) and (3). The p values in the two cases are 0.000 implying that both the TE and DE are statistically significant at 1 percent.

6. Discussions

Ghana continues to fight against high rates of fertility to ensure a sustainable economic growth and development. Wages that women earn plays a key role in influencing the number of children per woman. This study, therefore, explored the effect of wage on the number of children per woman in Ghana using the quantity-quality trade off theory as the direct effect while the indirect effect is explained by the implicit (opportunity cost) theory. Hours of work was used as a mediating variable in the analysis.

The Marginal Mediation Analysis (MMA) revealed that both the direct (DE) and indirect (IE) effects of wage on fertility were negative. The indirect effect reinforced the inverse direct relationship causing the total effect of wage on fertility to be also negative. The impact of the direct effect, nevertheless, is more pronounced than the indirect effect. Thus, the findings revealed that the effect of wage on fertility is partially mediated through hours of work, albeit the effect is quite minimal in the case of Ghanaian women. Explicitly, the DE indicated that a percentage increase in wage directly caused the number of children per woman in Ghana to reduce by 0.85. The indirect effect, on the other hand, showed that a percentage rise in wage caused Ghanaian women to increase their hours of work by 1.504 percent. The number of children per woman likewise reduced by 0.011 when there is a percentage increment in the hours of work. Therefore, the number of children per woman in Ghana dwindled by 0.016 through hours of work as a result of a percent rise of wage. In total, Ghanaian women reduced the number of children they have by 0.863 due to a percent rise in wage. Thus it is unearthed in the study that the effect of wage on fertility rate in Ghana is partially mediated by hours of work.

The finding of the study, especially with respect to the direct effect, is consistent with the assertion in the literature that there is a direct inverse relationship between wage and fertility rate (Alam and Pörtner 2018; Bono, Weber and Winter-Ebmer 2015; Kamaruddin and Khalili 2015; Schultz 2005). A plausible explanation for this effect is the quality-quantity trade off posited by Becker (1960). It is therefore evident that Ghanaian women place much premium on improving the quality of life they give to the children, such as providing better education, healthcare, housing and so on, rather than enlarging their family size when there is a rise in their income.

The stipulation of Mincer (1963) best explains the indirect effect of the analysis. It implies that wage serves as an opportunity cost of staying at home for Ghanaian women and therefore as the wage level rises, they will devote more time to working hours and this shrinks the number of children they have. Notwithstanding, this indirect effect elucidates only a minute percentage in the variation of fertility as much of the impact of wage on latter emanates from the direct effect.

Another importance of the study is that it applied the MMA to the analysis of fertility. This estimation technique made it possible to decompose the total effect of wage on fertility into direct and indirect effects irrespective of the distributional properties of the dependent variables of the equations in the mediation model. In our model, the estimated coefficients of the fertility equations had multiplicative properties while those in the hours of work equation had additive properties. The MMA transformed all the estimated parameters to a uniform metric using Average Marginal effect which made it possible to compute the indirect effect.

Additionally, the MMA allowed for the incorporation of different instrumental variable (IV) estimations in the same model in the event of endogeneity. The study used the two stage least squares (2SLS) instrumental approach to correct for the endogeneity in the labour supply equation because hours of work is a continuous variable. In contrast, the two stage residual inclusion (2SRI) method was applied in the fertility equations because their dependent variable, which is number of children per woman, is a count variable and hence has a non-normal distribution. It is also worth to note that association to a trade union, which was used as the instrumental variable, was found to be a strong and valid instrument.

7. Conclusion

Following the tracks of Gary Becker and Jacob Mincer, the study applied the quantity-quality trade off and family utility maximization models to analyze the effect of wage on fertility for Ghanaian women. Different from other studies on fertility, the study employed the Marginal mediation analysis which decomposed the total effect of wage on fertility into the quantity-quality trade off (the direct effect) and the opportunity cost of wage (the indirect effect). Most studies on fertility avoided the analysis of both the direct and indirect effects of wage in a single model due to the different measurement metrics of the number of children and hours of work which are the two dependent variables in the mediation model. The Marginal mediation analysis transformed the estimated coefficients into a uniformed metric for the indirect effect to be easily computed. It was revealed that a percentage rise in wage directly dwindled the number of children per woman by 0.85. On the other hand, a percentage increment in wage reduced fertility rate by 0.016 through hours of work.

The findings of the study imply that wage plays a significant role in Ghana's fight against rapid population growth. To cut down on the number of children per woman, the government and other policy makers should empower women in terms of both their earnings and job opportunities on the labour market. The more lucrative the job market is (in terms of earnings), the greater the opportunity cost of home production activities and hence fertility rate is likely to fall.

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Appendix

Table 4: OLS estimation to test the significance of the instrumental variable

Dependent variable: Log of wage

Variables	Coefficient	Std. Error	Z	P > |Z|
Yes_Trade Union	0.231	0.104	2.22	0.026
Non-Labor Income	0.032	0.040	0.80	0.426
Experience	0.044	0.007	6.52	0.000
Education				
Basic	1.027	0.478	2.15	0.032
Secondary	1.810	0.521	3.47	0.001
Tertiary	3.032	0.601	5.04	0.000
Age Cohort				
20 – 24	0.328	0.343	0.95	0.340
25 – 29	0.005	0.343	0.02	0.988
30 – 34	0.092	0.311	0.29	0.768
35 – 39	0.356	0.292	1.23	0.220
40 – 44	0.185	0.286	0.65	0.517
45 – 49	0.210	0.283	0.74	0.460
Migrants	-0.041	0.111	-0.37	0.714
Urban	0.052	0.115	0.45	0.654
Constant	2.084	0.599	3.48	0.001
No of Obs.	791			
F(14, 776)	7.39			
Prob > F	0.000			
R-squared	0.118			
Adj. R-squared	0.102			