Economics Bulletin

Volume 39, Issue 3

Convex relationship between fertility and gender gap

Yoko Nakagaki
National Graduate Institute for Policy Studies

Abstract

This study empirically confirms that fertility rebound in high income countries depends not only upon the so-called inverse J-shaped relationship between fertility and income confirmed by previous studies but also upon another convex relationship between fertility and narrowing of the gender gap measured by the Global Gender Gap Index. This study also confirms that the convex relationship between fertility and narrowing of the gender gap is attributable to a reduction in the gender gap in the area of economic participation.

This paper is based on a research project at the JICA Research Institute.
Citation: Yoko Nakagaki, (2019) "Convex relationship between fertility and gender gap", *Economics Bulletin*, Volume 39, Issue 3, pages 2014-2026
Contact: Yoko Nakagaki - y-nakagaki@grips.ac.jp.
Submitted: August 27, 2019. **Published:** September 07, 2019.

1. Introduction

1.1 Decline and recovery of fertility

The total fertility rate (TFR) – the theoretical number of children that would be born to a woman during her lifetime if she experienced the age-specific fertility rates observed in a calendar year – declined globally in the second half of the 20th century. In 2016, world TFR decreased to 2.4 from five in 1960 (World Bank 2019). The decline of fertility has been explained as the negative relationship between fertility and economic growth: Economic growth increases the opportunity cost of childrearing and reduces fertility via the narrowing of the wage gender gap (Becker and Barro 1988; Galor and Weil 1996).[1]

TFRs in most developed countries have slightly rebounded since the late 1990s, though they have remained below the population replacement level (around 2.1) (OECD 2011; World Bank 2019). Myrskylä, Kohler, and Billari (2009) explained the decline and subsequent rebound of TFR as an inverse J-shaped relationship between fertility and development. The study used the Human Development Index (HDI), a composite index published annually by the United Nations Development Programme (UNDP 2019), as a proxy of development. It confirmed the inverse J in cross-country data of 2005 as well as in longitudinal data for 1975–2005. The authors concluded that further development could reverse fertility decline at the advanced level of the HDI, though they identified some exceptional countries with low fertility despite having high incomes. The study suggested that failure of institutions to facilitate work-family balance and gender equality might explain the low fertility in those countries. Furuoka (2009, 2013) reexamined the inverse J by using threshold regression. Furuoka (2013) concluded that the negative relationship between TFR and HDI only weakened or flatter sloped. Harttgen and Vollmer (2014) also reexamined the inverse J, employing a methodology similar to Myrskylä, Kohler, and Billari (2009) on revised HDI data as well as on each of three HDI subindices. They found very little support for the simple interpretation that fertility would automatically start to increase beyond a certain level of development.

Another inverse J-shaped relationship was confirmed as a quadratic relationship between TFR and the logarithm of per capita income in higher-income countries (Luci-Greulich and Thévenon 2014; Dominiak, Lechman, and Okonowicz 2015; Lacalle-Calderon, Perez-Trujillo, and Neira 2017; Day 2018). Luci-Greulich and Thévenon (2014) and Dominiak, Lechman, and Okonowicz (2015) estimated the turning points of the inverse J as around 10.4 in constant 2005 US$ (PPP). Day (2018) estimated the turning point in OECD countries for 2005–2014 as around 10.3 in constant 2011 international$ (PPP). Conducting estimations on subsamples according to income levels, Lacalle-Calderon, Perez-Trujillo, and Neira (2017) confirmed that the inverse J existed only for higher-income countries. Those studies agreed that economic

[1] Increasing returns of investments in individual human capital is another important factor of declining fertility (Becker, Murphy, and Tamura 1990).

development was likely but not sufficient to lift fertility without additional changes.

The key to fertility rebound in higher-income countries is recognized as the change of the relationship between fertility and reductions in the gender wage gap. In the recovery of fertility phase, the relative cost of childcare services declines with growing female relative wage, and a positive relationship between fertility and female labor participation could appear (Martínez and Iza 2004). Day (2018) presented a theoretical model explaining what was behind the inverse J. In the model, economic growth, via gender wage gap reductions, encourages households to raise the paid female labor supply and have more children by substituting childcare services for maternal time. Cross-country differences in the gender wage gap, family policy, and willingness to substitute maternal time in childrearing are important factors in the inverse J-shaped effect. It seems that growth in per capita income does not filter through to higher female relative wages in societies with low fertility and high income (Day 2012).

Myrskylä, Kohler, and Billari (2011 (revised 2013)) confirmed that the inverse J between TFR and the HDI in Myrskylä, Kohler, and Billari (2009) was conditional on gender equality. The study focused on the change of the relationship between TFR and gender gap, using the Global Gender Gap Index (GGGI) as a proxy of gender equality. The GGGI, the composite index published annually for more than 100 countries from the World Economic Forum, ranges between 0 (inequality) and 1 (equality). Myrskylä, Kohler, and Billari (2011 (revised 2013)) observed that developed countries with average GGGI in 2006–2010 below 0.65 had a negative pace of TFR increase with respect to HDI, while countries with average GGGI above 0.75 had a positive pace. The result suggests that the relationship between TFR and the GGGI changes from negative to positive at the GGGI level between 0.65 and 0.75.

1.2 Purpose of this study

The purpose of this study is to empirically show that fertility rebound is dependent not only upon the inverse J-shaped relationship between TFR and per capita income but also upon the change of the relationship between TFR and narrowing of the gender wage gap. This study hypothesizes that the change of the relationship between TFR and gender gap in cross-country data (Myrskylä, Kohler, and Billari 2011(revised 2013)) might come from the convex relationship – the quadratic relationship – between the two variables over time. Such a quadratic relationship between fertility and gender related variables was found between TFR and people's attitudes regarding the gender-based division of roles by Arpino, Esping-Andersen, and Pessin (2015). Moreover, Feyrer, Sacerdote, and Stern (2008) suggested a convex relationship between TFR and female labor participation over time. They considered the negative (in the 1970s) / positive (after the late 1980s) relationship of the two variables for developed countries by Ahn and Mira (2002) as different pieces of the functions. Furthermore, Day (2012) explained that the formerly negative and emerging positive cross-country correlation between fertility and per capita income in OECD countries was due to the inverse

J-shaped relationship between the two variables.

To achieve the purpose, this study employs the GGGI (World Economic Forum 2006–2015) as a proxy of gender gap among several existing gender gap indices,[2] following Myrskylä, Kohler, and Billari (2011 (2013)). The index, which is dependent not on female performance level but solely on gender gap, is appropriate for this study, because this study employs both the gender gap index and per capita income as explanatory variables. The GGGI is calculated using fourteen gender gap indicators, all of which are in the form of female relative performance to male, ranging basically between 1 (equality) and 0 (inequality). Using the gender gap indicators, the report calculates four subindices: the Economy subindex, the Education subindex, the Health subindex, and the Politics subindex. The GGGI is calculated as an unweighted average of four subindices. Appendix I provides additional information on the GGGI.

This study also examines the relationship between TFR and the four GGGI subindices in order to address possible measurement error due to the different externality of each aspect of gender equality (Mitra, Bang, and Biswas 2015). This study assumes that the convex relationship could exist between TFR and the Economy subindex, which is calculated from five gender gap indicators including labor participation gap and wage gap.

2. Data and methodology

2.1 Dataset

The explained variable of the estimations is TFR.[3] Explanatory variables are the GGGI or its specific subindices, and the logarithm of per capita income. This study includes all explanatory variables as one-year-lagged forms in all estimations, because childbearing is fixed around one year before its realization. TFR and per capita GDP (constant 2011 international $ (PPP)) data are from the World Development Indicators (World Bank 2019).

Table I summarizes the dataset which spans from 2007 to 2016 and includes 144 countries. The unweighted average of GGGI(–1) increased from 0.662 in 2007 to 0.696 in 2016, while TFR decreased from 2.7 to 2.5 in the same period. Estimations are conducted on all samples, as well as on "higher-income (than average) samples (LnGDPpc(–1)≧9.377)" and on "lower-income (than average) samples (LnGDPpc(–1)<9.377)." This study assumes that the convex relationship exists in the relationship between TFR and gender gap for higher-income samples. Appendix II lists countries included in the dataset.

---

[2] Existing gender gap composite indices are well correlated with each other (van Staveren 2013; Stotsky, Shibuya, Kolovich, and Kebhaj 2016).

[3] TFR is the aggregation of age-specific fertility rates in a year. Hence, change in the timing of childbearing affects the level of TFR. Luci-Greulich and Thévenon (2014) and Myrskylä, Kohler, and Billari (2011 (revised 2013)) confirmed the robustness of their inverse J by using the "tempo-adjusted TFR" from the Human Fertility Database (MPIDR and VID 2019).

Table I: Summary of the dataset (2007–2016)

	TFR	GGGI(–1)	GGGI subindex(–1)				LnGDPpc(–1)	Number	
			Economy	Education	Health	Politics		Samples	Countries
Total	2.604	0.680	0.635	0.949	0.972	0.165	9.377	1,314	144
Std.dev.	1.319	0.060	0.117	0.088	0.010	0.124	1.137	1,314	144
Min.	1.149	0.451	0.195	0.468	0.919	0.000	6.573	1,314	144
Max.	6.901	0.881	0.914	1.000	0.980	0.754	11.728	1,314	144
By year									
2007	2.692	0.662	0.596	0.940	0.973	0.138	9.315	115	115
2016	2.547	0.696	0.660	0.956	0.973	0.194	9.389	142	142
By LnGDPpc(–1) level									
Lower-income samples	3.504	0.660	0.621	0.902	0.970	0.147	8.341	599	73
Higher-income samples	1.849	0.697	0.647	0.989	0.974	0.180	10.244	715	79

Note: This table shows the unweighted average of variables if not otherwise noted. "(–1)" stands for one-year-lag. "LnGDPpc" stands for the logarithm of per capita GDP (constant 2011 international$ (PPP)). "Lower-income samples" are composed of samples with lower than 9.377 in LnGDPpc(–1). "Higher-income samples" are composed of samples with equal or higher than 9.377 in LnGDPpc(–1).

Source: TFR and LnGDPpc are from the World Development Indicators (World Bank 2019). GGGI and its subindices are from the Global Gender Gap Reports (World Economic Forum 2006–2015).

2.2 Methodology

This study starts with the pooled OLS estimations on the relationship between TFR and GGGI/its subindices/per capita income by equation (1) or (2).

$$TFR_{it} = \alpha_0 + \alpha_1 GGI_{i,t-1}^2 + \alpha_2 GGI_{i,t-1} + Regdummy_i + \varepsilon_{it} \quad (1)$$

$$TFR_{it} = \alpha_0 + \alpha_1 LnGDPpc_{i,t-1}^2 + \alpha_2 LnGDPpc_{i,t-1} + Regdummy_i + \varepsilon_{it} \quad (2)$$

where TFR, GGI, LnGDPpc, Regdummy, ε, i, and t stand for total fertility rate, GGGI or its specific subindices (the Economy subindex (ECO), the Education subindex (EDU), the Health subindex (HEA), and the Politics subindex (POL)), log of GDP per capita, region dummy, error term, country i, and year t, respectively. Concerning region dummies, this study categorizes countries into nine regional groups: East Asia and the Pacific, South Asia, Central Asia, the Middle East and North Africa, sub-Saharan Africa, East Europe, West Europe, North America and, finally, Latin America and the Caribbean. If the coefficient for $GGI^2(-1)$/$LnGDPpc^2(-1)$ is positive and that for GGI(–1)/LnGDPpc(–1) is negative, it means that a convex relationship exists in the pooled data.

However, the convex relationship in the pooled data does not indicate the convex relationship within a country over time, because the pooled OLS estimator could be biased due to the presence of time-invariant heterogeneity. Therefore, previous studies estimating inverse J often employed fixed-effects estimators (Myrskylä, Kohler, and Billari 2011 (revised 2013); Luci-Greulich and Thévenon 2014; Dominiak, Lechman, and Okonowicz 2015; Lacalle-Calderon, Perez-Trujillo, and Neira 2017), which could capture unobserved time-invariant variables including country-specific characteristics. The estimator could also capture period effects such as lifestyle or institutions that might affect how per capita income influences fertility in the inverse J.

Furthermore, Luci-Greulich and Thévenon (2014) examined the robustness of the inverse J employing a dynamic panel estimator which could include the lag of the explained variables as additional explanatory variables in order to account for the dynamics of the process. Including lagged explained variables in OLS or fixed-effects estimators might cause the correlation between the lagged explained variables and the error term which would lead to a dynamic panel bias. The common strategy to deal with the issue is to employ either a system-GMM (Generalized Method of Moments) estimator by Blundell and Bond (1998) or a difference-GMM estimator by Arellano and Bond (1991). Both estimators are designed for "small t, large n" situations, and could accommodate autocorrelation, fixed-effects, and endogeneity (Roodman 2009). From these two estimators, Luci-Greulich and Thévenon (2014) employed a system-GMM estimator.

In this study, the explained variable (TFR) and the main explanatory variable (GGGI or subindices) might have endogeneity, which should be addressed. Moreover, TFR levels might be influenced by past values. Therefore, this study employs a dynamic panel estimator. Among two dynamic panel estimators, this study employs a difference-GMM estimator, because a system-GMM estimator requires that individuals sampled are in a kind of steady-state throughout the period (Roodman 2009), while the dataset of this study includes the declining fertility phase in developing countries. The difference-GMM estimates a first-differenced model which can deal with unobserved time-invariant variables, with lagged levels as instruments which allow treating the explanatory variables as endogenous.[4]

This study considers two diagonal tests for difference-GMM. One is the Sargan–Hansen test for the validity of overidentification restriction. Concerning the test, this study accepts the estimation if the null hypothesis "Overidentifying restrictions are valid" cannot be rejected at the 5% level. Concerning the second test of the Arellano–Bond test for serial correlation, this study accepts the estimation if it does not detect second-order autocorrelation (AR(2)) but first-order autocorrelation (AR(1)) at the 5% level. Furthermore, this study rejects the estimation if the coefficient for TFR(–1) is larger than 0.95 in order to avoid the possibility of a random walk. The model for the estimation is Equation (3).

$$TFR_{it} = \alpha_0 + \alpha_1 TFR_{i,t-1} + \alpha_2 TFR_{i,t-2} + \alpha_3 TFR_{i,t-3} + \alpha_4 GGI_{i,t-1}^2 + \alpha_5 GGI_{i,t-1}$$

$$\left(+\alpha_6 LnGDPpc_{i,t-1}^2 + \alpha_7 LnGDPpc_{i,t-1}\right) + Yeardummy_t + \varepsilon_{it} \quad (3)$$

where Yeardummy is year dummy. In the right-hand side, lagged TFRs from one to three years are included as explanatory variables, considering the adjustment of TFR with GGI which is

[4] Gaddis and Klasen (2014) employed the difference-GMM estimator in order to reexamine the frequently claimed quadratic relationship between female labor participation and per capita income.

originally lagged because of data availability (see Appendix I). All estimations include lagged variables of all explanatory variables as instruments. The estimation period for the difference-GMM estimations, which requires lagged variables, starts from 2011 and ends in 2016.

3. Results

3.1 Results of OLS estimations

Figure 1 shows the results of pooled OLS estimations. The dark circle dots stand for lower-income samples, while gray hollow diamonds stand for higher-income samples. Each line in the figures stands for the pooled OLS estimation results in Appendix III. Figure 1.1, Figure 1.2, and Figure 1.6 show the convex relationship between TFR and GGGI(–1)/ECO(–1)/LnGDPpc(–1) for pooled data. Regarding Figure 1.1 and Figure 1.2, higher-income samples are distributed closer to the estimated convex lines compared with lower-income samples with the same GGGI(–1)/ECO(–1) levels. Concerning TFR and EDU(–1) in Figure 1.3, and TFR and HEA(–1) in Figure 1.4, higher-income samples are distributed mainly at the right end of the figures. As for TFR and POL(–1) in Figure 1.5, higher-income samples are mainly situated in the lower left. Regarding the relationship between TFR and LnGDPpc(–1) in Figure 1.6, only higher-income samples are situated in the fertility recovery phase.

Figure 1: TFR and GGGI/its four subindices/LnGDPpc

Figure 1.1: TFR and GGGI (–1)

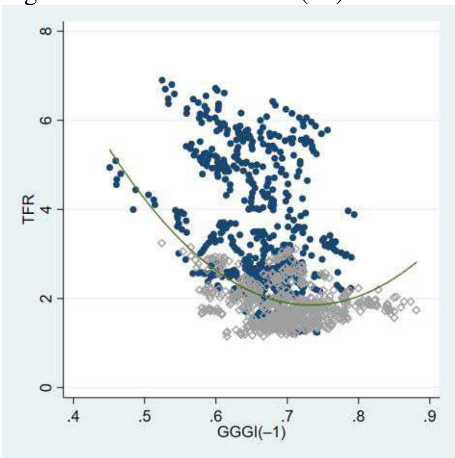


Figure 1.2: TFR and Economy subindex (–1)

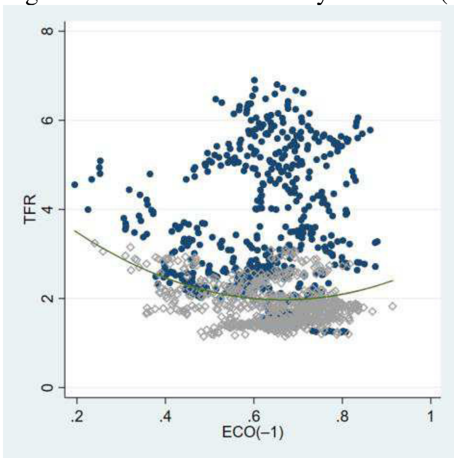


Figure1.3: TFR and Education subindex (–1)

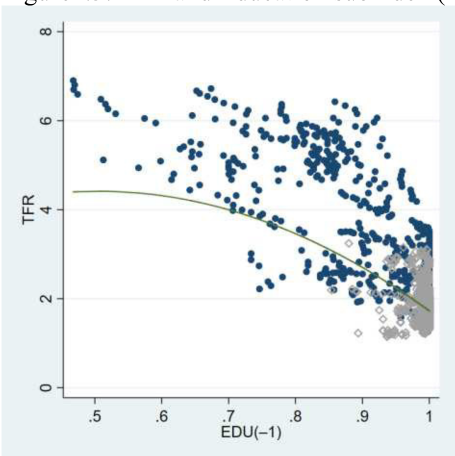


Figure 1.4: TFR and Health subindex (–1)

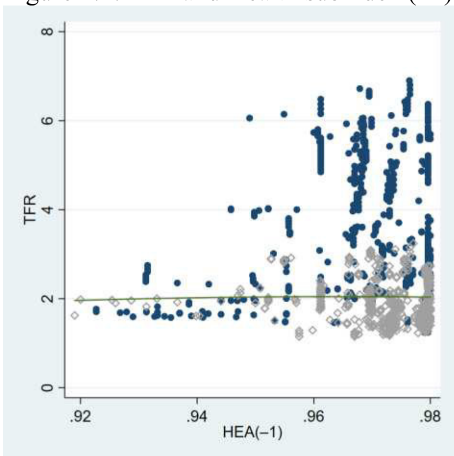


Figure 1.5: TFR and Politics subindex (–1)

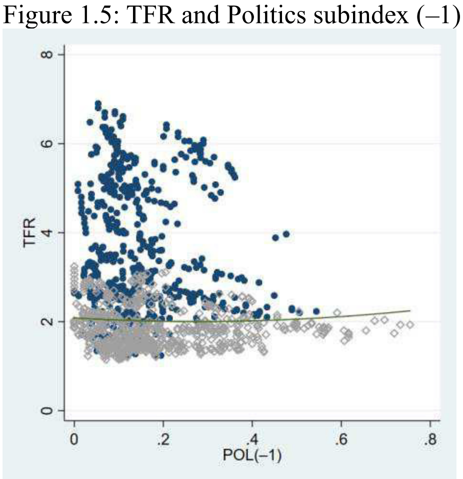
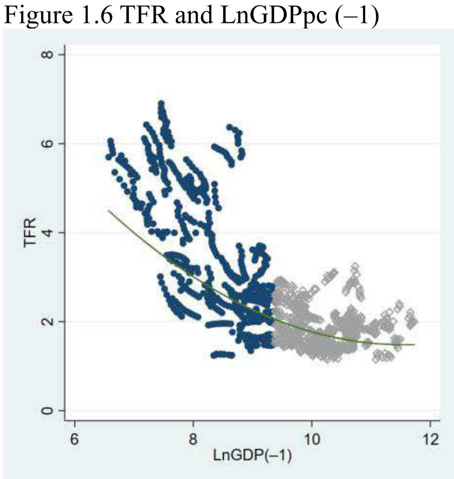


Figure 1.6 TFR and LnGDPpc (–1)



Note: Circle dots stand for "lower-income samples" with lower than 9.377 in LnGDPpc(–1). Gray hollow diamond dots stand for "higher-income samples" with equal or higher than 9.377 in LnGDPpc(–1). Lines in figures stand for results on OLS estimations summarized in Appendix III: App3.1 (Figure 1.1), App3.2 (Figure 1.2), App3.3 (Figure 1.3), App3.4 (Figure 1.4), App 3.5 (Figure 1.5), and App3.6 (Figure 1.6).

3.2 Results of difference-GMM estimations

Table II shows the results of difference-GMM estimations on the relationship between TFR and GGGI(–1)/LnGDPpc(–1). Est2.1–3 are the results using GGGI(–1) (and its squared value). Est 2.1 includes all samples, while Est2.2/Est2.3 includes lower-/higher- income samples only. In all of them, estimated coefficients are positives for $GGGI^2(-1)$ and negative for GGGI(–1), which represents a convex relationship. However, in Est2.1, the estimated coefficients are not statistically significant, and the estimation does not clear the Arellano–Bond serial correlation test. Est2.2 does not clear the Arellano–Bond serial correlation test. Est2.3 clears two diagonal tests, though the estimated coefficient for TFR(–1) is too large.

Est2.4–6 are the results on the inverse J between TFR and LnGDPpc(–1). All of them clear the plus/minus condition for coefficients. However, only Est2.6 (higher-income samples) clears two diagonal tests with the plausible coefficient for TFR(–1) (0.936).

Est2.7–9 are the results of estimations including both GGGI(–1) (and its squared value) and LnGDPpc(–1) (and its squared value). Though all estimations clear the condition on plus/minus signs, the estimated coefficients for Est2.7 (all samples) are not statistically significant. Est2.8 (lower-income samples) does not clear the Arellano–Bond serial correlation test. Only Est2.9 (higher-income samples) clears the two diagonal tests with the plausible coefficient for TFR(–1) (0.854). The estimated turning point for GGGI in Est2.9 (0.716) is consistent with Myrskylä, Kohler, and Billari (2011 (revised 2013)), which suggested that the relationship between TFR and the GGGI changed from negative to positive at the GGGI level between 0.65 and 0.75. The estimated turning point for LnGDPpc in Est2.9 (10.1) is smaller than 10.3, which Day (2018) estimated for OECD data in 2005–2014. In conclusion, Table II confirms that fertility rebound depends not only upon the inverse J-shaped relationship between fertility and income, but also upon another convex relationship between fertility and narrowing of the gender gap measured by the GGGI.

Table III reports the results on the relationship between TFR and ECO(–1)/LnGDPpc(–1). Regarding estimations including ECO(–1) (and its squared value) (Est3.1–3), Est3.1 (all samples) and Est 3.2 (lower-income samples) do not pass the Arellano–Bond serial correlation test. Est3.3 (high-income samples) clears the condition on plus/minus signs and two diagonal tests, though the coefficient for TFR(–1) is too high. Among Est3.4–6 including both ECO(–1) and LnGDPpc(–1), only Est3.6 (higher-income samples) clears two diagonal tests and the plus/minus condition with the plausible coefficient on TFR(–1) (0.815). The estimated turning point for LnGDPpc in Est3.6 (10.2) is closer to 10.3 by Day (2018) than 10.1 by Est2.9. For the relationship between TFR and EDU(–1) /HEA(–1)/POL(–1), this study finds no convex relationship (Appendix IV). The results suggest that the convex relationship between TFR and GGGI(–1) is attributable to the convex relationship between TFR and ECO(–1).

Table II: Results of difference-GMM estimations on the relationships between TFR and the GGGI (Global Gender Gap Index)/LnGDPpc

Explained variable: TFR	**All samples**		**Lower-income samples**		**Higher-income samples**	
Estimation No.	Est2.1		Est2.2		Est2.3	
	Coef.	Robust S.E.	Coef.	Robust S.E.	Coef.	Robust S.E.
TFR(–1)	0.911	0.079 ***	1.130	0.039 ***	0.963	0.088 ***
GGGI^2(–1)	1.071	2.084	4.749	0.970 ***	8.162	2.404 ***
GGGI(–1)	–1.440	2.789	–6.159	1.303 ***	–11.356	3.487 ***
Instruments	GGGI^2(–2), GGGI(–2)		GGGI^2(–2), GGGI(–2)		GGGI^2(–2), GGGI(–2)	
Prob (Sargan–Hansen test of overidentification restriction)	0.117		0.862		0.586	
Prob (Arellano–Bond serial correlation test)						
AR(1)	0.004		0.310		0.001	
AR(2)	0.012		0.911		0.302	
Estimated turning point for "GGGI(–1)"	0.672		0.648		0.696	
Estimation No.	Est2.4		Est2.5		Est2.6	
	Coef.	Robust S.E.	Coef.	Robust S.E.	Coef.	Robust S.E.
TFR(–1)	0.580	0.096 ***	1.044	0.017 ***	0.936	0.099 ***
LnGDPpc^2(–1)	0.089	0.020 ***	0.034	0.004 ***	0.335	0.086 ***
LnGDPpc(–1)	–1.601	0.353 ***	–0.480	0.059 ***	–6.733	1.772 ***
Instruments	LnGDPpc^2(–2), LnGDPpc(–2)		LnGDPpc^2(–2), LnGDPpc(–2)		LnGDPpc^2(–2), LnGDPpc(–2)	
Prob (Sargan–Hansen test of overidentification restriction)	0.214		0.008		0.306	
Prob (Arellano–Bond serial correlation test)						
AR(1)	0.026		0.295		0.004	
AR(2)	0.007		0.875		0.883	
Estimated turning point for "LnGDPpc(–1)"	9.036		7.119		10.054	
Estimation No.	Est2.7		Est2.8		Est2.9	
	Coef.	Robust S.E.	Coef.	Robust S.E.	Coef.	Robust S.E.
TFR(–1)	0.566	0.090 ***	1.139	0.065 ***	0.854	0.091 ***
GGGI^2(–1)	1.882	2.055	3.227	0.969 ***	4.263	1.807 **
GGGI(–1)	–2.371	2.763	–4.181	1.285 ***	–6.108	2.605 **
LnGDPpc^2(–1)	0.087	0.020 ***	0.029	0.011 ***	0.313	0.078 ***
LnGDPpc(–1)	–1.572	0.359 ***	–0.405	0.178 **	–6.313	1.577 ***
Instruments	GGGI^2(–2), GGGI(–2) LnGDPpc^2(–2), LnGDPpc(–2)		GGGI^2(–2), GGGI(–2) LnGDPpc^2(–2), LnGDPpc(–2)		GGGI^2(–2), GGGI(–2) LnGDPpc^2(–2), LnGDPpc(–2)	
Prob (Sargan–Hansen test of overidentification restriction)	0.298		0.942		0.406	
Prob (Arellano–Bond serial correlation test)						
AR(1)	0.048		N.A.		0.003	
AR(2)	0.030		0.975		0.801	
Estimated turning point for "GGGI(–1)"	0.630		0.648		0.716	
Estimated turning point for "LnGDPpc(–1)"	9.081		6.948		10.096	
N of samples	743		319		424	
N of countries	133		62		76	
Estimation period	2011–2016		2011–2016		2011–2016	

Note: ***, **. * denote statistical significance at the 1, 5 and 10 % levels, respectively. "Lower-income samples" are composed of samples with lower than 9.377 in LnGDPpc(–1). "Higher-income samples" are composed of samples with equal or higher than 9.377 in LnGDPpc(–1). For the Sargan–Hansen test of the validity of overidentification restriction, the null hypothesis is "Overidentifying restrictions are valid." For the Arellano–Bond serial correlation test, the null hypothesis is "No autocorrelation." Constant is added to instruments. Coefficients for TFR(–2),(–3) and year dummies are not reported.

Table III: Results of difference-GMM estimations on the relationships between TFR and the GGGI Economy subindex

Explained variable: TFR	All samples			Lower-income samples			Higher-income samples		
Estimation No.	Est3.1			Est3.2			Est3.3		
	Coef.	Robust S.E.		Coef.	Robust S.E.		Coef.	Robust S.E.	
TFR(–1)	0.819	0.101	***	1.227	0.034	***	1.003	0.066	***
ECOsubindex^2(–1)	1.580	0.672	**	0.134	0.115		0.865	0.288	***
ECOsubindex(–1)	–1.915	0.875	**	–0.151	0.140		–1.220	0.419	***
Instruments	ECO^2(–2), ECO(–2)			ECO^2(–2), ECO(–2)			ECO^2(–2), ECO(–2)		
Prob (Sargan–Hansen test of overidentification restriction)	0.397			0.500			0.346		
Prob (Arellano–Bond serial correlation test)									
AR(1)	0.011			0.331			0.001		
AR(2)	0.013			0.915			0.256		
Estimated turning point for "ECO(–1)"	0.606			0.566			0.705		
Estimation No.	Est3.4			Est3.5			Est3.6		
	Coef.	Robust S.E.		Coef.	Robust S.E.		Coef.	Robust S.E.	
TFR(–1)	0.503	0.109	***	1.115	0.023	***	0.815	0.084	***
ECOsubindex^2(–1)	1.072	0.535	**	0.295	0.105	***	1.026	0.314	***
ECOsubindex(–1)	–1.510	0.760	**	–0.408	0.133	***	–1.421	0.449	***
LnGDPpc^2(–1)	0.087	0.020	***	0.030	0.005	***	0.300	0.083	***
LnGDPpc(–1)	–1.535	0.345	***	–0.431	0.089	***	–6.135	1.703	***
Instruments	ECO^2(–2), ECO(–2) LnGDPpc^2(–2), LnGDPpc(–2)			ECO^2(–2), ECO(–2) LnGDPpc^2(–2), LnGDPpc(–2)			ECO^2(–2), ECO(–2) LnGDPpc^2(–2), LnGDPpc(–2)		
Prob (Sargan–Hansen test of overidentification restriction)	0.423			0.387			0.274		
Prob (Arellano–Bond serial correlation test)									
AR(1)	0.089			0.296			0.029		
AR(2)	0.012			0.984			0.251		
Estimated turning point for "ECO(–1)"	0.704			0.690			0.693		
Estimated turning point for "LnGDPpc(–1)"	8.858			7.263			10.219		
N of samples	743			319			424		
N of countries	133			62			76		
Estimation period	2011–2016			2011–2016			2011–2016		

Note: ***, **. * denote statistical significance at the 1, 5 and 10 % levels, respectively. "Lower-income samples" are composed of samples with lower than 9.377 in LnGDPpc(–1). "Higher-income samples" are composed of samples with equal or higher than 9.377 in LnGDPpc(–1). For the Sargan–Hansen test of the validity of overidentification restriction, the null hypothesis is "Overidentifying restrictions are valid." For the Arellano–Bond serial correlation test, the null hypothesis is "No autocorrelation." Constant is added to instruments. Coefficients for TFR(–2),(–3) and year dummies are not reported.

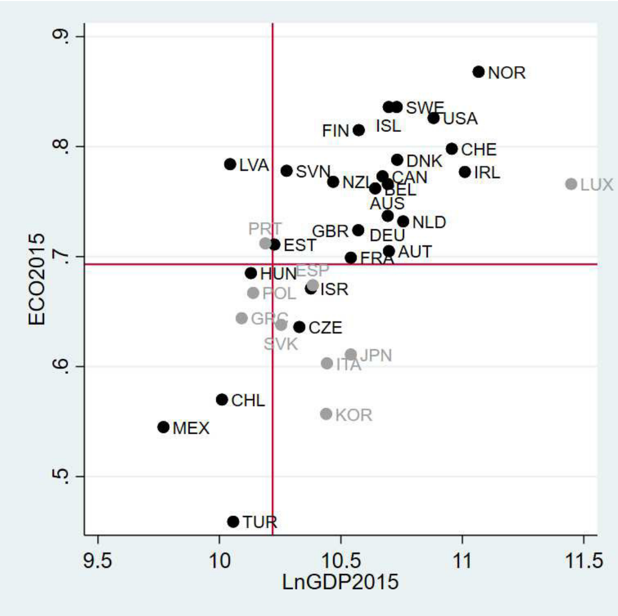
4. Conclusion

This study empirically confirms that fertility rebound in higher-income countries depends not only upon the inverse J-shaped relationship between TFR and income, but also upon the convex relationship between TFR and gender equality measured by the GGGI. This study also confirms that the convexity between TFR and the GGGI comes from the convexity between TFR and the GGGI Economy subindex.

Figure 2 plots the Economy subindex and per capita income in 2015 for OECD countries.

Two lines in the Figure stand for the estimated turning points for the variables by Est3.6. The dark dots stand for countries with TFR levels over 1.5 in 2016,[5] while gray dots stand for countries with TFR of 1.5 or below. As previous studies suggest, to accomplish higher (than the turning point of) income – to be situated on the right side of the vertical line – seems not to be a sufficient condition for fertility rebound. Countries such as Korea (KOR), Italy (ITA), Japan (Japan), Slovak Republic (SVK), and Spain (ESP) are situated in the lower right part, where the gender gap in economic participation seems to be still too large to make their fertility above 1.5.

Figure 2: Economy subindex and LnGDPpc for 35 OECD countries



Note: Black dots stand for countries over 1.5 of TFR in 2016. Gray dots stand for countries withTFR2016 of 1.5 or below. Two lines stand for estimated turning points from Est3.6 in Table III.

5 McDonald (2006) regarded the TFR level of 1.5 as the threshold of a "safety zone."

References

Ahn, N. and P. Mira. (2002) “A note on the changing relationship between fertility and female employment rates in developed countries.” *Journal of Population Economics* 15(4): 667–682.

Arellano, M. and S. Bond. (1991) “Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations.” *The Review of Economic Studies* 58(2): 277–297.

Arpino, B., G. Esping-Andersen, and L. Pessin. (2015) “How do changes in gender role attitudes towards female employment influence fertility? A macro-level analysis.” *European Sociological Review* 31(3): 370–382.

Becker, G.S. and R.J. Barro. (1988) “A reformulation of the economic theory of fertility.” *The Quarterly Journal of Economics* 103(1): 1–25.

Becker, G.S., K.M. Murphy, and R. Tamura. (1990) “Human capital, fertility, and economic growth.” *Journal of Political Economy* 98(5): S12–S37.

Blundell, R. and S. Bond. (1998) “Initial conditions and moment restrictions in dynamic panel data models.” *Journal of Econometrics* 87(1): 115–143.

Day, C. (2018) “Inverse J effect of economic growth on fertility: a model of gender wages and maternal time substitution.” *Journal of Family and Economic Issues* 39: 577–587.

Day, C. (2012) “Economic growth, gender wage gap, and fertility rebound.” *The Economic Record* 88: 88–99.

Dominiak, P., E. Lechman , and A. Okonowicz. (2015) “Fertility rebound and economic growth. New evidence for 18 countries over the period 1970–2011.” *Equilibrium. Quarterly Journal of Economics and Economic Policy* 10(1): 91–112.

Feyrer, J., B. Sacerdote, and A.D. Stern. (2008) “Will the stork return to Europe and Japan? Understanding fertility within developed nations.” *Journal of Economic Perspectives* 22(3): 3–22.

Furuoka, F. (2013) “Is there a reversal in fertility decline? An economic analysis of the ‘fertility J-curve.’” *Transformations in Business & Economics* 12(2(29)): 44–57.

Furuoka, F. (2009) “Looking for a J-shaped development–fertility relationship: Do advances in development really reverse fertility declines?” *Economics Bulletin* 29(4): 3067–3074.

Gaddis, I. and S. Klasen. (2014) “Economic development, structural change, and women’s labor force participation: a reexamination of the feminization U hypothesis.” *Journal of Population Economics* 27(3): 639–681.

Galor, O. and D.N. Weil. (1996) “The gender gap, fertility, and growth.” *The American Economic Review* 86(3): 374–387.

Harttgen, K. and S. Vollmer. (2014) “A reversal in the relationship of human development with fertility?” *Demography* 51(1): 173–184.

Lacalle-Calderon, M., M. Perez-Trujillo, and I. Neira. (2017) “Fertility and economic development: quantile regression evidence on the inverse J-shaped pattern." *European Journal of Population* 33(1): 1–31.

Luci-Greulich, A. and O. Thévenon. (2014) "Does economic advancement 'cause' a re-increase in fertility? An empirical analysis for OECD countries (1960–2007)." *European Journal of Population* 30(2): 187–221.

Martínez, D.F. and A. Iza. (2004) "Skill premium effects on fertility and female labor force supply." *Journal of Population Economics* 17(1): 1–16.

MPIDR (Max Planck Institute for Demographic Research) and VID (Vienna Institute of Demography). (2019) *The Human Fertility Database*. Online database.

McDonald, P. (2006) "Low fertility and the state: The efficacy of policy." *Population and Development Review* 32(3): 485–510.

Mitra, A., J.T. Bang, and A. Biswas. (2015) "Gender equality and economic growth: Is it equality of opportunity or equality of outcomes?" *Feminist Economics* 21(1): 110–135.

Myrskylä, M., H.-P. Kohler, and F.C. Billari. (2011(revised in 2013)) High development and fertility: Fertility at older reproductive ages and gender equality explain the positive link. Rostock: Max Planck Institute for Demographic Research (MPIDR working paper WP 2011-017).

Myrskylä, M., H.-P. Kohler, and F.C. Billari. (2009). "Advances in development reverse fertility declines." *Nature* 460(6): 741–743.

OECD (Organization for Economic Co-operation and Development). (2011) *Doing better for families*. OECD Publishing, DOI: https://dx.doi.org/10.1787/9789264098732-en.

Roodman, D. (2009). "How to do xtabond2: An introduction to difference and system GMM in Stata." *The Stata Journal* 9(1): 86–136.

Stotsky, J.G., S. Shibuya, L. Kolovich, and S. Kebhaj. (2016) Trends in gender equality and women's advancement. Washington, DC: International Monetary Fund (IMF working paper WP/16/21).

UNDP (United Nations Development Programme) (2019) *Human Development Reports: Human Development Index.* Online database.

van Staveren, I. (2013) To measure is to know? A comparable analysis of gender indices." *Review of Social Economy* 71(3): 339–372.

World Bank. (2019) *World Development Indicators.* Online database.

World Economic Forum. (2006–2015) *The Global Gender Gap Report*. Geneva: World Economic Forum.