Department of Economics

The Determinants of the Total Fertility Rate in Japan

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Abstract

The aim of the study is to analyze the impact of several socio-economic factors on total fertility rates in Japan in the period 1961–2015. The fall in fertility rates has been one of the country's main issues since it was first brought to light in 1989, and Japan is particularly interesting in this regard because of its resemblance to the west-world and homogenous culture. The variables of interest are education, marriage rate, urbanization and women's labor force participation rate. We employ a series of multiple regression models to test their relevance.

The study finds that the results are both consistent with theory and previous studies, except for urbanization, which is shown to have the opposite effect, a consequence of deficient data. Marriage is the strongest determinant of fertility rates, but education and employment are found to be powerful deterrents of marriage, which is a consequence of rapid urbanization. We conclude that fertility rates have decreased over time because of wider career and educational opportunities for women.

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1. Introduction

Economic welfare is often used as a measure of a country's prosperity. Most, if not all countries, set this as their main goal, even if what we define as welfare can be unclear and changes depending on countries and cultures. Economic welfare relies heavily on underlying factors such as labor, capital, and technology, but most importantly, the population, which sits at the heart of each economy. Ensuring welfare requires that the population prospers, or otherwise it will stagnate and die. In Japan, the issue of declining fertility rates is one of the country’s biggest challenges going forward. It is assumed to negatively affect the economic welfare of the country. Balanced fertility rates are vital for maintaining the age-dependency ratio at a sustainable level. If the age-dependency ratio increases, a growing share of people outside of the labor force need the support of a decreasing share of the working population, which is not sustainable long term (Jones, 2020). This is especially true in Japan where life expectancy is high. Decreasing fertility rates in the present lead to a decrease in economic growth in the long term. This is because economic growth is dependent on population growth (Franz, 2004). Because of this, we are interested in analyzing which socio-economic factors affect the total fertility rate in Japan as a means of finding an explanation to the problem. Figure 1 shows the age-dependency ratio in Japan from 1960 to 2020.

The objective of this paper is to estimate the determinants of women’s fertility rate in Japan. We consider a number of candidates, including socio-economic factors such as education, marriage, urbanization, and women’s labor force participation rate. Education, in the form of women’s participation rate in higher education. Marriage, measured as the mean age when first married and/or marriage rate. Third, urbanization, as a proxy variable for population density. This variable is thought to capture the opportunity cost of child rearing and being employed. Lastly, we assess the impact of women’s labor force participation rate. The definitions and choice of variables are explained below.

The issues discussed are not exclusive to Japan. Other countries suffer from similar problems, we focus specifically on Japan because of its culture, and implemented policies. Another interesting aspect of the Japanese economy is that immigration has been limited, which has exacerbated the problem of low birth rates.

Our main results suggest that women's enrollment in higher education have a significant negative effect on fertility rate, and a large significant positive effect of marriage on fertility rate. It also shows that urbanization has a positive effect on fertility rate, which is contrary to the results of previous studies. Marriage is found to be the most impactful variable on fertility, followed by education, and urbanization. In addition, we find that women's labor force participation rate is not significant. Despite this, we conclude that the multiple regression model is still a relevant method of analysis and that it is mostly consistent with real findings from previous studies.

The rest of the paper is structured as follows: Section 2 summarizes the findings of previous studies that will aid us in deciding variables and econometric methodology. In the second part of Section 2, we use economic theory to properly motivate our choice of variables and discuss what to expect from the estimations. Section 3 presents the data. Econometric methodology is presented in Section 4. Results are presented in Section 5 and discussed in Section 6. Section 7 concludes.

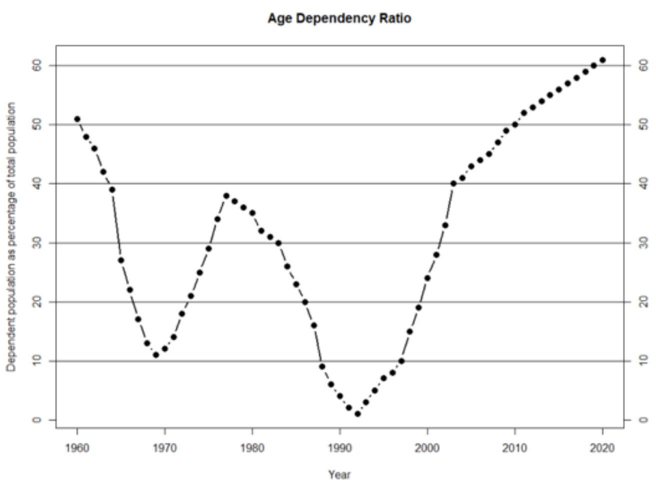

Figure 1: Total age dependency ratio Japan 1960–2020.

2. Theory

2.1 Previous studies

Kato (2018) focuses on analyzing differences in fertility rates across Japanese municipalities and prefectures with respects to population density, which is a proxy variable for variables such as "compatibility with child rearing and female labor supply, resources for child rearing, and housing space, etc." (Kato, 2018). They use this variable because location of residence is connected to urbanization, which affects the opportunity costs and direct costs of living in a given environment. Therefore, the author argues that the total fertility rate will be lower in urban areas because the opportunity cost is high, e.g., because of broader opportunities to work and study. Meanwhile, the total fertility rate is higher in rural areas where said cost is low and there are not as many opportunities to pursue a career, inducing more women (mainly) to marry and care for children instead. Kato (2018) uses two sets of data, one that is cross-sectional at one point in time and the other which compares two points in time. He tests various models in the study by gradually adding variables or switching data set.

The study finds that a defining factor in explaining fertility rate disparity is the mean age of first marriage, which is directly connected to the fertility rate because Japanese culture is strongly against the idea of extra marital childbirth. The decision to marry is therefore connected to the decision of having children. As Kato (2018) points out, it follows that the number of extra marital births in Japan is very low. In both datasets, population density and female labor participation rate are significant on the highest level, even when total fertility rate is regressed against them individually. The author concludes that population density is able to explain total fertility rate in Japanese municipalities and confirms that fertility rates are particularly low in densely populated areas such as the Tokyo Metropolitan area. They employ a regression model to achieve this. The main problem of the study is not being able to identify reliable causal effects due to the lack of historical data and knowledge of related policies.

Lutz, Testa, and Penn (2006) lay the groundwork for future studies in the field of behavioral economics by incorporating population density as a possible determinant of total fertility. They employ a fixed effects model to compare national data comprising 145 countries with data across 40 years in 5-year intervals. The purpose is to mainly analyze the effects of population density on total fertility rates, both directly and indirectly. The premise of the study is to apply a central idea in population biology, which says that population density affects fertility, a phenomenon observed in all animals. The authors find that there exists a negative relationship between total fertility and population density, which is by far the most significant and relevant variable. In addition, the study finds that population density affects individual fertility preferences, where population density symbolizes “living space, availability of interpersonal communication, etc.” (Lutz et al., 2006). Individual preferences refer to the “ideal number of children wanted under the hypothetical absence of constraints” (Lutz et al., 2006). They also speculate that population density might affect social norms concerning fertility. GDP is also used as an explanatory variable but is found to be insignificant.

Another relevant study is Edwards, Hasebe, and Sakai (2019). In 1985, Japan introduced the 1985 Equal Employment Opportunity Act, or EEOA for short, as a means to eliminate gender discrimination with respects to factors that might affect career opportunities. It is specifically targeting women who have to make a choice between either educating themselves and having a career or marrying and rearing children. The intention of the 1985 EEOA is to allow people (women in particular) to both attend higher education, pursue professional careers, and marry and have children simultaneously. Prior to 1985, these were disjoint events. Higher education in this case means attending universities, junior colleges, and specialized training colleges, though the authors find that it is mainly universities that impact marriage decisions.

The main purpose of the study is to examine the effects of the 1985 EEOA on marriage decisions for women who attend higher education. Three hypotheses are tested. In essence, the hypotheses ask if the implementation of the EEOA has widened career opportunities of women in higher education, if this has influenced their marriage decisions, and if the EEOA has made it more attractive to attend higher education and pursue careers.

Their study finds that the implementation of the EEOA has undeniably led to a decrease in fertility rate for women who attend higher education. University education specifically is the main deterrent of marriage decisions. Essentially, the implementation of the EEOA has doubled the likelihood of a woman not marrying if she has a university education, and it supports the hypothesis that highly educated women are more inclined to exploit their improved career options and delay marriage.

2.2 Economic theory

In this section we will discuss the economic theory behind the variables and their interactions. From previous studies, we find that the variables education, marriage and population density are the most prevalent variables. We are using urbanization as a proxy variable for population density and add women's labor force participation rate too.

Total fertility rate is defined as the average number of children per woman in reproductive age (15–49 years). Population density is a proxy for the opportunity cost of child rearing and being employed, and the motivation for its use is explained under the previous studies section by Kato (2018). Basically, since fertility is argued to be affected by the opportunity cost of child rearing and other related expenses, where opportunity costs are higher, e.g., in urban areas, fertility is expected to be lower, therefore population density should suffice as a proxy variable. However, because of a lack of data on this variable – which will be explained later in the data section – we are employing urbanization as a proxy variable for it instead. We assume that urbanization increases over time because it is more attractive to live in urban areas than rural due to wider career options, education, entertainment, etc., so people from rural areas are gradually migrating to urban ones. Because of this, we also assume that more women try to pursue careers, and since more people live in urban areas than rural, it would be fair to assume that total fertility rates also fall over time because of the high opportunity costs of working and/or studying in urban areas. Realistically, Kato (2018) utilized population density as a proxy variable to link opportunity costs to urbanization, so it is reasonable to use this variable as a substitute for population density.

We also employ female participation rate in higher education, which traditionally includes universities, junior colleges, and specialized training colleges. However, Edwards et al. (2019) finds that only universities impacts marriage decisions in a meaningful way, which in turn impacts fertility rates, so for the sake of consistency, we are also making this assumption. We deem this variable to be relevant because time investments in higher education often imply the wish to pursue a prestigious career, which in turn increases the opportunity costs of marrying and rearing children, therefore affecting fertility rates overall. Also, it is an interesting variable to analyze under the EEOA (Edwards et al. 2019).

When it comes to marriage, there are two variables we can use: marriage rate, which is defined as the annual number of marriages per 1000 people. Alternatively, we can use the mean age of first marriage for women, which is the preferred choice. The reason is that the Japanese culture is very conservative, which makes extra marital childbirth strongly discouraged, effectively containing it at low levels. Because of this, the extreme majority of women birth children after marrying, which makes the mean age of first marriage a suiting variable to denote when fertility rates are expected to rise. Another benefit is that it also shows how much this choice becomes delayed as a consequence of other factors such as education or employment. Marriage rate on the other hand is less specific and can include women who are very old that might be less likely or cannot birth children, which runs the risk of wrongly displaying the relationship between marriage decisions and fertility. We are using the marriage rate because of data availability, more on this under data section.

Women's labor force participation rate is defined as the proportion of women aged 15–64 that participate in the labor force. Higher participation rate leads to higher income which can affect fertility rate by reducing financial stress prior to marrying and child rearing, while it could also decrease fertility if it leads to women staying in the workforce rather than marrying and having children.

There are other variables we do not include that should still be acknowledged, such as female access to childcare centers. Access to childcare centers is assumed to increase fertility because it eases personal responsibility of child rearing and decreases stress, so it can encourage more women to marry and bear children without having to leave the workforce. However, we are not using it because the data is both scarce and non-intuitive.

We have already established that total fertility rate is assumed to affect GDP growth, and this is why we are examining the factors that influence the fertility rate. In Japan specifically, participation in higher education only affects fertility rate through marriage because it postpones marriage decisions if one prioritizes their professional careers. Therefore, the higher education one has, the later one will marry, and this leads to a decrease in the fertility rate. Marriage decisions are dependent on education, but also on the opportunity cost of rearing children and working simultaneously, which is dependent on the urbanization as we have established.

Urbanization is a proxy for population density, which we have argued is fitting since it shows how marriage decisions change based on region. Densely populated areas are more likely to be in the city where more opportunities to study and/or work exist, as opposed to rural areas whose populations are falling because of the lack of career options. This would mean that women in rural areas are more prone to marry early if the spouse can consistently provide for the family, in addition to the argument about education and career options. Therefore, the higher the level of urbanization the lower the fertility rate. So, urbanization affects fertility rate through marriage. Likewise, because urbanization is a proxy for opportunity cost in studying, working or rearing children, it would mean that education is much more expensive in urban areas, but widen future career options.

Women's labor force participation rate should be negatively correlated with fertility rate because of the same reasons as education, while urbanization should be positively correlated to it. We assume that employment will similarly to education, also postpone marriage, so both marriage rate and fertility rate are negatively correlated with women's labor force participation rate. It is unclear how it interacts with education, since both are similar in that they are time-consuming activities that delay marriage and eventually child rearing, if it is found that most people can both study and work at the same time, the relationship will be positive. Or, if they are somewhat mutually exclusive, the relation is negative because you cannot perform both simultaneously.

With this, we expect to observe the following results: education has a negative effect on marriage rates, and therefore also on fertility rate. Urbanization also has a negative effect on marriage rates and fertility rate. Meanwhile, urbanization should have a positive effect on education. Women's labor force participation rate should have a negative effect on marriage rate and fertility rate, while positive with urbanization. In what follows, the total fertility rate will be referred to as TFR and women's labor force participation rate as $WLFP$, while marriage rate and urbanization may in some graphs and figures be referred to as MR and $Urban\ Pop$ respectively. Also, when we say GDP, we mean $GDP\ per\ capita$.

3. Data

We are using annual time-series data at the national level which spans the period 1960–2020. Data on some of the variables are not available for the entire period, which leads us to removing observations from other variables in order to keep the same data length for all variables. The main data set spans the time period 1961–2015, but when we include $WLFP$, it spans period 1968 – 2015 instead.

'The World Bank' has data on $GDP\ per\ capita$ measured in US dollars with reference year 2015, total fertility rate, population density per sq. km of land area, and urbanization. The data spans 1961–2019. The 'Ministry of Health, Labour and Welfare' of Japan provide data for mean age of first marriage and marriage rate in the interval 1975–2015 and 1899–2020, respectively. Note that the mean age of first marriage variable is measured at 5-year intervals during the period 1975–2000, but after 2000 it is measured continuously (annually) up till 2015. It is because of this fact that we are using marriage rate instead of the mean age. Data on female participation in higher education is recorded for the period 1955–2016, and it is supplied by the 'Research Institute for Higher Education at Hiroshima University in Japan. Note that the data on education we have access to are specifically 18-year-old girls that enroll in universities, which we do not see as a problem because most teens in that age either go straight to work or educate themselves further, not many take breaks from school or return to it later (OECD, 2019). Women's labor force participation rate is measured in % in the interval 1968–2020 by 'OECD'.

As previously stated, we are using national data, but we would have preferred to use prefectural data because it can better portray the differences between rural and urban areas and provide an in-depth look at the situation. This is mostly problematic for the population density variable which is replaced with urbanization for this exact reason. Since geographic area is constant over time, while population is ever changing, the population density variable becomes a function of the total population. Therefore, it is not accurate in explaining how population density actually affects fertility, which can be remedied if we have access to prefectural data. Also, population density is one of the most important variables in previous studies and is undoubtedly a relevant variable. Therefore, instead of omitting it from the model, we use urbanization as proxy for it. Optimally, we would have used population density on prefectural data to mimic previous studies as much as possible. However, with national data, our second-best alternative is to use urbanization as a proxy for this. Below are descriptive statistics on our variables.

In figure 2 we have the total fertility Rate, TFR. In 1961, $TFR = 2.05$ and mostly remains that way until 1974, and it peaks at 2.16 in 1971. In 1973, TFR begins to drop drastically, and experiences occasional "growths". For reference, in 1980, $TFR = 1.75$, a decade later, it is 1.54. 1989 marks the year of the "1.570 shock". TFR continues to decline and reaches its lowest point in 2005 at a value of 1.26. It has been steadily increasing in the following decade, reaching 1.45 in 2015, something that was previously recorded in back in 1994. The steep decline of

TFR in 1966 equals 1.58.

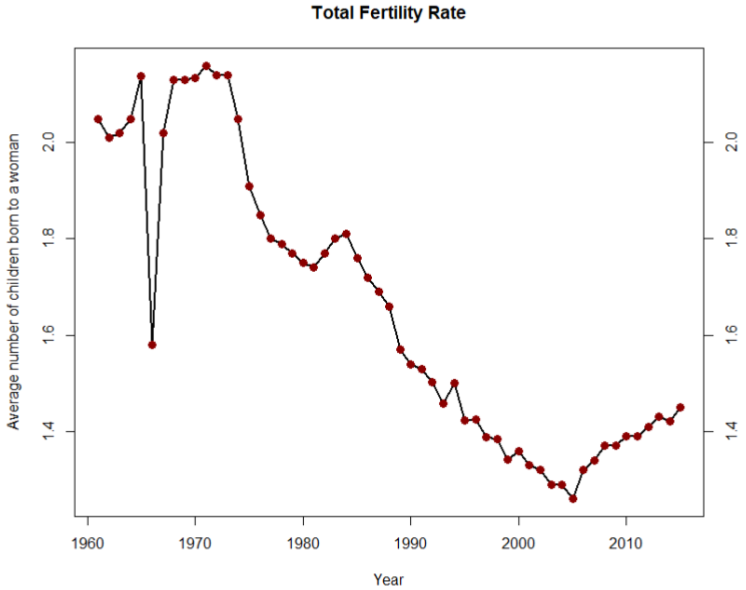

Figure 2: Total fertility rate in Japan between 1960–2015.

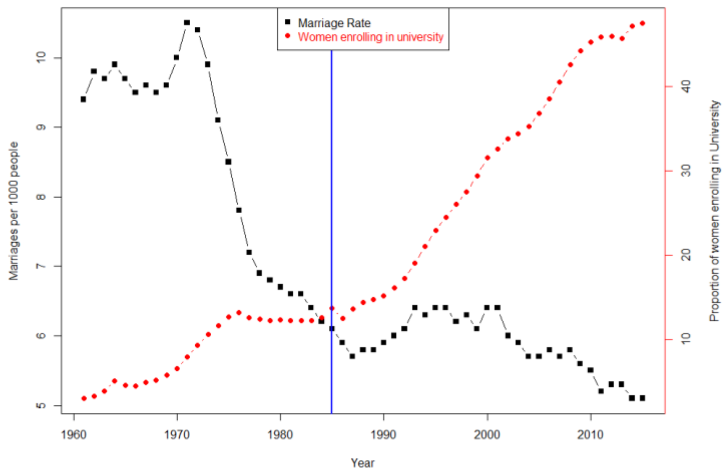

Figure 3: In black, marriage rate with scales on the y-axis. In red, the percentage of women aged 18 that enrolls in university, scales on the right y-axis. Datasets from 1961 – 2015.

Figure 3 shows us the time series for the variables Education and Marriage rate. In 1961, the percentage of 18-year-old females enrolling in university was 3%. We see a steady increase in enrolment until 1976 where it equals 13.2%. It stays at the 12– 13% level until 1988. A blue line has been marked in the graph for the year that the EEOA was implemented in Japan. From 1988, we see a steady increase in enrolment until the end of the dataset in 2015 where enrollment peaks at an all-time high of 47.5%.

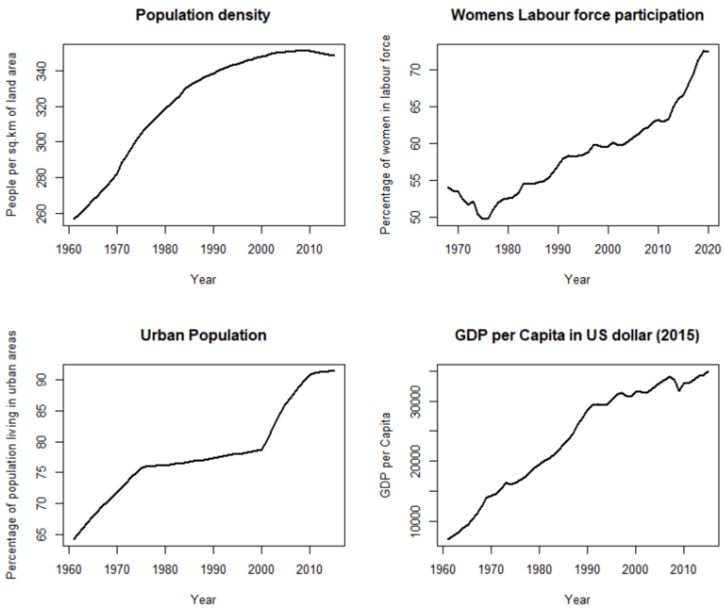

Figure 4: Top left: Population density, measured in people per sq. km. Top right: $WLFP$, women's labor force participation, shown as percentage of women aged 15-64 in the labor force. Bottom left: The percentage of the population living in urban areas. Bottom right: The $GDP\ per\ capita$ given in US dollar reference year 2015. All datasets are annual data from 1961–2015, except for $WLFP$ with is from 1968–2020.

The marriage rate is the number of marriages per 1000 population. In 1961 the marriage rate was 9.4, it peaks in 1971 where the rate is 10.5. In the decade between these values, the level stayed around $9.5 - 10$. In 1973, the marriage rate falls below 10.0 and has never recovered since. The decline from 1972 to 1977 looks to be linear, dropping from 10.4 to 7.2. After a couple of years of bouncing around, the 2000's marks the beginning of a consistent downward trend, equating 5.1 in 2015, the thus far lowest observation.

The top left graph in figure 4 shows the population density. Since population density is a function of the population of the country this graph can also be seen as the population of Japan. We see a rapid increase in population density from 1961–1984, followed by a period of slower growth. In 2010 the population density, and therefore the population peaks and have since been declining.

In the top right graph in figure 4, we have the dataset for $WLFP$. The dataset shows annual data from 1968 to 2020, it shows the percentage of women that partakes in the labor force aged 15–64. In 1968 it was 54.1% and it falls steadily until 1975 where it is 49.7%. From there, it experiences a steady increase until 2012 where it is 63.4%. It increases rapidly from 2012 until 2020 where it sits at 72.5%.

In the bottom left graph in figure 4, we see urban population. It is annual data from 1961 to 2015. It measures the percentage of the population living in urban areas in Japan. In the graph we can see two time periods of rapid increase in urbanized population, and two period of slow increase. We never see a decrease in urbanization. In 1961 it is at 64.2% and rises rapidly until 1975 where it is at 75.7%. From there it grows slowly until 2000 where it is at 78.6%. From then it rapidly increases to 90.8% in 2010 and at the end of the dataset, 2015 we see it at 91.4%.

In the bottom right graph in figure 4 we see the GDP. The GDP sees an increase from 1961 to 2015, with only small dips for some years. We see a higher rate of change in GDP from 1961 to 1990 than we see from 1990 to 2015. It starts at 6952 dollars in 1961 and ends at 34960 dollars in 2015.

Figure 5 is a graph that shows the change in three variables related to women's employment. The variable "Full-time Employment" is shown in black. The "Part-time Employment" variable is shown in red and the "Women's share of part time employment" is shown in blue. The variables are measured in percentage, so an increase in part time employment leads to a decrease in Full-Time employment because they sum up to 1. The variable "Share of part time employment" shows how large a percentage women make up of part time employees. The other share is men's percentage of part time employment (not shown in figure). The dataset shows us data from 1980–2020. "Full-time employment" has decreased from 78.6% to 60.5%. "Part-Time employment" has increased from 21.4% to 39.5%.

“Women’s share of part time employment” has decreased from 74.6% to 67.4%.

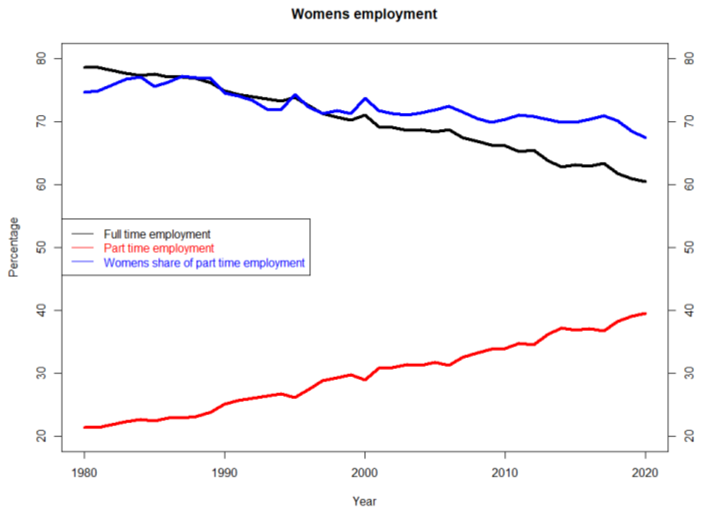

Figure 5: Percentage of women in different types of employment.

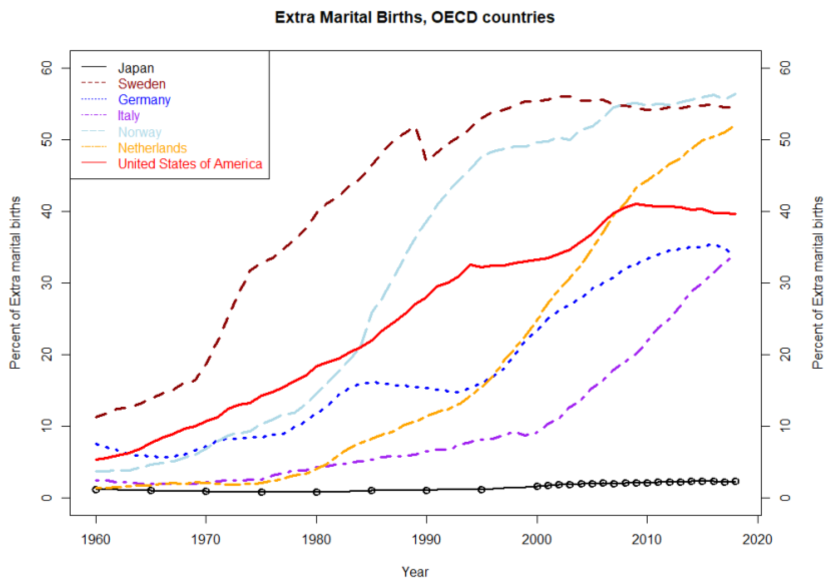

Figure 6: Extra marital births in a sample of OECD countries between 1960¬2015

Figure 6 shows us the data for extra marital births (EMB) from 1960–2018. It shows the percentage of births happening outside of marriage. This variable is not used for analysis, it is rather used to display how the Japanese culture acts when it comes to marriage decisions. We see several western European countries and the USA in the graph, and the black timeseries is Japan. The data for Japan is collected every 5 years from 1960 to 2000. In the year 2000, data begins to be recorded annually, and we have access to it until 2018. The points in the bottom curve represent the observed values. We see stark differences in the time series for western countries and Japan when it comes to EMB. Sweden (brown) had 11.4% in 1960, and peaks at 56% in 2002. Italy (purple) had 3.1% in 1960, and 34% in 2018. In contrast to this we can see that Japan had 1.2% in 1960 and increased to 2.3% in 2018. This confirms the findings of the first study.

4. Econometric methodology

The purpose of the thesis is to shed light on the relationship between TFR and the explanatory variables. Therefore, a multiple OLS regression is a natural starting point. Because our goal with this paper is to provide understanding for the subject and its importance, we stick with a simple model that can point us in the right direction, even if it does not provide a perfect fit. The main problem we are expecting from this model is highly autocorrelated variables. As a result, a normal OLS regression produces a model with autocorrelation and clearly heteroskedastic errors. Autocorrelation causes the estimation of the error terms to no longer be minimum variance estimates, this means that the coefficients significance is overestimated, and it also leads to a higher R^2 in the model. The effects of heteroskedasticity are similar in that it makes the error terms to be unreliable. To deal with the effects of autocorrelation in the model, we are using Cochrane-Orcutt estimation. We elaborate on the workings of this method in Section 4.3.

A quick note regarding multicollinearity and omitted variable bias (OVB), is that dealing with OVB is more important than handling multicollinearity because OVB can be dealt with by adding more variables without sacrificing the integrity of the model. Meanwhile, since econometric variables are almost always correlated, an attempt to rid the model of it will induce more harm than benefit, so we have to accept that there might be multicollinearity in our models.

4.1 Stationarity

For time series data to be used in modelling we need to make the series stationary, meaning that the probability distribution of any given series is constant over time periods. This restriction is often too strict for assumption, and it will suffice for us to use a covariance stationary series, which implies that the mean, variance, and covariance of the series is constant over time.

$$\begin{cases} E(x_t) = \mu \text{ for } t \geq 1 \\ V(x_t) = \sigma^2 \text{ for } t \geq 1 \\ Cov(x_t, x_{t+h}) = f(h) \text{ for } h \geq 1 \end{cases} \quad \text{(Wooldridge, 2016, pp. 345– 346)}$$

This means that its properties are not dependant over time. One way to check for stationarity is by controlling for autocorrelation, if autocorrelation is present then the time series is non-stationary. Autocorrelation is the relationship between a time series present value and the past values. The autocorrelation function, ACF, is used to detect autocorrelation. For a ACF test, at least 50 observations are recommended, and the function should be using K lags where $K = T/4$ and T is number of periods. In our case, we have 55 observations in our dataset and that would lead to $K = 13.75$, we choose to use $K = 15$, a slightly higher value. Below is the autocorrelation function:

$p_k = \frac{E[(y_t - \mu)(y_{t+k})}{\sqrt{E[(y_t - \mu)^2]E[(y_{t+k})^2]}}$, $\rho_0 = 1$ by definition (Montgomery, 2015, p. 33).

The ACF is displayed in figure 7 for four variables, when a lag exceeds the blue dotted line, it means that we have autocorrelation for that lag. As can be seen in the graph, autocorrelation is present in the timeseries for all the variables at several lags, which means that the time series are not stationary and can give us misleading results if we try to use them in our regression model. Two common ways to solve non-stationarity is by either adding more variables to the regression or by differencing the data until it is stationary, which we can test using an augmented Dickey–Fuller test. In our case, the latter alternative is not desirable since it leads to a data loss, and it makes it impossible for us to interpret the regression coefficients in a meaningful way. We therefore opt to use the Cochrane–Orcutt method, which is a way of transforming a regression model so that it becomes stationary. To detect autocorrelation, we use the Durbin–Watson test.

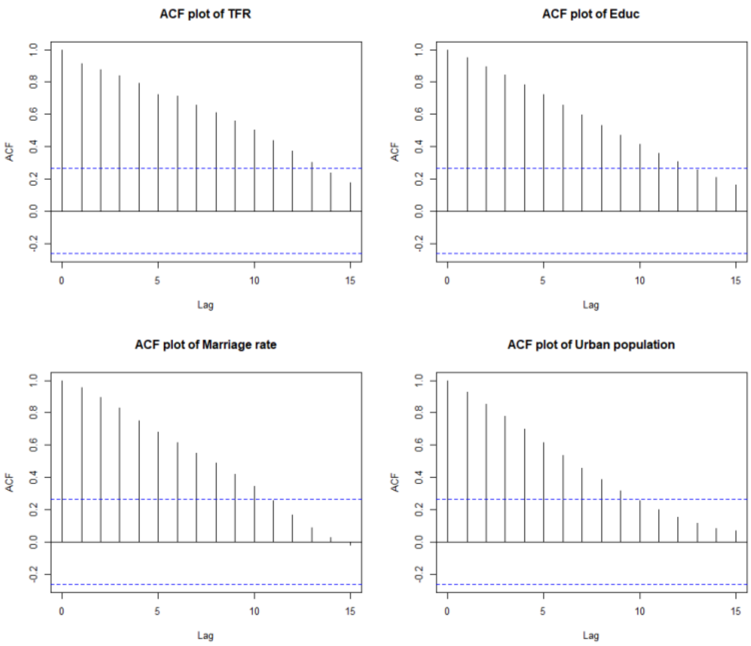

Figure 7: Autocorrelation function plot for numerous variables.

4.2 Durbin–Watson Test

One way to formally test for autocorrelation in the regression model is by using the Durbin–Watson test which is presented below: the hypothesis of the test assumes that the error terms are created by a first order autoregressive process

$$\varepsilon_t = \phi\varepsilon_{t-1} + \alpha_t \text{ (1)}$$

where ϕ is the autocorrelation which means that we can construct a simple linear regression with the error term from equation (1) in the following way:

$y_t = \beta_0 + \beta_1 x_t + \varepsilon_t$ (2) where $\varepsilon_t = \phi\varepsilon_{t-1} + \alpha_t$ (2).

Hypothesis for the Durbin-Watson test:

$$\begin{cases} H_0: \phi = 0 \\ H_1: \phi > 0 \end{cases}$$

The null hypothesis states that there is no correlation between two time periods and therefore there is no autocorrelation. The alternate hypothesis says that the autocorrelation is greater than zero. The Durbin-Watson test statistic:

$$d = \frac{\sum_{t=2}^{T}(e_t - e_{t-1})^2}{\sum_{t=1}^{T} e_t^2} = \frac{\sum_{t=2}^{T} e_t^2 + \sum_{t=2}^{T} e_{t-1}^2 - 2\sum_{t=2}^{T} e_t e_{t-1}}{\sum_{t=1}^{T} e_t^2} \approx 2(1 - r_1)$$

where ε_t are the residuals of an OLS regression and r_1 is the first lag autocorrelation between residuals (Montgomery, 2015, p. 180).

$$if\ d < d_L \text{ reject } H_0: \phi = 0$$
$$if\ d > d_U \text{ do not reject } H_0: \phi = 0$$
$$if\ d_l \le d \le d_U \text{ the test is inconclusive}$$

The upper and lower bounds for the Durbin–Watson statistic are found in tables, but in practice we use a function that will perform the test on the regression model and give us a p-value that tells us if there is autocorrelation in the model. The results of the stationarity test are presented in tables 1–2 in Section 5.

4.3 Cochrane–Orcutt

Regression models tend to suffer from non-stationarity, we can try to add variables as a means of removing omitted variable bias, which is when there are variables excluded from the model (treated as error) that are correlated with the rest of the model, so errors become autocorrelated. However, because of the lack of data on relevant variables, this option is not feasible. Another option is to difference the time-series, but this incurs a great data loss which will most likely worsen the model by reducing its significance and relevance. Instead, we decide to use the Cochrane–Orcutt estimation method to deal with non-stationarity, which incurs a smaller data loss than with differencing, while also producing interpretable results.

The following example of the Cochrane–Orcutt method is for transforming the simple linear regression seen in equation (2). The purpose is to transform the dependent variables so that we get:

$$y'_t = y_t - \phi y_{t-1} \text{ (3)}$$

When substituting in y_t and y_{t-1} into equation (3) we get:

$$\begin{aligned} &\beta_0 + \beta_1 x_t + \varepsilon_t - \phi(\beta_0 + \beta_1 x_{t-1} + \varepsilon_{t-1} \\ &\qquad = \beta_0(1-\phi) + \beta_1(x_t - \phi x_{t-1}) + \varepsilon_t - \phi\varepsilon_{t-1} \\ &\qquad = \beta'_0 + \beta'_1 + a_t, where\ \beta'_0 = \beta_0(1-\phi), \beta'_1 = \beta_1(x_t - \phi x_{t-1}) \end{aligned}$$

Running an OLS regression on $\varepsilon_t = \phi\varepsilon_{t-1} + \alpha_t$ gives us the unknown parameter $\hat{\phi}$ where $\hat{\phi} = \frac{\sum_{t=2}^{T} e_t e_{t-1}}{\sum_{t=1}^{T} e_t^2}$. Now, we calculate y_t' and x_t':

$$y_t' = y_t - \hat{\phi}y_{t-1}$$
$$x_t' = x_t - \hat{\phi}x_{t-1}$$

If the model still is not stationary, the process is repeated until the errors are uncorrelated (Montgomery, 2015, pp. 184–187). We are using a function that automatically perform the process until the model is stationary. The function will also give us the Durbin–Watson statistic and p-value for both the original and transformed model. A normal regression gives us an unbiased estimator, but the coefficients are no longer minimum variance estimates and we would not be able to perform t-test and F-tests for significance. When we transform the regression using the Cochrane–Orcutt method, the estimations change, but we are now able to interpret the coefficients despite the data loss, and we can be confident in the coefficient's significance.

4.4 Heteroskedasticity

The error terms are heteroskedastic if the variance is dependent on the explanatory variables over time, meaning that there is a pattern to the error terms rather than being randomly distributed. Heteroskedasticity does not lead to bias in the coefficient estimates, but it does lead to overestimation of the residuals and their significance, which in turn causes the R^2 and the significance of the coefficients to be overestimated, effectively leading to a better "fit" than what is the case. For time series data, it is important that the errors are not heteroskedastic over time t.

$Var(\varepsilon_t|X) = Var(\varepsilon_t) = \sigma^2 \ for \ t = 1,2 \dots, n$ (Wooldridge, 2016, p. 320)

Usually, we compute robust standard errors in the statistical software, but since we are using the Cochrane–Orcutt method, the object that is created in the software does not allow us to produce robust standard errors, therefore we will be checking for the heteroskedasticity in all our models instead. We check for heteroskedasticity by using the Breusch-Pagan test:

$$\begin{cases} H_0: \text{Homoskedasticity is present} \\ H_1: \text{Heteroskedasticity is present} \end{cases}$$

If the p-value of the test is smaller than the critical value, we reject the null-hypothesis in favour of the alternative and we conclude that there is heteroskedasticity in the residuals.

4.5 Econometric specification

We decide to use multiple linear regression models as our main tool of analysis, but instead of using all variables at once, we are adding variables one at the time to see how other variables react. We use a standard significance level of 5% in all tests and coefficient verifications, anything over this level is rejected. Equation (4) below is an example of one of the regressions.

$$
\begin{aligned}
&Total\ Fertility\ Rate = \\
&\qquad = \beta_0 + \beta_1 Education_t + \beta_2 Education^2{}_t + \beta_3 Marriage\ Rate_t \\
&\qquad + \beta_4 Urban\ population\ _t \\
&\qquad + [\beta_5 Women's\ labor\ force\ participation\ rate] + \varepsilon_t \ (4)
\end{aligned}
$$

The model has five explanatory variables: there are two education variables, one of which is squared to provide a better fit for the non-squared $Education$ variable. Then there is $Marriage\ rate$, $Urban\ Pop$ and $WLFP$, but for $WLFP$ we create a separate set of models using shortened datasets because the $WLFP$ variable is for a shorter period.

5. Results

*Table 1: Regression models 1–4 and other related output. Significance level is denoted by ' ***' 0.001, ' **' 0.01, '*' 0.05, ' ´ ' 0.1.*

Variable	Model 1	Model 2	Model 3	Model 4
TFR	1.927*** (0.139)	2.335*** (0.108)	1.650*** (0.284)	-1.317 ´ (0.721)
$Education$	-0.013** (0.0048)	-0.0547*** (0.0106)	-0.036** (0.0116)	-0.043*** (0.007)
$Education^2$		0.00074*** (0.000198)	0.0005* (0.0002)	0.0003** (0.0001)
MR			0.065* (0.025)	0.101*** (0.0186)
$Urban\ Pop$				0.0376*** (0.0087)
DW $Transformed$ $P-value$	2.45318 0.9403	2.18930 0.6613	2.21336 0.6442	1.98470 0.2583
R^2 / $Adj\ R^2$	0.1251 / 0.1083	0.5704 / 0.5535	0.6743 / 0.6548	0.8782 / 0.8683
$F-statistic$	7.4 on 1 and 52 DF	33.9 on 2 and 51 DF	34.5 on 3 and 50 DF	88.4 on 4 and 49 DF
$P-value$	0.008691	4.402×10^{-10}	3.132×10^{-12}	8.872×10^{-22}
$Breusch-Pagan\ Test$	0.04892	0.03666	0.1377	0.3213

Let us go through the results: regression model 4 is written down below:

$$TFR = -0.043EducUni + 0.0003EducUni^2 + 0.101MR + 0.038UrbanPop.$$

The model explains 86.53% of the variance, all coefficients except for the intercept are statistically significant on an 99.9% level. In total there are nine different models presented in this paper. Models 1–4 are found in table 1 and models 5–9 in table 2. The models of table 1 are created for the time period 1961–2015 and include up to 4 different variables. The first value in the table under model i denotes the coefficient for the variable in the model and standard error is given in parenthesis under the coefficient. The first row of values is comprised of intercepts, and the following rows contain the variable coefficients according to the leftmost column. DW is the Durbin–Watson test statistic for the transformed model and the p-value tells us that the model is stationary if the $p - value >$ 0.05. Both the R^2 and adjusted R^2 are given for the models as well as the F-statistic and the p-value.

In model 1, we regress TFR on $Education$, and we see that the $Education$ coefficient is highly significant on the 1% level and the sign is consistent with set expectations. The interpretation of the regression model is that 1% increase in women enrolling in university decreases TFR by 0.013. While the model does not suffer from autocorrelation according to the Durbin–Watson p-value, the Breusch–Pagan test indicates that the errors are indeed heteroskedastic. In model 2 we add $Education^2$, which only has a small direct effect on TFR, but it changes the coefficient of $Education$. The $Education$ coefficient decreases from -0.013 to -0.0547, it is now also of a higher significance level, 0.001%. This indicates that $Education^2$ is a useful variable in the model, and that the $Education$ variable effects TFR with diminishing returns. It also greatly increases the R^2 and adjusted R^2 of the model, going from 0.1251 and 0.1083 to 0.5704 and 0.5535 respectively. There is still heteroskedasticity in the model.

In model 3 we add the variable $Marriage\ Rate$ which is shown as significant on the 5% level, both the $Education$ and $Education^2$ variables are still significant on at least 5% but their significance has decreased from the previous model. The coefficient for $Marriage\ Rate$ is 0.065, meaning that for each additional person out of 1000 marrying, TFR increases with 0.065. The effect of $Marriage\ Rate$ on TFR is also consistent with theoretical expectations. When we add $Marriage\ Rate$ to the model, we see that the coefficients on both $Education$ variables decrease in absolute value, $Education$ goes from -0.0547 to -0.036. $Education^2$ goes from 0.00074 to 0.0005. With $p - value = 0.1377$, we cannot reject the null hypothesis and conclude that the error terms are homoscedastic.

In model 4 we add $Urban\ population$ to the regression. All the explanatory variables have maximum significance except for $Education^2$ which is only significant on 0.01%, while disregarding the intercept which is only significant on 10%. The estimates of the coefficients $Education$ and $Marriage\ Rate$ have increased in absolute value but maintain their former signs. The coefficient $Urban\ Pop$, is 0.0376, which means that each additional 1 percentage point of the population that move to an urban area increases TFR by 0.0376. All other tests perform well in the model. It is stationary and with a $p - value = 0.3213$, we cannot reject the null hypothesis and conclude that the error terms are homoscedastic. We also have a high R^2 and adjusted R^2 in the model at 0.8782 and 0.8683.

Models 5–8 from table 2 are identical to models 1–4 in table 1 but uses data in a shorter period because of the $WLFP$ variable. Do note though that models 5 and 6 does not pass the stationarity requirement. All models in the table pass the test for homoskedasticity. We are most interested in model 9 from table 2 because it includes the variable $WLFP$. The model has significant coefficients for $Education,\ Education^2$ and $Marriage\ Rate$ but not for $Urban\ Pop$ and $WLFP$. The significant coefficients are largely unchanged from model 8. The signs of the $Urban\ Pop$ coefficient are negative in both model 8 and 9, though statistically insignificant.

*Table 2: Regression models 5–9 and other related output. Significance level is denoted by '***' 0.001, '**' 0.01, '*' 0.05, ' ' 0.1.*

$Variable$	$Model\ 5$	$Model\ 6$	$Model\ 7$	$Model\ 8$	$Model\ 9$
TFR	1.156*** (0.274)	1.225** (0.3996)	1.817*** (0.131)	1.874* (0.878)	2.38* (0.978)
$Education$	0.00203 (0.0052)	-0.0143 (0.0136)	-0.057*** (0.00669)	-0.057*** (0.0072)	-0.0566*** (0.0067)
$Education^2$		0.00029 (0.0002)	0.00085*** (0.0001)	0.00086*** (0.00016)	0.00089*** (0.00016)
MR			0.0782*** (0.0122)	0.0779*** (0.0137)	0.0705*** (0.014)
$Urban\ Pop$				-0.0007 (0.01)	-0.002 (0.0104)
$WLFP$					-0.0069 (0.0063)
DW $Transformed$ $P - value$	1.46522 0.02	1.59139 0.0482	1.94742 0.2659	1.94846 0.2269	1.94149 0.1826
$R^2 /\ Adj\ R^2$	0.0034 / -0.0188	0.052 / 0.0089	0.8584 / 0.8485	0.8578 / 0.8443	0.8915 / 0.8782
$F - statistic$	0.2 on 1 and 45 DF	1.2 on 2 and 44 DF	86.9 on 3 and 43 DF	63.3 on 4 and 42 DF	67.3 on 5 and 41 DF
$P - value$	0.6976	0.3091	2.779×10^{-18}	3.084×10^{-17}	1.098×10^{-18}
$Breusch\text{–}Pagan$ $test$	0.7989	0.07653	0.2356	0.2985	0.3105

6. Discussion

We can tell two things from the coefficients on the $Education$ variables: education is definitely negatively correlated with TFR, but it also exhibits diminishing returns, as we can see when we square the variable in model 2. We argue that women at the age of 18 who are prone to marry early are also more likely to seek employment or a partner rather than attending university, but that this pattern has slowly faded with time as attending university is becoming more common in society in general. Therefore, it is not unreasonable to think that education has diminishing returns to TFR.

Marriage rate has a positive effect on TFR. We expected education to have a negative effect on marriage rate and model 3 confirms this suspicion when the inclusion of marriage rate lowers the coefficient estimate on both education variables, while also reducing their significance level. This means that we had omitted variable bias before in model 2.

In model 4, we see that the inclusion of urbanization almost doubles the coefficient of marriage rate while also greatly increasing the significance of the other variables in the model. Only the intercept is insignificant, and this is generally speaking the least interesting coefficient from a regression output because it is hard or meaningless to interpret. What is interesting in the model is that the sign of the coefficient for urbanization is positive. This is contrary to our expectations and previous studies we referenced that surmise that an increase in urbanization would lead to a fall in TFR. Either we were wrong in our expectations, or this indicates that there is a problem with omitted variable bias in the model that switches the sign. Given the limitations and nature of our datasets, we assume it is the latter reason. This conclusion is strengthened by the fact that when removing urbanization from the model, all other variables become drastically less significant and the R^2 also falls with approximately 20 percentage units. It tells us that urbanization is a relevant variable and useful for the model, but there is some underlying factor that is disrupting the real relationship. The underlying factor is most likely the insufficient data supply.

When we move on to the second batch of data that spans 1968–2015, referring to models 5–9, we find that the first two models are completely insignificant without the addition of marriage rate, which confirms that it is likely due to omitted variable bias. Adding $Urban\ Pop$ in model 8 brings no value to the model whatsoever, and the same goes for $WLFP$ in model 9. We can draw two conclusions from this: firstly, omitting $WLFP$ from the model is seemingly not a problem because the model does not change in a meaningful way, so it has no interaction with the other variables and holds therefore no apparent explanatory power, at least with our data. Similarly, the addition of $Urban\ Pop$ into model 8 and 9 is as worthless as $WLFP$. This brings us to our second conclusion, which is that accommodating for the reduced data supply of $WLFP$ induces a significant penalty on model significance.

Let's compare our findings with the results of previous studies. In Kato (2018), the coefficients on population density (throughout all models) are approximately equal to the regression results we obtain, which we cannot say is a parallel because the author uses completely different types of data in regressions of different types, but the resemblance is still surprising. Granted, we are using a different variable in a regression model with several variables, but it is meant to be a proxy for population density, so it is only natural that we compare these results. The result does not apply to $WLFP$, though it is at least significant in his model, which means that there is merit in using it. The main problem with the cross-sectional analysis is that one cannot possibly draw reliable causal effects from the results because we they are not indicative of temporal changes. Despite this, the coefficients in the regression results of these two data sets are relatively similar. Given the resemblance, and that the study's results seem to be consistent with theory, it tells us that the analysis has merit despite the lack of historical data.

Lutz et al. (2006) find that population density is by far the most significant and relevant variable, even though the value of the coefficient is not similar to that of Kato's results (2018). We surmise that this is a consequence of using cross-national data, which are much more varied. $WLFP$ coefficient values are similar to Kato's results (2018) and significant.

A direct comparison to Edwards et al. (2019) study is impossible because they are using a much more complicated and unrelated model. However, both ours and their results point toward the conclusion that education and marriage rate are strongly negatively correlated, even if the model coefficient values are unrelated. Other than that, there is not much to compare since the types of analyses are not similar at all.

7. Conclusion

The study finds that the main determinants of fertility rates in Japan are enrollment in universities, marriage rate and urbanization, while women's labor force participation is not found to be significant in the alternative model. The latter is partially due to a shortage of data, as proven by the comparison between models 4 and 8, and partially because of the variable. $Marriage\ rate$ seems to be the strongest variable out of the selection. All variable signs are consistent with theoretical expectations except for urbanization, which we believe is the result of deficient data. The majority of the results are also in line with the results from previous studies to the extent that we can actually compare them. Two studies find that population density and women's labor force participation are very influential factors in TFR, but we can only partially confirm this result. Gradually adding variables to the model shows us that some variable relationships are more sensitive than others, like $Education$ and TFR, who suffer from omitted variable bias prior to adding $Marriage\ rate$ as remedy. $Urban\ Pop$ is a very valuable addition to the model significance despite being a flawed proxy, another result which is surprising.

Based on our analysis alone, we can say that there are at least three determinants on total fertility in Japan. As for the intricate relationships between variables, we can only refer to the results of previous studies, which have provided the theoretical framework for our study. Collectively, we can say that increased urbanization and women's rights have led to wider career and educational opportunities. In turn, this has generated a deterring effect on marriage decisions, effectively delaying marriage and causing a decrease in fertility rates over time.

This conclusion relies heavily on the fact that the decision of marriage and having children occur simultaneously, as prescribed by Japanese tradition.

There are some things that we wish we could have changed or done differently to improve upon the relevance of this study, which includes using additional socio-economic variables, prefectural data, and more historical data without discontinuities. One of the socio-economic variables we would have wanted to incorporate is the female labor participation rate after specifically enrolling in universities. By including this variable, it could have shown us if higher education affects career options and the time to get a job after graduation. This could then be connected to the EEOA by comparing the situation for pre- and post-EEOA cohorts, an analysis in itself. Naturally, we would need more historical data in order to analyze this, which was also a problem with some of the variables because they were often discontinuous due to discrete documentation. Therefore, we needed to accommodate for this by removing observations from other variables to maintain a consistent data set. We would have ideally liked to use prefectural data to take a deeper look at the causal relationships and depict those with greater accuracy than we have currently done. The problem was knowing that the data exists but not being able to find it. This is the case for other variables as well, such as our data for education, which only captures enrolment for 18-year-olds instead of all women. Similarly, it would have been better to use employment data with regards to education levels. Lastly, age-divided marriage rate and marriage status or continuous data on mean age of first marriage to see if marriages become more common after education and establishing a career.

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