Duration of maternity leave and fertility in developing countries: Empirical analysis

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Context

- In developed countries some studies have found a positive association between the duration of maternity and parental leave and fertility.
- In developing countries duration of maternity leave, as well as compliance with it, are lower. Still, cross country empirical studies have found that longer leaves in developing countries are associated with lower infant mortality (Nandi,2015), better nutrition, and more vaccination (Nandi et al 2016).
- No cross country empirical studies have investigated the link between duration of maternity leave and fertility in developing countries.

Summary of studies in developed countries

Paper	Results about maternity leaves	Results on other policies
Gauthier& Hatzius (1997)	No effect of maternity leaves	An increase of 35% in the allowances-earnings ratio leads to an increase of 0.56% in fertility rate (0.01 child per woman)
Adeserá (2004)	28 weeks of fulltime equivalent leave is associated with an increment of 0.1 in fertility rate	Expenditure in cash allowances and day care of 3% of GDP adds 0.3 points to TFR relative to spending 0.35% of GDP
D'Addio& d'Ercole (2005)	Duration of maternity leave slightly lowers fertility Higher replacement rate slightly boosts fertility	A 25% in transfers to families with children leads to 0.05 more children per woman in the long run.
Hilgeman & Butts (2009)	Maternity leave is not significantly associated with fertility.	Increasing child care enrollment from 6% to 30% leads to expected increase in realized fertility of 0.27 children per woman
Kalwij (2010)	A 10% in in leave benefits reduces childlessness by 3.2% No effect on subsequent births	A 10% increase in child-care subsidy does not affect first births, but increases completed fertility by 0.4%
Luci-Greulich& Thevenon(2013)	Length of leave is very weakly associated with fertility	Expenditure on benefits per child as % of GDP and childcare enrollment boost fertility
Harknett& Billari et al (2014)	1% in parental leave benefits raises the odds of first child by 1% with no impact on higher order births	A 1% in public expenditure on families has no effect on first order births but raises the odds of higher order by 23%.

Aim of this study

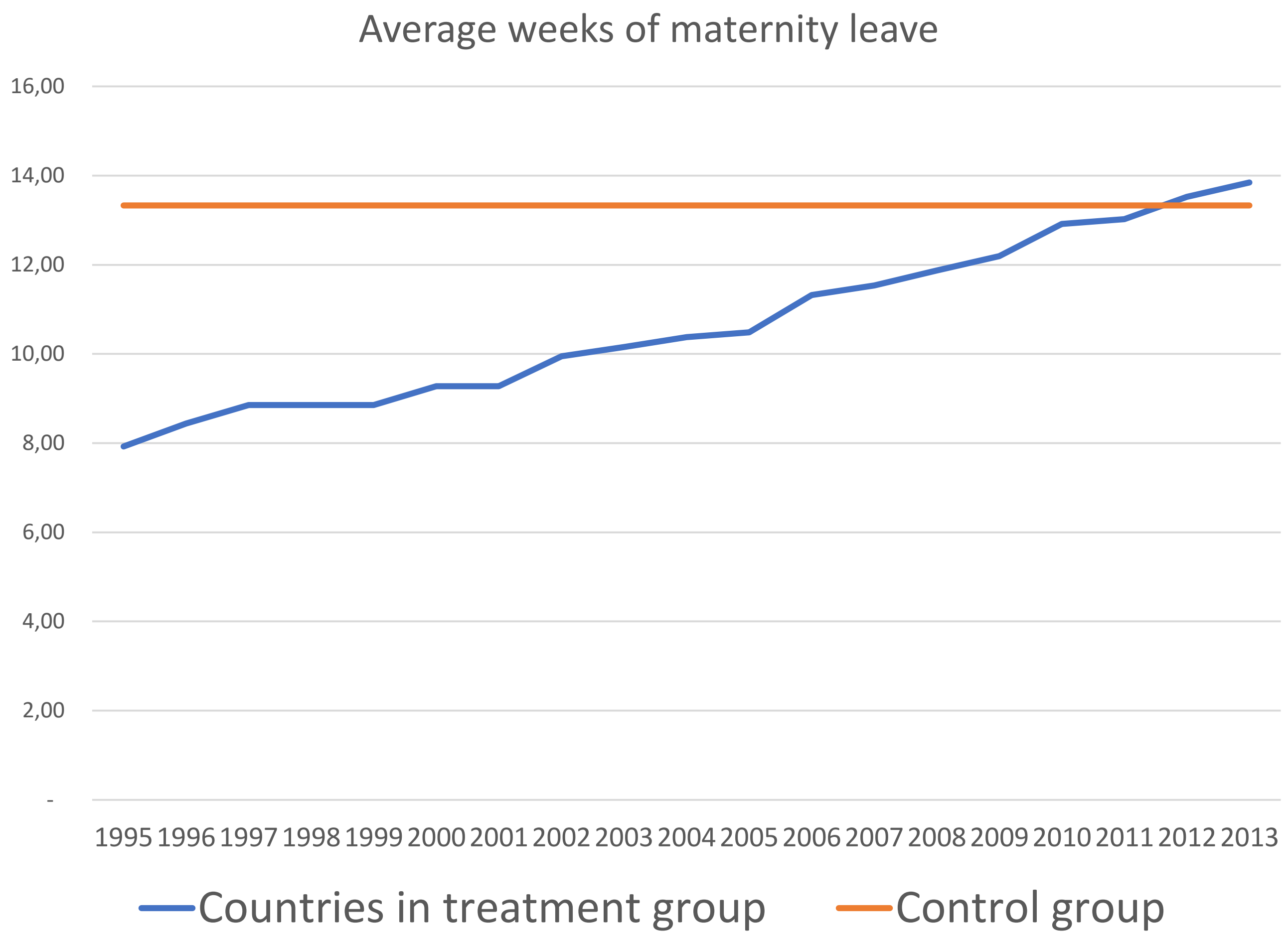
Assess the impact (if any) of the duration of maternity leave on fertility in developing countries.

Data

The MACHEquity project has published a database with the duration of paid maternity leave in 121 countries, between 1995 and 2013.

There has been variation in the duration of leaves in a subset of countries, which can be exploited to assess their impact on fertility.

Weeks of paid leave available to mothers



Of countries with DHS data 19 have changed duration of leave, and 65 have not. Averages on the left.

Not all countries have births data for all years and age groups, so the final sample will be 67 countries, 17 of them in the treatment group that has changed duration of leave.

DHS data

- I use 215 DHS surveys from 71 countries, with births in the years of interest.
- Selected variables are:
  - Caseid
  - Date of birth
  - Date of interview
  - Urban/Rural
  - Education (categorical)
  - Birth History
- Other variables like wealth are not included because of being frequently missing.
- Number of births and exposure time in each year are estimated at the individual level, applying normalized sample weights.
- Birth count and women-years of exposure are aggregated in the cells defined by: country-year-age group-urban-educ-parity.

Estimating fertility

- Direct estimation has number of births in the numerator and women-years of exposure in the denominator.
  - Since the hazard of giving birth varies with age, estimation is done separately by age group.
- Equivalently, fertility can be estimated with a Poisson regression (Shoumaker 2000). This is a count data model, applied as follows:
  - Dependent variable: number of births
  - Explanatory variables:
    - Woman-years of exposure to the risk of giving birth (the offset)
    - Dummies for age groups and periods (e.g. calendar years).
    - Potentially other covariates.

Poisson regression

- Poisson distribution has a single parameter (λ) that indicates the average number of times an event occurs per unit of time. This parameter can be modelled as depending on covariates through a link function:

$$\lambda = \exp(x'\beta)$$

- The conditional mean is given by:

$$\mathrm{E}(y|x) = \lambda = \exp(x'\beta)$$

Poisson regression

- The number of events is proportional to the period at risk, which can be incorporated as follows:

$$\begin{aligned} \mathrm{E}(y|x) &= t\exp(x'\beta) \\ &= \exp(x'\beta + \log t) \end{aligned}$$

- This is equivalent to a piece-wise exponential proportional hazards model in duration analysis (the likelihood functions coincide). Poisson focuses on number of events per unit of time. PH model estimates time to event.
- Poisson model can be equivalently estimated at the individual level, or with grouped data (e.g. adding up births and exposure time of women of the same age group and characteristics).

The single country model

$$birth\ count = \exp(\alpha + \beta age + \beta year$$
$$+\beta educ + \beta urban + \beta parity + \log(woman\ years)$$

Interpretation of the coefficients:

- $\exp(\alpha)$ is the baseline hazard of birth.
- $\exp(\beta)$ is the multiplicative effect of the covariate. E.g., if $\exp(\beta)$ = 2 the covariate duplicates the baseline hazard.

Drivers of fertility in Colombia

Intercept corresponds to women age 15-19, urban, with no kids and no education.

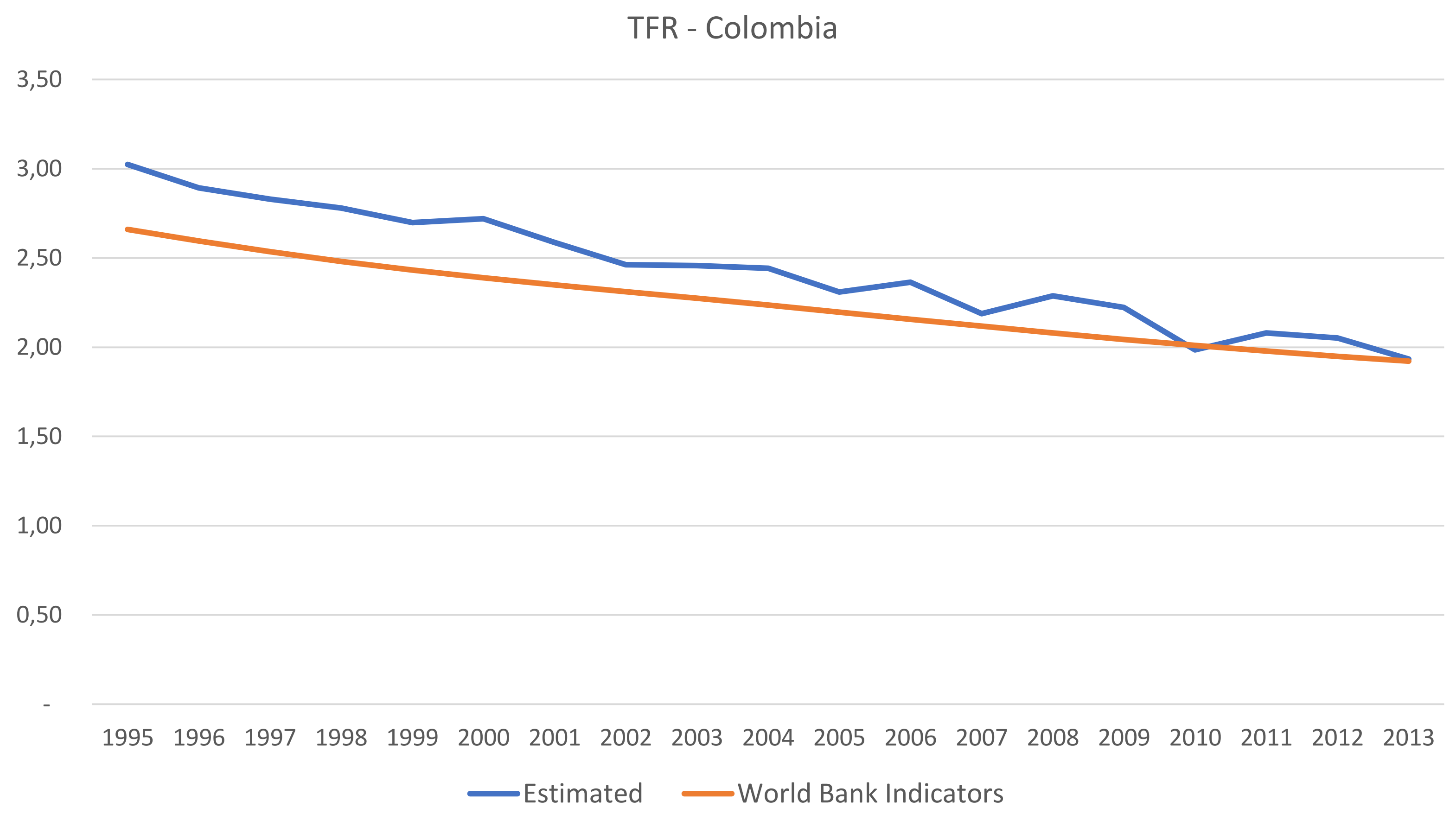
Baseline hazard = exp(-1.58) = 0.2 kids/year.

Education lowers the hazard of giving birth. Rural raises it. Multiplicative effect of age and parity has inverted U shape

	Estimate	Pr(>|z|)	Multiplicative effect
(Intercept)	-1.58	< 2e-16 ***	
age.group 20-24	0.48	< 2e-16 ***	1.61
age.group 25-29	0.35	< 2e-16 ***	1.42
age.group 30-34	0.05	1.20e-06 ***	1.05
age.group 35-39	-0.55	< 2e-16 ***	0.58
age.group 40-44	-1.64	< 2e-16 ***	0.19
age.group 45-49	-3.63	< 2e-16 ***	0.03
rural	0.19	< 2e-16 ***	1.21
incomplete primary	-0.19	< 2e-16 ***	0.82
complete primary	-0.36	< 2e-16 ***	0.70
incomplete secondary	-0.44	< 2e-16 ***	0.65
complete secondary	-0.76	< 2e-16 ***	0.47
higher education	-1.20	< 2e-16 ***	0.30
parity1	0.01	0.167423	1.01
parity2	-0.43	< 2e-16 ***	0.65
Parity3+	-0.55	< 2e-16 ***	0.58

Estimation with pooled data from DHS surveys implemented in 2000, 2005, 2010, 2015.

Total Fertility Rate



The multi-country model

- Shoumaker(2000) has proposed:

$$
\begin{gathered}
birth\ count = \exp(\alpha + \beta country\ membership \\
+\beta agegroup \\
+\beta year + \log(woman\ years)
\end{gathered}
$$

This implies that the multiplicative effects of each age group are the same in all countries, which is implausible. Moreover, the older age groups have very few observations in the DHS data in the period 1995-2013.

I estimate a separate model for each age group.

Explanatory variables

- Individual characteristics:
  - Education, urban/rural, and parity.
- Country level:
  - Log of GDP, and national unemployment rate
- Policy variable:
  - Duration, in weeks, of paid maternity leave each year.

The model

Specification A:

$$birth\ count_{age\ g} = \exp(\alpha + \beta * country\ membership$$
$$+\beta * year + \beta * urban + \beta * educ + \beta * parity +$$
$$+\beta * logGDP + \beta * Unemployment\ rate$$
$$\beta * ML\ weeks + \log(woman\ years)$$

This model estimates the effect of the duration of paid maternity leave after controlling for the calendar year (dummy), the country effect, as well as macro economic variables and individual characteristics.

The model – Diff in diff

Specification B:

$$
\begin{gathered}
birth\ count_{age\ g} = \exp(\alpha + \beta * country\ membership \\
+\beta * year + \beta * urban + \beta * educ + \beta * parity + \\
+\beta * logGDP + \beta * Unemployment\ rate \\
\beta * t.post + \log(woman\ years_{age\ g})
\end{gathered}
$$

t.post is an interaction of the treatment group and the post-treatment years. Treatment is modeled as being binary.

It is based on a diff-in-diff identification strategy, applied to a Poisson model as illustrated by Winkelman (2003) chapter 3.

The model – Controlling for female employment

Specification C:

$$birth\ count_{age\ g} = \exp(\alpha + \beta * country\ membership$$
$$+\beta * year + \beta * urban + \beta * educ + \beta * parity +$$
$$+\beta * logGDP + * \beta Unemployment\ rate$$
$$\beta * fraction\ of\ women\ employed$$
$$+\beta * ML * fraction\ of\ women\ employed$$
$$+\log(woman\ years_{age\ g})$$

Fraction of women employed is female employment to population ratio (for a ages 15+). This equation controls for fraction of women employed and also interacts weeks of paid maternity leave (ML) with that fraction. The more women are working, the greater the intensity of treatment.

Results - Specification A education

	age.group	effect	Std. Error.1	Pr(>|z|)	signif
urb.rurrural		1.163647	0.003705	0	***
educincomplete primary		0.86814	0.004493	2.19E-217	***
educcomplete primary		0.749216	0.005642	0	***
educincomplete secondary		0.51547	0.005253	0	***
educcomplete secondary		0.311771	0.007756	0	***
educhigher		0.134492	0.012008	0	***
parity1		1.420201	0.003704	0	***
parity2		1.096725	0.006658	9.96E-44	***
parity3		1.031232	0.012533	0.014133	**
urb.rurrural3		1.204055	0.002912	0	***
educincomplete primary3		0.948231	0.003603	2.84E-49	***
educcomplete primary3		0.86118	0.004499	6.02E-242	***
educincomplete secondary3		0.753048	0.004287	0	***
educcomplete secondary3		0.635874	0.005274	0	***
educhigher3		0.38834	0.00701	0	***
parity13		1.489488	0.003111	0	***
parity23		1.142156	0.003547	3.05E-307	***
parity33		0.936964	0.004115	2.22E-56	***
urb.rurrural6		1.198277	0.003205	0	***
educincomplete primary6		0.955686	0.003913	4.92E-31	***
educcomplete primary6		0.882582	0.004961	7.42E-140	***
educincomplete secondary6		0.810746	0.004885	0	***
educcomplete secondary6		0.791731	0.005852	0	***
educhigher6		0.738826	0.006742	0	***
parity16		1.994655	0.004875	0	***
parity26		1.733119	0.004788	0	***
parity36		0.004447	0	***	
urb.rurrural9		1.225556	0.004007	0	***
educincomplete primary9		0.943249	0.004724	3.87E-35	***
educcomplete primary9		0.852246	0.006097	1.46E-151	***
educincomplete secondary9		0.786724	0.006224	0	***
educcomplete secondary9		0.808579	0.007701	1.38E-167	***
educhigher9		0.867336	0.008376	9.26E-65	***
parity19		2.399435	0.008372	0	***
parity29		2.204356	0.007954	0	***
parity39		2.23026	0.00691	0	***

Results - Specification A policy variables

	age.group	effect	Std. Error.1	Pr(>|z|)	
logGDP		0.965742	0.012203	0.004284	***
UR.ILO		0.996207	0.001042	0.000267	***
M1	15 to 19	0.999467	0.000914	0.55972	
logGDP3		1.012661	0.009701	0.194679	
UR.ILO3		0.996525	0.000832	2.87E-05	***
M12	20 to 24	0.999107	0.000749	0.233039	
logGDP6		1.011171	0.01065	0.296893	
UR.ILO6		0.998503	0.000918	0.102712	
M14	25 to 29	0.998744	0.000843	0.136066	
logGDP9		0.989757	0.013435	0.443481	
UR.ILO9		0.998112	0.001122	0.092018	
M16	30 to 34	0.998623	0.001067	0.196506	

Results - Specification B policy variables

	age.group	effect	Std. Error.1	Pr(>|z|)	
logGDP1		0.960585	0.012391	0.001173	***
UR.ILO1		0.996146	0.001041	0.000208	***
t.post	15 to 19	0.983509	0.006518	0.010737	**
logGDP4		1.006574	0.009884	0.507401	
UR.ILO4		0.996471	0.00083	2.06E-05	***
t.post1	20 to 24	0.982125	0.005273	0.000624	***
logGDP7		1.001647	0.010846	0.87938	
UR.ILO7		0.998385	0.000916	0.07765	
t.post2	25 to 29	0.971552	0.005947	1.22E-06	***
logGDP10		0.981384	0.013674	0.169363	
UR.ILO10		0.998025	0.00112	0.077369	
t.post3	30 to 34	0.973092	0.007577	0.000318	***

Results - Specification C Policy variables

	age.group	effect	Std. Error.1	Pr(>|z|)	
logGDP2		0.950957	0.012911	9.83E-05	***
UR.ILO2		0.995848	0.001067	9.72E-05	***
M11		0.977832	0.004008	2.24E-08	***
WEP.Ratio		0.993002	0.001038	1.31E-11	***
M1:WEP.Ratio	15 to 19	1.000358	6.39E-05	2.05E-08	***
logGDP5		0.999121	0.010269	0.931728	
UR.ILO5		0.995565	0.000855	1.98E-07	***
M13		0.984712	0.00293	1.45E-07	***
WEP.Ratio1		0.994333	0.000785	4.65E-13	***
M1:WEP.Ratio1	20 to 24	1.000234	4.74E-05	8.21E-07	***
logGDP8		1.005608	0.011265	0.619593	
UR.ILO8		0.997331	0.000945	0.004667	***
M15		0.982433	0.003188	2.72E-08	***
WEP.Ratio2		0.993582	0.000866	1.05E-13	***
M1:WEP.Ratio2	25 to 29	1.000273	5.22E-05	1.61E-07	***
logGDP11		0.989167	0.014165	0.441929	
UR.ILO11		0.99655	0.001154	0.002753	***
M17		0.982511	0.004146	2.08E-05	***
WEP.Ratio3		0.994299	0.001107	2.38E-07	***
M1:WEP.Ratio3	30 to 34	1.000279	6.77E-05	3.91E-05	***

Results – comments

- Treatment effect is one minus the multiplicative effect.
- The treatment effect of paid maternity leave duration appears to be slightly negative, although consistently significant in diff-in-diff specification.
- Unemployment is weakly associated with fertility. GDP coefficient is significant only for the younger age group.
- Once we control for female employment to population ratio the effect of maternity leave ceases to be negative.
- When estimated on the subset of middle income countries, results are similar.
- Next step: check robustness of standard errors to miss-specification of the variance of the birth count.