Supplementary Information

More father leave, more babies? Father-exclusive parental leave periods and fertility

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1 Variables

Variable	Definition	Source
Mortgages	Monthly mortgages constituted (number of dwellings)	INE- Financial and Monetary Statistics
Affiliates	Average monthly affiliation. All regimes (national)	Social Security- Affiliation Statistics
CPI	National Consumer Price Index (monthly overall index). Base 2021	INE- Standard of living and living conditions Statistics
Income	Quarterly available gross income. Households and private non-profit institutions serving households (NPISH). Base 2016; millions of euros.	INE- Living Quality Indicators. *Quarterly to monthly adjustment using the best-fit linear trend.
Fertility rate	Monthly number of births of women aged 16-39 over the population of 16-39 women x 1000. (Spanish and non Spanish mothers)	INE- Demographic and Population Statistics

Table S1: Variables Description

	(First & second order)		(Third & higher order)		(Difference)	
Variable	mean	sd	mean	sd	b	t
Working mother	0.73	0.44	0.51	0.50	0.23***	(338.18)
Working father	0.91	0.29	0.85	0.36	0.06***	(131.73)
Both parents working	0.72	0.45	0.57	0.50	0.15***	(234.63)
College graduate mother	0.25	0.43	0.17	0.38	0.08***	(150.94)
College graduate father	0.18	0.38	0.16	0.36	0.02***	(42.65)
Married	0.59	0.49	0.66	0.48	-0.07***	(-107.97)
Maternal age	31.09	5.01	32.84	4.39	-1.75***	(-294.02)
Paternal age	33.94	5.78	36.67	6.13	-2.73***	(-332.04)
Spanish mother	0.81	0.39	0.66	0.48	0.16***	(254.61)
Spanish father	0.83	0.38	0.69	0.46	0.14***	(222.73)
N	5,323,435		629,499		5,952,934	

Table S2: Descriptive statistics by birth order. The set of sociodemographic characteristics is averaged over time from 2007 to 2021 by the two birth order categories. All variables are binary variables except for age. The two last columns refer to simple t tests to check for significant differences in mean among the two birth order categories. The data comes from the birth registers of the Spanish National Institute. *** refers to statistically significant differences at the 1% significance level

1.1 Auxiliary variables

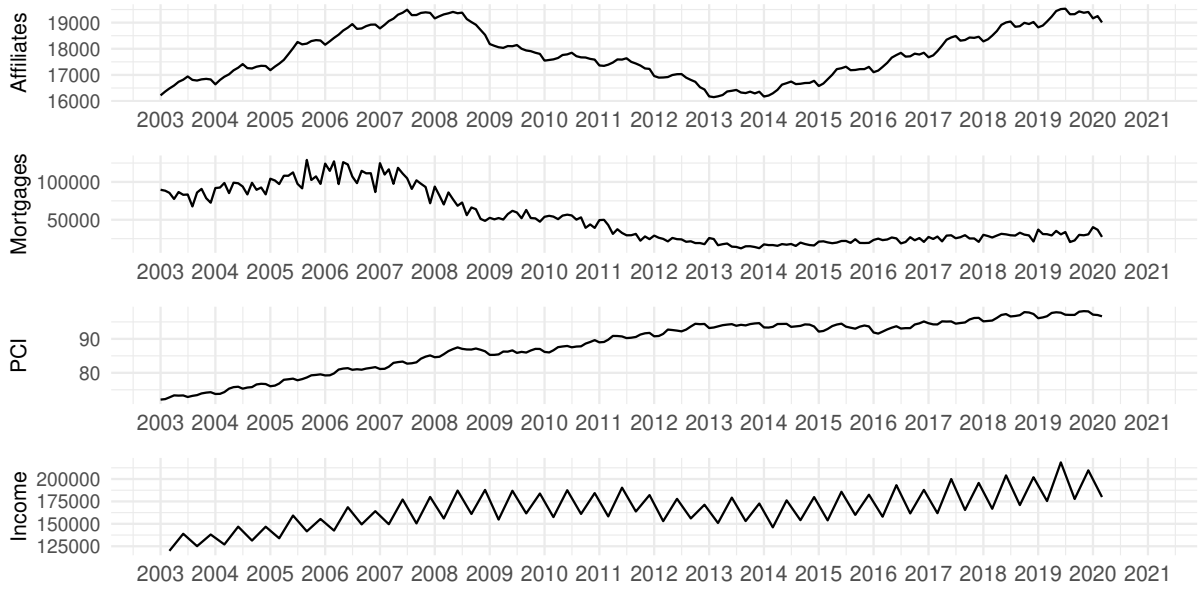

Fig. S1: Auxiliary variables. From the top to the bottom: monthly average of the number of affiliates to Social Security (all regimes); monthly number of constituted mortgages (dwellings); price consumer index (PCI); and gross disposable income of households. Data sources are the Spanish Institute of Statistics and Spanish Social Security

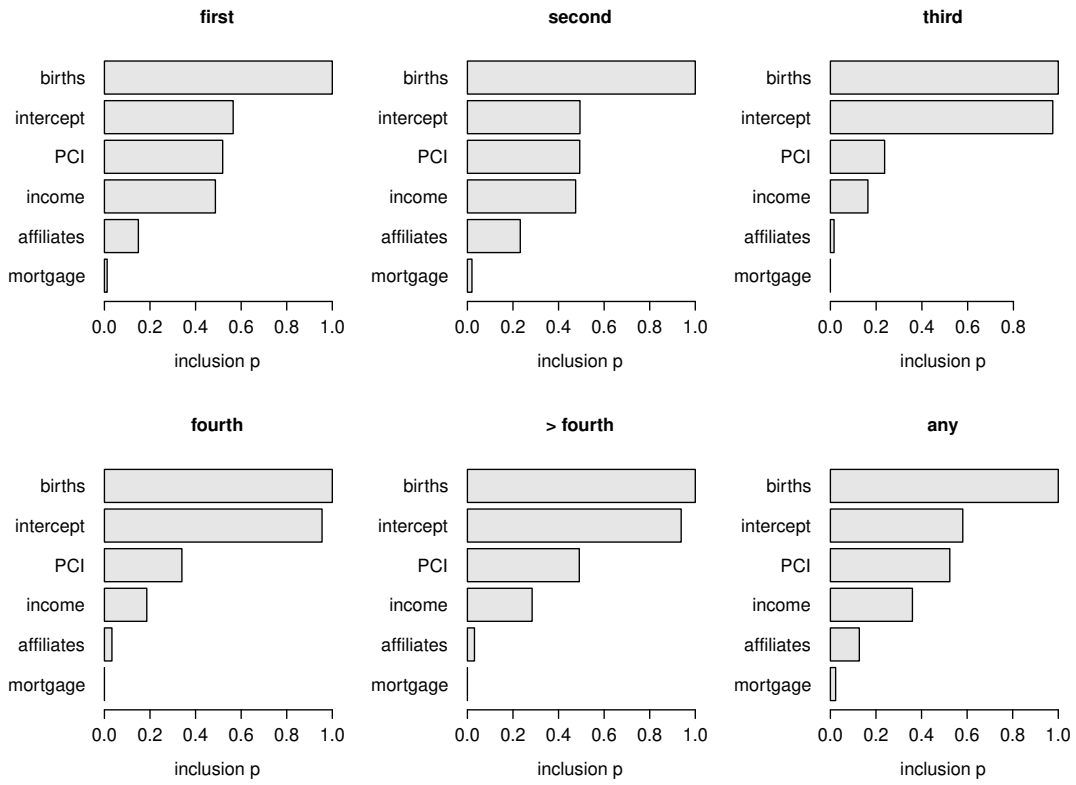

Fig. S2: Posterior inclusion probabilities for the predictors. Posterior inclusion probabilities attached to the auxiliary variables in the BSTS model linked to the 4-week intervention. Bars are shaded on a continuous interval [0, 1] in proportion to the probability of a non-zero coefficient. The variable selection is based on a spike-and-slab regression, choosing those variables more correlated to the outcome variable. The spike and slab regression consists of two parts. The spike part governs the probability of a given variable being included in the model (i.e., having a non-zero coefficient). The slab part moves the non-zero coefficients toward the expectations specified in the priors, zero in this case. See Brodersen et al., (2015); Scott & Varian, (2014)

1.2 Response variables

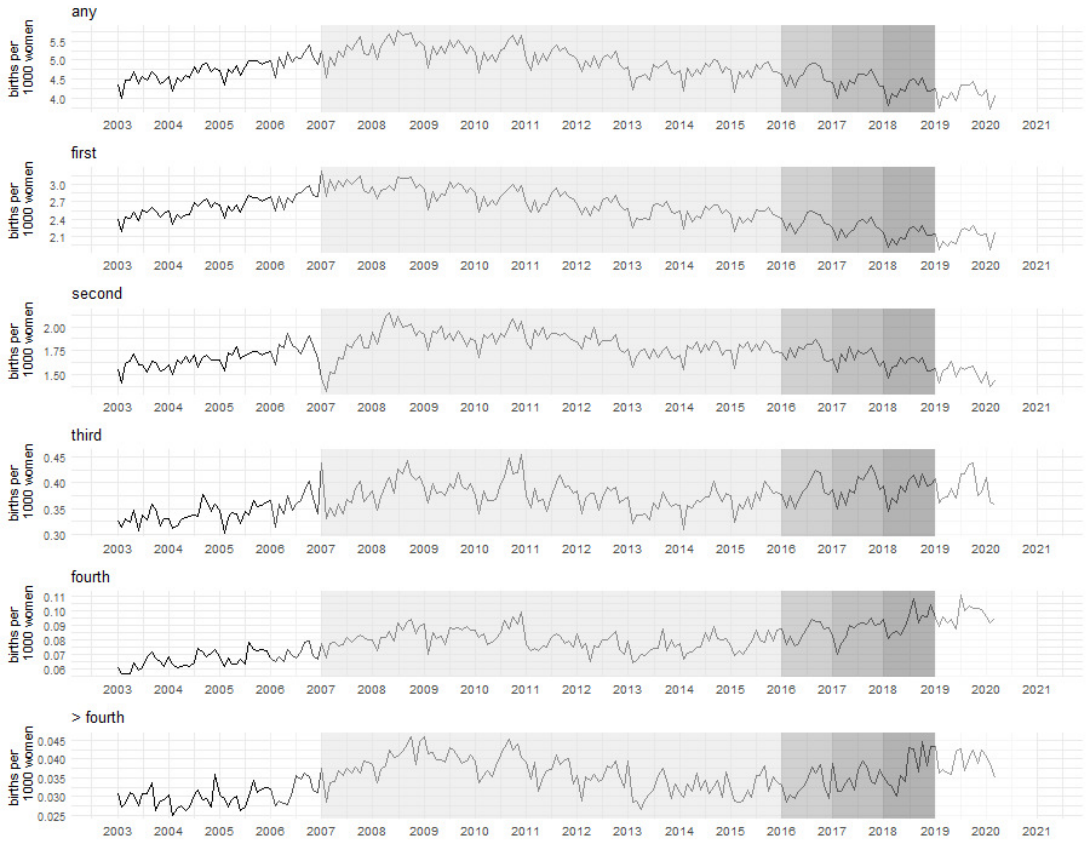

Fig. S3: Number of births per 1000 women of childbearing age by birth order. Shaded areas refer to the policy reforms linked to the introduction of 2 weeks, 4 weeks, 5 weeks and 8 weeks of father-exclusive leave. Longer leave extensions are not considered in the analysis

2 The model

A BSTS model can be defined by a pair of equations.

$$y_t = Z_t^T \alpha_t + \epsilon_t \quad where \quad \epsilon_t \sim \mathcal{N}(0, H_t) \tag{1}$$

$$\alpha_{t+1} = T_t \alpha_t + R_t \eta_t \quad where \quad \eta_t \sim \mathcal{N}(0, Q_t) \tag{2}$$

Equation (1) is the observation equation that links the observed data y_t to a latent state vector α_t. Equation (2) is the state or transition equation that defines the evolution of the state vector α_t through time. ϵ_t and η_t are independent of all other unknowns. In our model, we add a regression component that incorporates the effects of other unobserved causes that are otherwise not accounted for to the "basic structural model," which just contains a trend and a seasonal component of the response variable. It is

$$y_t = \mu_t + \tau_t + \beta_t^T \mathbf{x}_t + \epsilon_t \quad where \quad \epsilon_t \sim \mathcal{N}(0, \sigma_t^2) \tag{3}$$

$$\mu_t = \mu_{t-1} + \delta_{t-1} + u_t \quad where \quad u_t \sim \mathcal{N}(0, \sigma_u^2) \tag{4}$$

$$\delta_t = \delta_{t-1} + v_t \quad where \quad v_t \sim \mathcal{N}(0, \sigma_v^2) \tag{5}$$

$$\tau_t = -\sum_{s=1}^{12-1} \tau_{t-s} + w_t \quad where \quad w_t \sim \mathcal{N}(0, \sigma_w^2) \tag{6}$$

The state vector would be $\alpha_t = (\mu_t, \tau_t, \beta_t)$ which respectively refers to the trend, seasonal and regression components. We allow for a local linear trend (4) and (5) that assumes both the mean and the slope

of the trend follow random walks.[1] The seasonal component is defined over a set of 12 dummies which are constrained to have zero expectation over a year and τ_{t-s} denotes the month contribution to the observed response y_t. The vector $\eta_t = (u_t, v_t, w_t)$ contains independent components of Gaussian random noise. Q_t, in this case, is a constant diagonal matrix with diagonal elements σ_u^2, σ_v^2 and σ_w^2. H_t is a constant equal to σ_ϵ^2.

The model is estimated in a Bayesian framework stating the prior distributions of the set of unknown parameters $\theta : (\sigma_\epsilon^2, \sigma_u^2, \sigma_v^2, \sigma_w^2, \beta)$.

For further details see: Brodersen et al., (2015) and Scott & Varian, (2014).

2.1 Priors

For the set of unknown parameters the default priors are assumed to be non-informative priors. The variance parameters of the state equations $(\sigma_u^2, \sigma_v^2, \sigma_w^2)$ are assumed to follow a non-informative Gamma distribution. It is $1/\sigma^2 \sim Gamma(10^{-2}, 10^{-2}s_y^2)$ where s_y^2 refers to the sample variance of the response variable. With respect to the variance of the disturbance of the observation equation, it is assumed a Gamma distribution of the form $1/\sigma_\epsilon^2 \sim Gamma(n_\epsilon/2, s_\epsilon/2)$ where n_ϵ refers to the prior sample size. For the coefficients of the explanatory variables, it is a assumed a conjugate normal-inverse Gamma distribution. $\beta_\varrho|\sigma_\epsilon^2 \sim N(\beta_\varrho^0, \sigma_\epsilon^2(\sum_\varrho^{-1})^{-1}$ where the vector $\beta_\varrho^0$is assumed to be the zero vector (Brodersen et al., 2015).

To check for the sensibility of our results to the specification of the priors, we perform a sensibility test with respect to the grid of expected R^2 of the model, the standard deviation of the disturbance of the observation equation, the inclusion probabilities of explanatory variables, prior sample size, and prior degrees of freedom, which govern the impact of prior distribution assumptions on the posterior estimates (Table S3).

[1] We will check for the best suitable specification for the trend in the model in each case allowing for a local linear trend (4) and (5) or a local level model where the trend is a random walk. It is

$$\mu_t = \mu_{t-1} + \varepsilon_t \quad where \quad \varepsilon_t \sim \mathcal{N}(0, \sigma_\varepsilon^2)$$

3 Sensitivity Analysis

PANEL A: 4 weeks father quota- 3rd birth					
expected.R2	prior.sd	inclusion.probabilities	prior.sample.size	prior.df	probability
.6	.001	.5	30	1	.062
.6	.001	.5	30	0.1	.047
.6	.001	.5	30	0.01	.037
.6	.001	.5	60	0.01	.037
.6	.001	.16	60	0.01	.092
.4	.001	.16	60	0.01	.087
.8	.01	.16	60	0.01	.082
PANEL B: 4 weeks father quota- 4rth birth					
expected.R2	prior.sd	inclusion.probabilities	prior.sample.size	prior.df	probability
.6	.001	.5	30	1	.054
.6	.001	.5	30	0.1	.032
.6	.001	.5	30	0.01	.029
.6	.001	.5	60	0.01	.131
.6	.001	.16	60	0.01	.145
.4	.001	.16	60	0.01	.052
.8	.01	.16	60	0.01	.042
PANEL C: 4 weeks father quota- > 4rth birth					
expected.R2	prior.sd	inclusion.probabilities	prior.sample.size	prior.df	probability
.6	.001	.5	30	1	.096
.6	.001	.5	30	0.1	.039
.6	.001	.5	30	0.01	.029
.6	.001	.5	60	0.01	.037
.6	.001	.16	60	0.01	0.093
.4	.001	.16	60	0.01	.092
.8	.01	.16	60	0.01	.056

Table S3: Sensitivity analysis with respect to the prior distribution of model parameters. The set of parameters considered changes throughout a grid built up based on perturbations to the default, which is automatically chosen by the *bsts package* following the optimization of the model performance. *Probability* refers to the probability of obtaining the effect by chance (Bayesian one-sided tail-area probability). *Expected R2* refers to the expected fraction of the variation in the response variable explained by the model. *Prior.sd* accounts for the prior knowledge about the variance parameters linked to the diffusion of the state components. This is the scaling parameter of the sample variance of the response. *Inclusion.prob* encompasses the prior probability of each regressor being included in the model. *Prior.sample.size* refers to the sample fraction used to govern the weight of the prior distribution on the posterior estimates. *Prior.df* accounts for the prior degrees of freedom for computing the residual variance. See Brodersen et al., (2015) and George & McCulloch, (1997) for further details.

4 Robustness Analysis

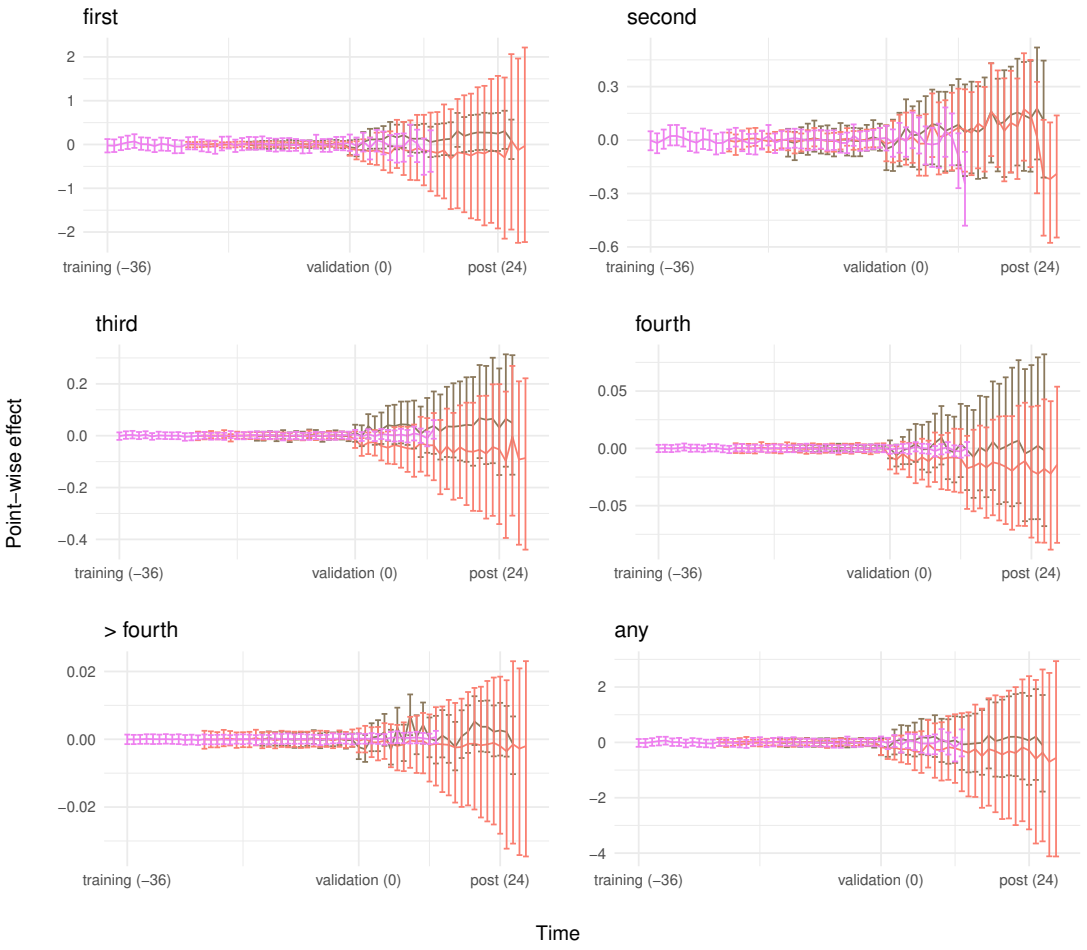

Fig. S4: Placebo exercise. Point-wise causal effect of two placebo intervention dated April 2004 and January 2005 on the birth count of 1000 childbearing-age women. The placebo exercise is analyzed by birth order. The prior period is divided in half to account for a training sample and a model validation sample prior to the prediction of the effect. Post-period accounts for 24-month observations after the intervention. See 95% credible intervals to account for estimates' uncertainty. The effect of the placebo interventions is not different from zero for any birth order. The model selection is based on model performance based on minimization of root mean square error (RMSE) and mean absolute percentage error (MAPE).