Unpacking the Birth Order Effects

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- In a seminal paper, Black et al. (2005) find a negative effect of family size on labor market and education outcomes using exogenous variation in family size induced by twin births.
- BUT once **birth order** is introduced this effect becomes negligible.
- This implies that family size affects marginal children through birth order effects.

Birth order effects

- Follow-up on birth order effects: cognitive (Booth & Kee, 2009; Conley & Glauber, 2006), non-cognitive skills (Black et al., 2018) and criminal behavior (Breining et al., 2020).
- Estimates of birth order effects vary and are sometimes positive.
- Evidence suggests that their direction/magnitude are context-specific.
  - Ecuador (De Haan et al., 2014): First-born receive less education and more likely to participate in child labor; completely driven by low-income families.
  - Philippines (Ejrnæs and Pörtner, 2004): Positive birth order effects, which are especially pronounced in low-educated families.

Sibling spillover effects

- Separate literature finds evidence of sibling spillovers for a number of educational outcomes.
- Studies on schooling achievement find a positive spillover effect (Gurantz et al., 2020; Nicoletti & Rabe, 2018; Qureshi, 2018).
- Studies on choice of college institution and major provide mixed evidence (Altmejd et al., 2021; Dahl et al., 2020).

Main findings

1. We find negative birth order effects.
2. We find a **negatively** signed spillover effect which implies:
   - Birth order effects are overstated.
   - The multiplier effect arising from the sibling interaction process is **(i)** less pronounced compared to the case where the spillover effects are positive and **(ii)** dissipates faster as the family size increases.

Our findings suggest that an intervention that improves the outcomes of some of the siblings will be less effective in larger families.

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We first consider a **linear-in-means** model with **endogenous effects**.
For each sibling $i = 1, ..., m_g$ in household $g = 1, ..., N$ of size $m_g = 2, ..., M$

$$y_{ig} = x'_{1,ig}\beta_1 + x'_{2,ig}\beta_{2,m_g} + \underbrace{\frac{\gamma}{m_g - 1}\sum_{j \neq i} y_{jg}}_{\text{Endogenous Effect}} + \eta_g + \varepsilon_{ig}$$

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- η_g: Household fixed effect.
- ε_{ig}: Error term

In matrix from

$$Y_g = X_{1,g}\beta_1 + X_{2,g}\beta_{2,m_g} + \gamma W_{m_g} Y_g + 1_{m_g}\eta_g + \varepsilon_g$$

where the interaction matrix is

$$W_{m_g} = \frac{1}{m_g - 1}\left(1_{m_g}1'_{m_g} - I_{m_g}\right)$$

where 1_{m_g} an m_g-vector of 1s and I_{m_g} the identity matrix.

Identification & Estimation Challenges

(1) $W_{m_g} Y_g$ is endogenous w.r.t. η_g.

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(2) Household size m_g possibly correlated with η_g.

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Identification & Estimation Challenges

(3) Left-multiplying by the within operator $Q_{m_g} : Q_{m_g} 1_{m_g} = 0$ to eliminate the household FE induces correlation between $Q_{m_g} W_{m_g} Y_g$ and $Q_{m_g}\varepsilon_g$.

Assumptions

We assume that

$$\mathrm{E}\left[\varepsilon_{ig} \mid X_g, W_{m_g}, m_g, \eta_g\right] = 0 \text{ for all } i, g$$

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- Not so restrictive: $\left(X_g, W_{m_g}, m_g\right)$ can be related to the household FE.

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- Allows us to assess the total effect of a change in one of the model's exogenous regressors.

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- Not so restrictive: $\left(X_g, W_{m_g}, m_g\right)$ can be related to the household FE.
- Allows us to assess the total effect of a change in one of the model's exogenous regressors.
- **Note:** The identification analysis will not assume that we observe all siblings within a household. No selectivity bias is additionally assumed.

Identification Challenges: An Illustration

Provided that $\gamma \neq 1 - m_g$ and $\gamma \neq 1$ we get:

$$Y_g = \left(I_{m_g} - \gamma W_{m_g}\right)^{-1} \left(X_{1,g}\beta_1 + X_{2,g}\beta_{2,m_g} + 1_{m_g}\eta_g + \varepsilon_g\right)$$

where

$$\left(I_{m_g} - \gamma W_{m_g}\right)^{-1} = \frac{1}{1 + \gamma/\left(m_g - 1\right)} \left[I_{m_g} + \frac{\gamma}{\left(1-\gamma\right)\left(m_g - 1\right)} 1_{m_g} 1'_{m_g}\right]$$

Applying the within transformation:

$$\begin{aligned} Q_{m_g} Y_g = & Q_{m_g} X_{1,g} \frac{\beta_1}{1 + \gamma/\left(m_g - 1\right)} \\ & + Q_{m_g} X_{2,g} \frac{\beta_{2,m_g}}{1 + \gamma/\left(m_g - 1\right)} + Q_{m_g} \frac{\varepsilon_g}{1 + \gamma/\left(m_g - 1\right)} \end{aligned}$$

Recovering $\left(\beta_1, \beta_{2,m_g}, \gamma\right)$ thus analogous to identifying the parameters of time-invariant covariates in panel fixed effects regression (see also Graham and Hahn, 2005).

Identification

To seperately identify $(\beta_1, \beta_{2,m_g}, \gamma)$ we rely on group size variation (Lee 2007, Davezies et al. 2009).

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- As long as $\beta_1 \neq 0$ and at least two group sizes are observed, (β_1, γ) are identified.

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- Is identified under standard assumptions.
- Is an 1-to-1 function of m_g.
- As long as $\beta_1 \neq 0$ and at least two group sizes are observed, (β_1, γ) are identified.
- Knowledge of γ allows us to recover the remaining parameters, β_{2,m_g}.

We next consider a model with both **endogenous** and **contextual** effects:

$$Y_g = X_{1a,g}\beta_1 + X_{2,g}\beta_{2,m_g} + X_{1b,g}\beta_3 + W_{m_g}X_{1b,g}\beta_4 + \gamma W_{m_g}Y_g + I_{m_g}\eta_g + \varepsilon_g$$

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- **Contextual effects:** Individuals are also affected by exogenous characteristics of their reference group.
- Additional identification challenge: The **reflection problem** (Manski, 1993). Hard to distinguish between *endogenous* and *contextual effects*.

Estimating Equation: Reduced Form + within-transformation

$$Q_{m_g} Y_g = Q_{m_g} X_{1a,g} \frac{\beta_1}{1+\gamma/\left(m_g-1\right)} + Q_{m_g} X_{2,g} \frac{\beta_{2,m_g}}{1+\gamma/\left(m_g-1\right)} + Q_{m_g} X_{1b,g} \frac{\left(m_g-1\right)\beta_3-\beta_4}{m_g-1+\gamma} + Q_{m_g} \frac{\varepsilon_g}{1+\gamma/\left(m_g-1\right)}$$

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- $X_{1a,g}$ non-empty: Birth order is mutually exclusive and hence does **not** generate contextual effects.

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- **Note:** (β_3, β_4) cannot vary by group sizes.

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Marginal Effects

We assume that $\min_g(m_g) < \gamma < 1$. Let h, g be given by

$$h(\gamma, m) = 1 - \frac{\gamma^2}{(\gamma + m - 1)(\gamma - 1)}$$
$$f(\gamma, m) = -\frac{\gamma}{(\gamma - 1)(\gamma + m - 1)}$$

Then, for those regressors that generate individual effects only

$$\frac{\partial}{\partial x_{1a,ig}} \mathrm{E}\left[y_{ig} \mid X_g, W_{m_g}, m_g, \eta_g\right] = \beta_1 h(\gamma, m_g)$$

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Then, the marginal effect of x_{1a} is

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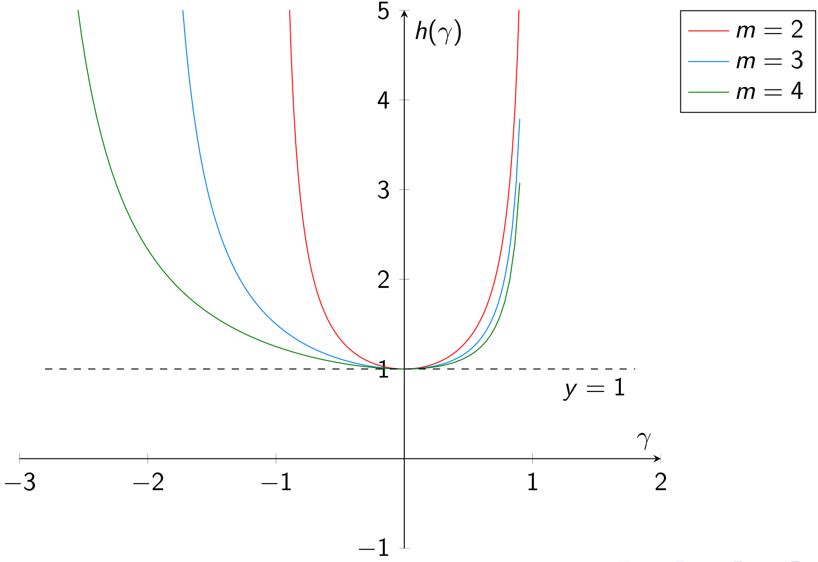
- The effect dissipates as group sizes become larger.

Marginal Effects



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Then, the marginal effect of x_{1b} is

$$\frac{\partial}{\partial x_{1b,ig}} \mathrm{E}\left[y_{ig} \mid X_g, W_{m_g}, m_g, \eta_g\right] = \beta_2 h(\gamma, m_g) + \beta_3 f(\gamma, m_g)$$

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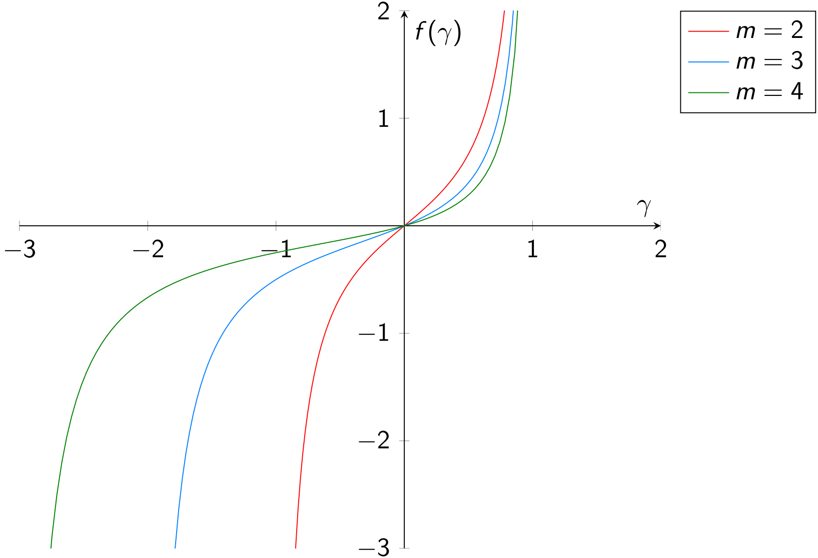
- For fixed m, $f > 0\,(< 0)$ if $\gamma > 0\,(< 0)$.
- This additional term might inflate, zero out, or even reverse the direction of the total effect depending on the values of the parameters $(\gamma, \beta_2, \beta_3)$.

Marginal Effects



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Germany: Reduced Form & Structural parameters

	OLS	Fixed-effects	Fixed-effects (by size)			Minimum Distance
Household Size			$m_g = 2$	$m_g = 3$	$m_g = 4$	
γ						-0.599***
						(0.176)
Second child	-0.420***	-0.462***	-0.447***	-0.303*	-0.674**	-0.218**
	(0.09)	(0.09)	(0.13)	(0.15)	(0.26)	(0.091)
Third child	-0.432***	-0.760***		-0.747***	-1.166***	-0.427***
	(0.14)	(0.17)		(0.27)	(0.36)	(0.140)
Fourth child	-0.442	-1.103***			-1.688***	-0.637***
	(0.29)	(0.29)			(0.52)	(0.225)
J-test						15.33
						[0.88]
N	3157	3260	1694	1059	507	3260

Notes: Standard errors (in parentheses) allow for correlation of errors within households. All regressions include indicators for year of birth and sex. The specification estimated by OLS additionally includes indicators for sibship size and parents education.

Germany: Marginal Effects with Endogenous Effects

	Structural Parameters	Marginal Effects		
Household Size		$m_g = 2$	$m_g = 3$	$m_g = 4$
γ	-0.599***			
	(0.176)			
Second child	-0.204**	-0.34***	-0.253***	-0.238***
	(0.084)	(0.071)	(0.088)	(0.09)
Third child	-0.419***		-0.496***	-0.467***
	(0.131)		(0.138)	(0.139)
Fourth child	-0.657***			-0.697***
	(0.219)			(0.231)
J-test	15.33 [0.88]			
N	3260	1694	1059	507

Egypt: Marginal Effects with Endogenous Effects

	Structural Parameters	Marginal Effects			
Household Size		$m_g = 2$	$m_g = 3$	$m_g = 4$	$m_g = 5$
γ	-0.558**				
	(0.233)				
Second child	-0.272**	-0.395***	-0.31***	-0.294**	-0.288**
	(0.126)	(0.105)	(0.119)	(0.123)	(0.124)
Third child	-0.384**		-0.438**	-0.416**	-0.407**
	(0.177)		(0.177)	(0.177)	(0.177)
Fourth child	-0.526**			-0.569**	-0.556**
	(0.267)			(0.275)	(0.273)
Fifth child	-0.645				-0.683
	(0.427)				(0.441)
J-test	20.81 [0.11]				
N	3196	536	962	973	725

Germany: Marginal Effects with Endogenous & Contextual Effects

	Structural Parameters	Marginal Effects		
Household Size		$m_g = 2$	$m_g = 3$	$m_g = 4$
γ	-0.664***			
	(0.158)			
Second child	-0.183**	-0.327***	-0.219***	-0.204**
	(0.083)	(0.07)	(0.084)	(0.084)
Third child	-0.377***		-0.451***	-0.419***
	(0.129)		(0.131)	(0.131)
Fourth child	-0.59***			-0.657***
	(0.210)			(0.219)
Individual Effects				
Sex	0.248	0.198**	0.236*	0.241
	(0.161)	(0.101)	(0.142)	(0.15)
Contextual Effects				
Sex	0.207	0.075	0.019	0.011
	(0.169)	(0.134)	(0.036)	(0.021)
N	3260	1694	1059	507

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Conclusions

- We employ an econometric model that allows us to study birth order effects on educational attainment accounting for sibling interactions.
- Birth order effects are found to be negative in both Germany and Egypt.
- Failing to account for sibling interactions leads to an overstatement of the birth order effects.
- The parameter characterizing sibling interactions is found to be negative implying, among other things, more pronounced family size effects.