Online supplement for "Heterogeneous workplace peer effects in fathers' parental leave uptake in Finland"

1 Variables used in the analysis

1.1 Dependent variable

Took father's quota, a binary variable with a value of 1 if the father took at least 19 days of parental leave in total (i.e., beyond the 18 days fathers can take with the mother around birth) and 0 if not. These were obtained from the parental allowance registers of KELA. For multiple births (e.g. twins), leave was linked to only one child and was therefore not calculated differently to a single birth.

1.2 Father-specific independent variables

- *Reform* indicated father's eligibility for the 2013 reform.
- *Birth month* was the calendar month of birth of the child for whom father leave was assessed.
- *Experienced* indicated whether father had earlier children.
- *Earlier births and quota use* indicated whether the experienced father was eligible for the 2013 reform for the previous child, whether they used quota then, and whether they were eligible for the 2013 reform with the focal birth. Eight categories:

    1. Birth before 2009, not eligible (previous child), not eligible (focal child),
    2. Birth before 2009, not eligible, eligible,
    3. No quota use, not eligible, not eligible,
    4. No quota use, not eligible, eligible,
    5. No quota use, eligible, eligible
    6. Quota use, not eligible, not eligible,
    7. Quota use, not eligible, eligible,

8. Quota use, eligible, eligible

- *Region* was the region of Finland in which the father resided.
- *Occupation* was the broad classification of the father's occupation (10 levels).
- *Father age* and *partner age* were ages in years.
- *Father education* and *partner education* were categorical variables with the highest educational qualification of the father or father's partner. There were four categories: basic education (at most compulsory schooling only), upper secondary (including general and vocational), lower tertiary (bachelor's degree or equivalent), and upper tertiary (master's degree or equivalent, doctorate etc.).
- *Income decile* and *partner's income decile* were the yearly deciles in which the father's/partner's income fell. Partner deciles were defined based on partners with nonzero income (84% of partners) and partners with no income were included in the lowest decile.
- *Partner higher income* was an indicator of whether the partner had a higher income than the father or not.

1.3 Workplace- and peer-specific independent variables

- *Peer leave* indicated whether the peer took father's quota.
- *Time since the peer's child* was the time between the birth of the peer's child and the focal father's child, categorised into three-month intervals between 0 and 48 months, with an additional category of over 48 months.
- *Peer education difference* indicated whether the peer had the same, higher, or lower education.
- *Sex ratio* and *number of employees* were calculated as rolling three-year means (not including the current year) of the proportion of men in the workplace and number of employees in the workplace, respectively. Employees were considered as part of a specific workforce if their employment in that workplace was the main activity in a calendar year. When the 3-year rolling mean could not be calculated due to too few years, these variables were calculated off whichever years were available.
- *Industry* of the workplace was classified as a modification of the TOL 2008 scheme (see below).
- *Sector* of the workplace, either private or public.
- *Number of earlier quota users* indicated how many fathers had used quota since 2009 and before the peer, categorised as 0, 1, 2, 3, 4, 5 or more fathers.

1.4 Industry classification

Whilst the TOL 2008 classification scheme is useful for cross-country comparisons, some of the classifications are inappropriate groupings for our study question. As such, we used the following reclassification, where characters and numbers in square brackets correspond to the original TOL 2008 values:

1. Agriculture, forestry and fishing [A]
2. Mining and quarrying [B]
3. Manufacturing [C]
4. Electricity, gas, steam and air con supply [D]
5. Water supply; sewerage, waste management and remediation activities [E]
6. Construction [F; excluding 432, 433, 4391 (see 7 for details)]
7. "Home labourers", containing electrical, plumbing and other construction installation activities [432], building completion and finishing [433], and roofing activities [4391]. These were separated from construction as they are the fields that homeowners can make use of.
8. Wholesale and retail trade [G]
9. Transportation (freight) and storage [H, excluding 491, 493, 501, 503, and 511 (see 10)]
10. Transportation (passenger), containing train [491], other land [493], sea/coast [501], inland water [503], and air [511]. Freight and passenger transportation were separated as the nature of the work differs substantially. Whilst some occupations will be similar across the same type of transport (e.g., train), there are also occupations that are found in passenger but not freight and vice versa.
11. Accommodation [55]. Separated from I - Accommodation and food service activities.
12. Food service activities [56]. Separated from I - Accommodation and food service activities.
13. Information and publishing [J]
14. Financial and insurance activities [K]
15. Real estate activities [L]
16. Legal and accounting [69]. Separated from M - Professional, scientific and technical activities.
17. Activities of head offices; management consultancy [70]. Separated from M - Professional, scientific and technical activities.
18. Architecture and engineering [71]. Separated from M - Professional, scientific and technical activities.
19. Scientific research and development [72]. Separated from M - Professional, scientific and technical activities.
20. Advertising and market research [73]. Separated from M - Professional, scientific and technical activities.
21. Other professional activities [74]. Separated from M - Professional, scientific and technical activities. This category is still broad and encompasses professional activities that don't group together particularly well but also are too specific to be standalone industries, such as specialised design, photography (ranging from taking photographs to processing in a red room), translation and interpretation, and weather forecasting, among many others.
22. Veterinary activities [75]. Separated from M - Professional, scientific and technical activities.
23. Administrative and support service activities [N]
24. Administration of state, including administration of the State and the economic and social policy of the community [841], foreign affairs [8421], and compulsory social security activities [843]. Separated from O - Public administration and defence.

25. Provision of services to the community as a whole [842], excluding 8421 (see 24) and 8422 (see 26). Separated from O - Public administration and defence. This category includes frontline services such as police and border guard, fire services, and judicial services.
26. Defence activities [8422]. Separated from O - Public administration and defence.
27. Education [P]
28. Human health activities [86]. Separated from Q – Human health and social work activities.
29. Social work activities, including residential care activities [87] and social work activities without accommodation [88]. Separated from Q - Human health and social work activities.
30. Creative, arts and entertainment [90]. Separated from R – Arts, entertainment and recreation.
31. Libraries, archives, museums and other cultural attractions [91]. Separated from R – Arts, entertainment and recreation.
32. Sports activities [931]. Separated from R - Arts, entertainment and recreation.
33. Other, including other service activities [S], amusement and recreation [932, separated from R - Arts, entertainment and recreation], gambling and betting [92, separated from R - Arts, entertainment and recreation], activities of households as employers and undifferentiated goods and services providers [T], and activities of extraterritorial organisations [U]. This 'industry' is very broad, encompassing all subclassifications that are not large enough to be considered as separate industries for the purposes of this study, but are also not suited to being included within other industries.

2 Details on the causal inference

Our causal inference approach is based on structural causal models (SCM; (Pearl, 2009)). An intervention on an SCM is denoted by $\mathrm{do}(X = x)$, which changes the functional relationships of the model such that the variables in X always attain the values x irrespective of its causes in the SCM. The joint probability distribution of another set of variables Y under this intervention is denoted by $P(Y|\mathrm{do}(X = x))$ (or just $P(Y|\mathrm{do}(X))$ as a shorthand notation). This distribution is the causal effect of X on Y. For example, what is the probability of the next father using quota if we were to make their peer use their quota (as opposed to prohibiting them from using their quota)? Identifiability of the causal effect means that we can express this distribution using purely observational quantities, i.e., the joint distribution over the observed variables of the SCM. We call such expressions identifying functionals. If our causal effect of interest is identifiable, we can, based on the form of the identifying functional and the characteristics of our data, choose a suitable statistical model for the estimation of these causal effects from observed data.

SCMs can be represented visually by directed acyclic graphs (DAG) where vertices correspond to variables of interest and directed edges denote causal functional relationships, e.g. an edge from A to B denotes that A is a cause of B. We call such DAGs causal graphs. Figure S1 shows the assumed causal graph related to fathers' parental leave uptake from the perspective of the focal father L_i. The uptake is assumed to depend on the workplace characteristics W_i, the family characteristics F_i, leave-taking of the peer father L_{i-1}, as well as longer leave-taking history in the workplace Z_{i-1}, and the timing of the births T_i and T_{i-1} for focal and peer fathers respectively. Here W_i and F_i are actually a clustered set of variables, which simplifies the representation of the DAG and the causal effect identification without affecting the results (Tikka et al., 2023) More specifically,

- Node W_i contains workplace-specific variables: Industry classification, sex ratio and number of employees in the workplace.
- Node F_i represents father's individual and family-specific variables: Occupation, place of residence (region), education level, wage, and age, as well as the partner's education level, wage, and age. As occupation and wage naturally depend on the workplace, we have included a direct effect from W_i to F_i to the DAG.
- Node T_i represents the calendar time of birth of the child. Arrows from W_i and F_i to T_i indicate that both workplace and family characteristics can have an impact on the timing.
- Node L_i represents the father's leave uptake, more precisely it indicates whether the father took solo leave or not. We assume that this can depend on W_i, F_i, T_i, as well T_{i-1} and L_{i-1}, i.e., whether the previous peer took leave and the timing of the birth of the peer's child. In addition to the time gap, the timing of the births can affect leave due to changes in the family leave policies, changing norms in society, and seasonality (e.g., via availability of child care). We also take into account the longer history of leave-taking of the peers, by using variable Z_{i-1}, which is a conditionally deterministic variable containing the information about the number of fathers who took independent leave before father $i-1$ in the workplace.

In addition, while not drawn in the causal graph for simplicity, the probability of taking a leave depends on whether the father has earlier children, whether he took leave at that time, and the timing of this previous child. We have also omitted potential unobserved confounders from the figure; namely our results hold even if the graph contains unobserved confounders affecting all W, F, and T variables.

Our interest is in estimating the causal effect of L_{i-1} on L_i given education E_i (contained in F_i) and time of birth T_i. First, we must identify the effect, which can be accomplished using backdoor adjustment in this causal graph. We obtain the following identifying functional for the causal effect:

$$P(L_i|\mathrm{do}(L_{i-1}), E_i, T_i) = \int_{S_i} P(L_i|L_{i-1}, E_i, T_i, S_i)P(S_i|E_i, T_i)$$

where S_i is a shorthand notation for $\{W_i, F_i \setminus E_i, T_{i-1}, Z_{i-1}\}$. This formula can be understood such that we in order to estimate our causal effect of interest, we must model the leave uptake of the focal father given L_{i-1}, E_i, T_i, and S_i, adjusted by the distribution of S_i given E_i, T_i. Instead of modelling $P(S_i|E_i, T_i)$ as well, we can use its empirical distribution to form a Monte

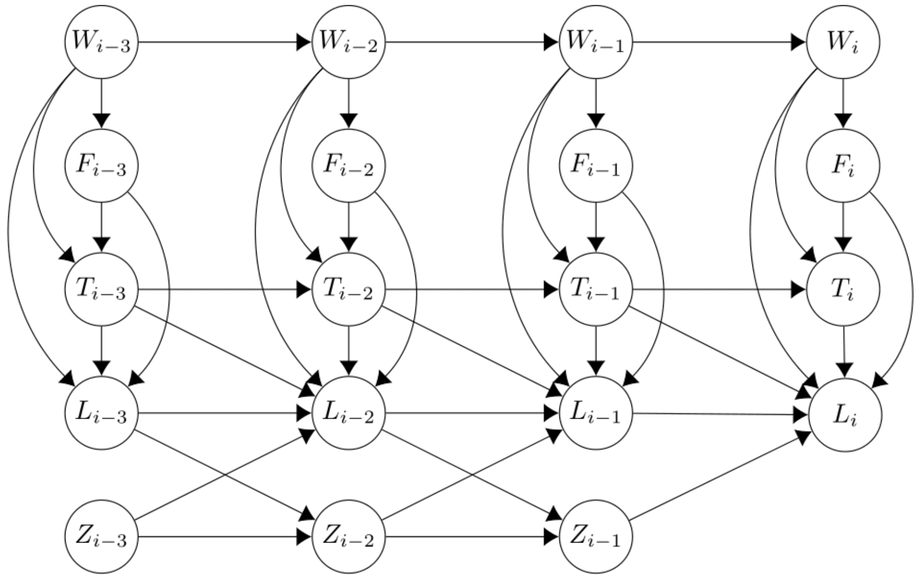

Figure S1. A causal graph depicting the assumed causal relationships between variables related to fathers' parental leave uptake, from the perspective of the focal father L_i.

Carlo approximation of $(L_i|\text{do}(L_{i-1}), E_i, T_i)$ by computing the average of $P(L_i|L_{i-1}, E_i, T_i, S_i)$, with fixed values of L_{i-1}, E_i, T_i, over our dataset (Hernán & Robins, 2020).

We model the $P(L_i|L_i - 1, E_i, T_i, S_i)$ as Bayesian multilevel logistic model, with the logit-link. In addition to covariates L_{i-1}, E_i, and S_i, as well as several interaction terms of these, we use time-invariant workplace-specific intercepts capturing the unobserved workplace characteristic, as well as time-varying intercept common to all workplaces and fathers, which we model as Bayesian P-spline. We also model the effect of time difference $\Delta_i = T_i - T_{i-1}$ as a monotonic (Bürkner & Charpentier, 2020). Therefore the linear predictor η_i of the log-odds of the probability of taking leave is

$$\eta_i = \mu_{t_i} + u_{g_i} + \phi^1_{\Delta_i} + \xi^1_{Z_{i-1}} + X^1_i\beta + (\phi^2_{\Delta_i} + \xi^2_{Z_{i-1}} + X^2_i\gamma)L_{i-1}.$$

The first term μ_{t_i} is the time-varying intercept at the birth date of the focal father's child, parameterized as a penalized B-spline (Eilers & Marx, 1996; Lang & Brezger, 2004)

$$\mu_{t_i} = \boldsymbol{b}_{t_i}^\top \boldsymbol{\omega},$$

where $\boldsymbol{b}_{t_i}$ is a vector of B-spline values at time t_i obtained from a cubic B-spline basis that we assume has been constructed with equally spaced knots on the time interval from 0 to $T = 2891$, the number of days since 1 February 2010, and $\boldsymbol{\omega}$ is a vector of corresponding spline coefficients. For constructing the spline basis, we used $D = 45$ degrees of freedom, translating to 41 inner knots approximately 69 days apart. We used random walk prior for the spline coefficients, i.e.,

$$\begin{aligned}
\omega_1 &\sim N(0, 2^2), \\
\omega_d &\sim \mathrm{N}(\omega_{d-1}, \tau^2), \quad d = 2, \dots, D \\
\tau &\sim N(0, 1).
\end{aligned}$$

The second term u_{g_i} is the zero-mean random intercept for the focal father's workplace g_i, modelled as $u_{g_i} \sim N(0, \sigma_u^2)$, $\sigma_u \sim N(0, 1)$, capturing unobserved time-invariant factors of workplace g_i affecting the quota use of its employees.

Terms $\xi^1_{Z_{i-1}}$, $\xi^2_{Z_{i-1}}$ are the monotonic effect of number of quota users before the peer and the corresponding monotonic interaction effect of peer's quota use, whereas $\phi^1_{\Delta_i}$ and $\phi^2_{\Delta_i}$ are monotonic main effect of age gap Δ_i and the interaction effect of time gap and peer's quota use. More specifically, we have for $i = 1, 2$ and categories $1 \leq K' \leq K$ and $1 \leq M' \leq M$

$$\begin{aligned}
\xi^i_{K'} &= \beta^i_\xi \sum_{k=1}^{K'} \delta^i_{\xi,k}, \quad \beta^i_\xi \sim N(0, 1), \quad \delta^i_{\xi,2}, \dots, \delta^i_{\xi,K} \sim \mathrm{Dirichlet}(1), \\
\phi^i_{M'} &= \beta^i_\phi \sum_{m=1}^{M'} \delta^i_{\phi,m}, \quad \beta^i_\phi \sim N(0, 1), \quad \delta^i_{\phi,2}, \dots, \delta^i_{\phi,M} \sim \mathrm{Dirichlet}(1),
\end{aligned}$$

with $\delta^i_{\xi,1} = \delta^i_{\phi,1} = 0$, $K = 6$ (categories $0, 1, 2, 3, 4, 5+$ for the past quota users), and $M = 17$ $(0 - 3, 3 - 6, \dots, 45 - 48, 48+$ months of age gap).

Finally, X^1_i is the design matrix related to W_i and F_i, and β corresponding coefficients, and similarly X^2_i and γ for the interaction terms with L_{i-1}. Using the Wilkinson-Rogers syntax (Wilkinson & Rogers, 1973), the X^1 is constructed as

$$\begin{aligned}
\sim\ &\mathrm{month} + \mathrm{sector} + \mathrm{region} + \mathrm{occupation} + \mathrm{employees} + \mathrm{sexratio} + \mathrm{age} + \mathrm{partnerAge} \\
&+ \mathrm{partnerIncome} + \mathrm{partnerHigherIncome} + \mathrm{educationDifferencePeer} \\
&+ \mathrm{peerBefore2010Reform} + \mathrm{peerBefore2013Reform} + \mathrm{previousBirth} \cdot \mathrm{education} \\
&+ \mathrm{reform2013} \cdot (\mathrm{education} \cdot \mathrm{partnerEducation} + \mathrm{income} + \mathrm{industry})
\end{aligned}$$

where the $\cdot$ corresponds to both the main and interaction terms and : only interaction term. The design matrix X^2 corresponding to the effect modifiers (interaction terms with the quota use of the peer) was constructed as

$$\begin{aligned}
\sim\ &\mathrm{reform} + \mathrm{educationPeer} + \mathrm{sector} + \mathrm{logEmployees} \\
&+ \mathrm{education} \cdot \mathrm{partnerEducation} + \mathrm{experienced} : \mathrm{education} \\
&+ \mathrm{incomeDecile} \cdot \mathrm{partnerHigherIncome} \\
&+ \mathrm{partnerIncomeDecile} + \mathrm{experienced} + \mathrm{experienced} : \mathrm{reform}
\end{aligned}$$

We used QR factorization of centered X^1 and X^2 for computational efficiency, with standard normal priors defined on the corresponding scaled regression coefficients.

3 Additional results

3.1 Descriptive statistics

In our final analytic sample, the majority of focal fathers did not have their immediate peer taking father's quota (60%, Table S5), and a lower percentage of these fathers took quota compared to those whose peer did take some or all of the quota (Table S1). Higher educated fathers were more likely to use quota, both before and after the 2013 reform.

Table S1. Proportions of focal fathers in the analytic sample from April 2008 to December 2017 taking quota and leave durations (in total) by peer leave status and focal father's education level. Leave durations are median number of leave days for all fathers, those taking any leave (minimum 1 day of leave), and those taking at least some of the quota (minimum 19 days of leave).

Focal father's quota use	Peer's quota use		Focal father's education			
	Quota	No quota	Basic	Upper secondary	Lower tertiary	Upper tertiary
Quota, all (%)						
Pre-2013	49	29	20	29	48	58
Post-2013	58	43	34	46	59	66
Duration, all (days)						
Pre-2013	18	18	18	18	18	40
Post-2013	36	18	18	18	36	45
Duration, leave users						
Pre-2013	36	18	18	18	35	44
Post-2013	42	19	18	24	41	49
Duration, quota users						
Pre-2013	54	54	54	54	54	54
Post-2013	54	53	53	53	53	54

Slightly under half of births to focal fathers were first births 46%, see Table S5, with a median leave of 18 days ineligible and 37 days for births eligible for the 2013 reform for those using at least some leave (Table S2). In comparison, experienced fathers' median leave was 28 after the reform (and 18 before).

Table S2 also shows how our analytic sample differs from all fathers and all employed fathers. The lower uptake in the pre-2010 reform group is due to the fact that leave information is available only fathers taking leave in 2009 or later, so those fathers taking leave only in 2008 are counted as not using any leave. As expected, the proportions of fathers taking any parental leave (including paternity leave) and the father's quota are both higher in the analytical sample than in the full population, because non-employed fathers generally take less leave. In terms of quota use, focal fathers had about 2 percentage points higher uptake in comparison to all employed fathers. The most probably reason for this is due to missing all workplaces with only one eligible father (predominately relatively small workplaces). Average leave durations are comparable across the three groups.

Table S2. Descriptive information about parental leave uptake for children born in Finland from April 2008 to December 2017 for all fathers, employed fathers, and focal fathers in the analytic sample (distinguishing between all, first-time, and experienced focal fathers). Durations are median number of days for all leave users and quota users. Note that before 2010 reform, the maximum quota length was 42 days.

	All fathers	Employed fathers	All focal fathers	First-time focal fathers	Experienced focal fathers
Any leave uptake (%)					
Pre-2010	63	69	-	-	-
Pre-2013	77	85	87	87	86
Post-2013	78	86	88	89	87
Quota uptake (%)					
Pre-2010	22	25	-	-	-
Pre-2013	32	36	36	39	33
Post-2013	44	49	50	54	46
Duration, leave users					
Pre-2010	18	18	-	-	-
Pre-2013	18	18	18	18	18
Post-2013	34	35	33	37	28
Duration, quota users					
Pre-2010	42	42	-	-	-
Pre-2013	54	54	54	54	54
Post-2013	54	54	53	53	53

Table S3 shows the distribution of workplaces by the number of employees, based on the number of workplaces or the number of (all) employed fathers, and Table S4 shows further descriptive statistics about workplaces. About a quarter of fathers work in large workplaces that were excluded from the analyses, and the rest have 20–30 percent in each category (most typically

10–49 employees). All in all, workplace characteristics remained relatively stable across the years, apart from male employees' leave use.

Table S3. Proportions of workplaces and employed fathers by the total number of employees in the workplace in the full data.

	1–9	10–49	50–249	250+
Workplaces (%)				
2008-2009	43	40	13	3
2010-2012	50	38	10	2
2013-2017	52	37	9	2
Fathers (%)				
2008-2009	20	29	24	28
2010-2012	21	29	23	27
2013-2017	21	31	24	24

Table S4. Descriptive statistics about workplaces for all fathers and focal fathers of the analytical sample: Average proportion of eligible fathers taking any parental leave or father's quota, mean and median number of employees, and average share of male employees.

	Any leave (%)	Quota (%)	Mean N	Median N	Male (%)
Full data					
2008-2009	64	19	51	12	75
2010-2012	79	28	39	9	76
2013-2017	80	41	35	9	76
Analytical sample					
2010-2012	84	32	36	21	78
2013-2017	85	46	31	18	78

Table S5 shows descriptive statistics of the relevant explanatory variables used in the model, based on the analytical sample.

Table S5. Descriptive statistics of some of the variables used in the model: For categorical variables, number of observations and proportions; median and standard deviation for the others.

Variable	n (%) or median (SD)
2013 reform	
Not eligible	43,581 (37%)
Eligible	74,256 (63%)

Variable	n (%) or median (SD)
Occupation	
Unknown	5,483 (4.7%)
Managers	2,371 (2.0%)
Professionals	22,440 (19%)
Technicians and associate professionals	16,834 (14%)
Clerical support workers	2,217 (1.9%)
Service and sales workers	10,665 (9.1%)
Skilled agricultural, forestry and fishery workers	448 (0.4%)
Craft and related trades workers	32,261 (27%)
Plant and machine operators, and assemblers	20,137 (17%)
Elementary occupations	4,981 (4.2%)
Age (years)	32 (5.8)
Partner's age (years)	30 (5.1)
Education	
Basic	15,178 (13%)
Upper Secondary	64,723 (55%)
Lower tertiary	23,624 (20%)
Higher tertiary	14,312 (12%)
Partner's education	
Basic	12,557 (11%)
Upper Secondary	52,129 (44%)
Lower tertiary	33,992 (29%)
Higher tertiary	19,159 (16%)
Peer's education compared to focal father	
Lower	24,143 (20%)
Same	70,716 (60%)
Higher	22,978 (19%)
Partner's income compared to focal father	
Lower	96,005 (81%)
Higher	21,832 (19%)
Peer used quota	47,094 (40%)
Experience	
First birth	54,636 (46%)
Experienced	63,201 (54%)
Experienced extra (for experienced)	
Birth before 2009, not eligible, not eligible	11,531 (18%)
Birth before 2009, not eligible, eligible	11,067 (18%)
No quota use, not eligible, not eligible	8,757 (14%)
No quota use, not eligible, eligible	11,587 (18%)
Quota use, not eligible, not eligible	3,484 (6%)
Quota use, not eligible, eligible	5,895 (9%)

Variable	n (%) or median (SD)
Quota use, eligible, eligible	5,776 (9%)
Age gap (months) of the peer's and focal's child	
0-3	29,584 (25%)
3-6	18,967 (16%)
6-9	13,762 (12%)
9-12	10,446 (9%)
12-15	8,374 (7%)
15-18	6,727 (6%)
18-21	5,288 (5%)
21-24	4,302 (4%)
24-27	3,258 (3%)
27-30	2,268 (2%)
30-33	2,212 (2%)
33-36	1,839 (2%)
36-39	1,475 (1%)
39-42	1,247 (1%)
42-45	1,080 (1%)
45-48	950 (1%)
48+	5,716 (5%)
Peer not eligible to 2010 reform	17,683 (14%)
Peer eligible to 2010 reform	52,154 (42%)
Peer eligible to 2013 reform	55,116 (44%)
Past leave takers before the peer	
0	65,679 (56%)
1	20,966 (18%)
2	10,311 (9%)
3	6,117 (5%)
4	3,887 (3%)
5+	10,877 (9%)
Share of male employees in the workplace	0.87 (0.2)
Sector	
Private	109,959 (93%)
Public	74,256 (7%)
Number of employees in the workplace	34 (51.4)
Logarithm of the number of employees	3.53 (1.1)

3.2 Posterior densities of the peer effect

Figure S2 shows the posterior densities of the average peer effect

$$\mathbb{P}(L_i = 1 \mid \mathrm{do}(L_{i-1} = 1), E_i) - \mathbb{P}(L_i = 1 \mid \mathrm{do}(L_{i-1} = 0), E_i)$$

for first-time and experienced fathers by education level. The peer effects are somewhat smaller for the experienced fathers, especially in the lower educational groups.

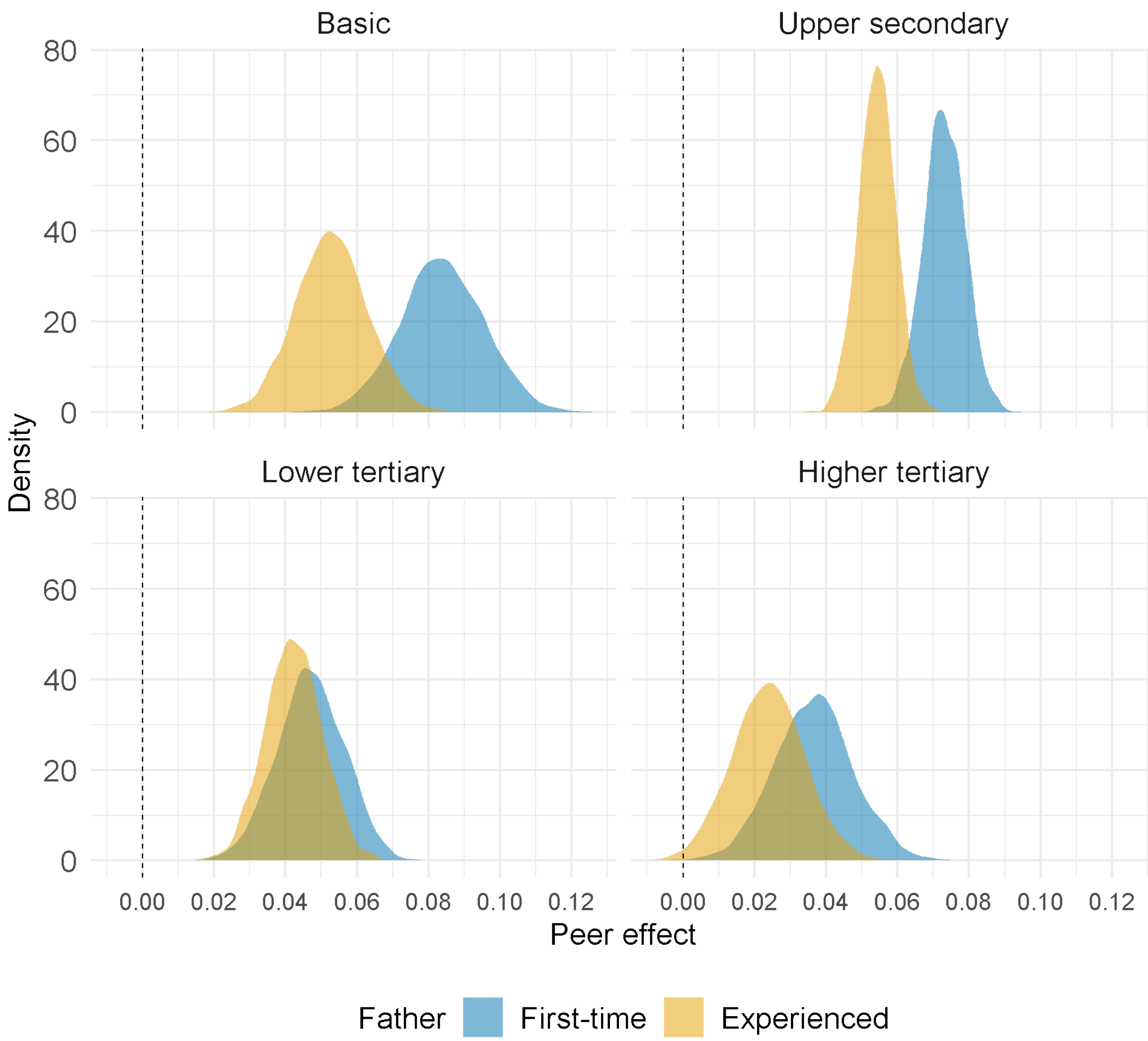

Figure S2. The posterior density of the peer effect $\mathbb{P}(L_i = 1 \mid \mathrm{do}(L_{i-1} = 1), E_i) - \mathbb{P}(L_i = 1 \mid \mathrm{do}(L_{i-1} = 0), E_i)$, by by education E_i and father's experience.

Figure S3 shows the posterior densities of causal effects $\mathbb{P}(L_i = 1 \mid \mathrm{do}(L_{i-1} = 1), E_i, S_i) - \mathbb{P}(L_i = 1 \mid \mathrm{do}(L_{i-1} = 0), E_i, S_i)$ over empirical distribution $P(S_i|E_i)$. While these covariate specific effects are highly variable, the effects are predominantly positive especially in lower education groups.

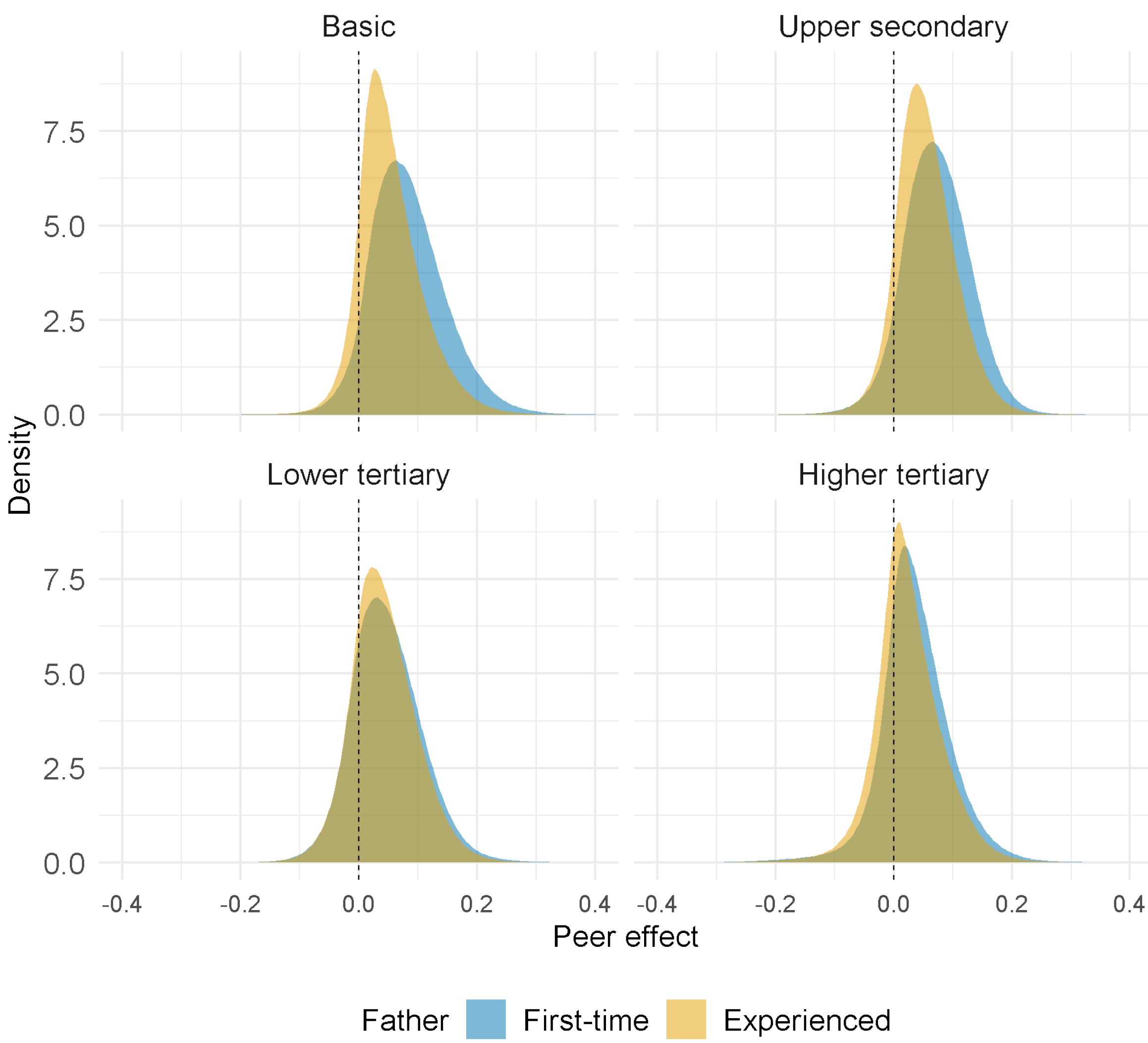

Figure S3. The posterior density of covariate-specific causal effects $\mathbb{P}(L_i = 1 \mid \mathrm{do}(L_{i-1} = 1), E_i, S_i) - \mathbb{P}(L_i = 1 \mid \mathrm{do}(L_{i-1} = 0), E_i, S_i)$ by education and father's experience.

3.3 Peer effects by sector and mother's education

We also considered whether mother's education or the sector of the workplace modified the peer effect (Tables S6 and S7). Given the somewhat large uncertainty intervals of these estimates, there is no clear effect of these factors on the peer effect. However, in relative terms, the low-education families are more affected by the father's peer (Table S8).

Table S6. Posterior mean and 95% posterior interval of the peer effect conditional on timing with respect to the 2013 reform and the education levels of the father and the mother.

2013 Reform	Father's education	Mother's education	Mean (ppts)	2.5%	97.5%
Before	Basic	Basic	5.1	3.4	7.0
Before	Basic	Upper secondary	5.6	3.8	7.5
Before	Basic	Lower tertiary	11.1	7.4	14.4
Before	Basic	Higher tertiary	7.5	1.2	13.8
Before	Upper secondary	Basic	4.6	2.9	6.3
Before	Upper secondary	Upper secondary	7.2	6.1	8.4
Before	Upper secondary	Lower tertiary	8.1	6.4	9.7
Before	Upper secondary	Higher tertiary	3.9	1.2	6.7
Before	Lower tertiary	Basic	7.2	2.0	12.3
Before	Lower tertiary	Upper secondary	5.0	2.7	7.3
Before	Lower tertiary	Lower tertiary	6.4	4.4	8.3
Before	Lower tertiary	Higher tertiary	4.9	2.4	7.4
Before	Higher tertiary	Basic	-3.1	-11.6	5.4
Before	Higher tertiary	Upper secondary	6.3	2.1	10.5
Before	Higher tertiary	Lower tertiary	5.1	2.2	8.0
Before	Higher tertiary	Higher tertiary	4.1	2.0	6.3
After	Basic	Basic	7.1	4.0	10.1
After	Basic	Upper secondary	5.6	3.2	8.0
After	Basic	Lower tertiary	10.0	6.0	13.9
After	Basic	Higher tertiary	5.4	-1.0	11.9
After	Upper secondary	Basic	4.9	2.6	7.2
After	Upper secondary	Upper secondary	6.7	5.6	7.9
After	Upper secondary	Lower tertiary	6.0	4.5	7.5
After	Upper secondary	Higher tertiary	1.6	-0.9	4.2
After	Lower tertiary	Basic	5.9	-0.3	12.3
After	Lower tertiary	Upper secondary	3.2	0.6	5.6
After	Lower tertiary	Lower tertiary	4.0	2.2	5.8
After	Lower tertiary	Higher tertiary	2.4	0.2	4.7
After	Higher tertiary	Basic	-6.3	-15.6	3.2
After	Higher tertiary	Upper secondary	4.2	-0.1	8.7
After	Higher tertiary	Lower tertiary	2.8	0.0	5.5

2013 Reform	Father's education	Mother's education	Mean (ppts)	2.5%	97.5%
After	Higher tertiary	Higher tertiary	1.7	-0.2	3.5

Table S7. Posterior mean and 95% posterior interval of the peer effect conditional on timing with respect to the 2013 reform, father's education level, and workplace sector.

2013 Reform	Father's education	Sector	Mean (ppts)	2.5%
Before	Basic	Private	6.6	5.1
Before	Basic	Public	7.5	5.1
Before	Upper secondary	Private	6.9	5.9
Before	Upper secondary	Public	7.2	4.9
Before	Lower tertiary	Private	5.7	4.3
Before	Lower tertiary	Public	5.6	3.2
Before	Higher tertiary	Private	4.5	2.8
Before	Higher tertiary	Public	4.6	2.2
After	Basic	Private	6.8	5.1
After	Basic	Public	6.5	3.7
After	Upper secondary	Private	5.1	5.1
After	Upper secondary	Public	3.4	3.4
After	Lower tertiary	Private	3.4	2.1
After	Lower tertiary	Public	3.8	1.6
After	Higher tertiary	Private	2.0	0.5
After	Higher tertiary	Public	2.3	0.0

Table S8. Posterior mean and 95% posterior interval of percentage increase of quota use when peer used quota vs. not, conditional on timing with respect to the 2013 reform and the education levels of the father and the mother.

2013 Reform	Father's education	Mother's education	Mean (%)	2.5%	97.5%
Before	Basic	Basic	47.9	28.1	68.7
Before	Basic	Upper secondary	33.1	21.5	45.5
Before	Basic	Lower tertiary	37.4	24.1	51.5
Before	Basic	Higher tertiary	18.9	2.7	37.0
Before	Upper secondary	Basic	35.8	22.0	50.3
Before	Upper secondary	Upper secondary	31.9	26.4	37.6
Before	Upper secondary	Lower tertiary	20.4	15.9	24.8
Before	Upper secondary	Higher tertiary	7.7	2.3	13.5
Before	Lower tertiary	Basic	35.4	8.7	66.5
Before	Lower tertiary	Upper secondary	14.5	7.4	21.6

2013 Reform	Father's education	Mother's education	Mean (%)	2.5%	97.5%
Before	Lower tertiary	Lower tertiary	13.2	9.0	17.4
Before	Lower tertiary	Higher tertiary	8.1	3.9	12.6
Before	Higher tertiary	Basic	-7.5	-27.1	15.6
Before	Higher tertiary	Upper secondary	16.9	5.2	29.6
Before	Higher tertiary	Lower tertiary	9.9	4.1	15.9
Before	Higher tertiary	Higher tertiary	6.6	3.1	10.2
After	Basic	Basic	30.7	16.5	45.5
After	Basic	Upper secondary	17.9	9.9	26.2
After	Basic	Lower tertiary	22.5	13.0	32.3
After	Basic	Higher tertiary	10.0	-1.7	22.7
After	Upper secondary	Basic	19.5	10.0	29.6
After	Upper secondary	Upper secondary	17.1	14.0	20.2
After	Upper secondary	Lower tertiary	10.8	7.9	13.7
After	Upper secondary	Higher tertiary	2.5	-1.3	6.6
After	Lower tertiary	Basic	19.8	-0.9	44.0
After	Lower tertiary	Upper secondary	6.7	1.2	12.1
After	Lower tertiary	Lower tertiary	6.8	3.7	10.0
After	Lower tertiary	Higher tertiary	3.5	0.2	6.8
After	Higher tertiary	Basic	-11.7	-27.4	6.7
After	Higher tertiary	Upper secondary	8.6	-0.2	18.5
After	Higher tertiary	Lower tertiary	4.7	0.0	9.4
After	Higher tertiary	Higher tertiary	2.3	-0.2	5.0

3.4 Restriction on 2013 reform

In order to check whether the 2013 reform affected the peer effects in ways not accounted by our model, we also estimated the peer effects based on only those focal fathers who were eligible to 2013 reform. We used the same model as in our main analysis, except the variable indicating the eligibility of the focal father to 2013 reform and related interactions were omitted from the model. Figure S4 shows some differences within the uncertainty intervals. The estimates from the post-reform model differ most for the highest educated experienced fathers, where the estimated peer effect is in line with pre-reform estimates of the main model, while the main model suggests a drop in the peer effect after the reform. Nevertheless, even these differences are within the 95% posterior intervals.

3.5 Restriction on children's age gap

To assess the potential issues due to reciprocal influences between peers that had a child close to each other, we also estimated our main model using only focal fathers whose child was born

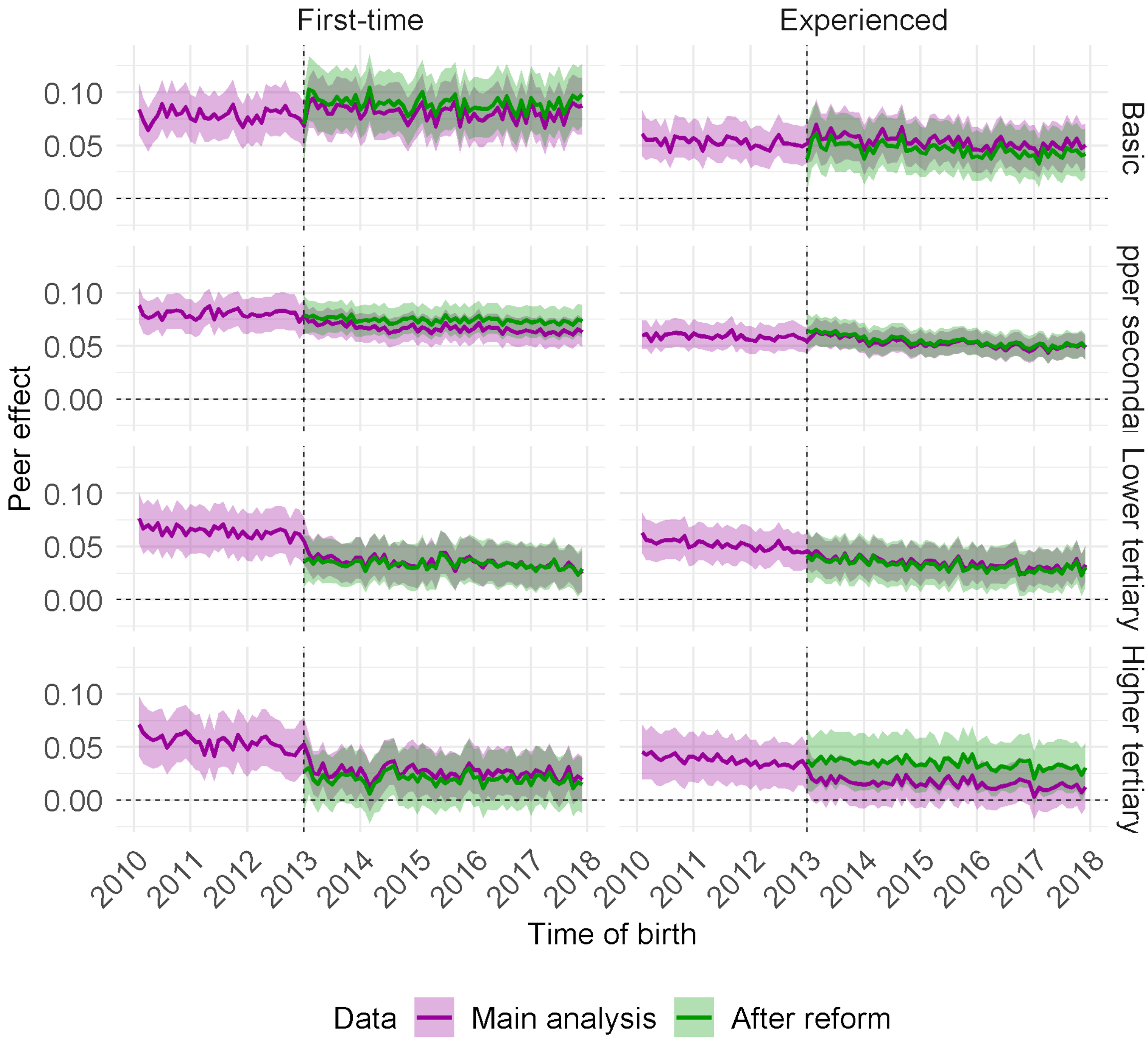

Figure S4. Peer effects of using father's quota of parental leave by focal father's education level, experience, and time of birth of the focal father's child. Showing posterior means and 95 percent posterior intervals from the main analysis and using only fathers eligible for the 2013 reform as responses.

at least 12 months after their peer's child. Figure S5 show the peer effects from this model and the main model. While there is some discrepancy for the first-time fathers in lowest education group, the uncertainty intervals from the two analysis clearly overlap in all groups.

3.6 Relaxing workplace size restriction

We also estimated the main model without restricting the analysis to only workplaces with less than 250 employees. Instead, we restricted the number of employees with same occupation category to be less than 250. Here we also considered only private sector workplaces, as the separation of large public enterprises to separate establishments was not possible based on our data. Figure S6 s shows the results from this analysis, which are comparable to the main analysis, with slightly smaller estimates especially before the reform.

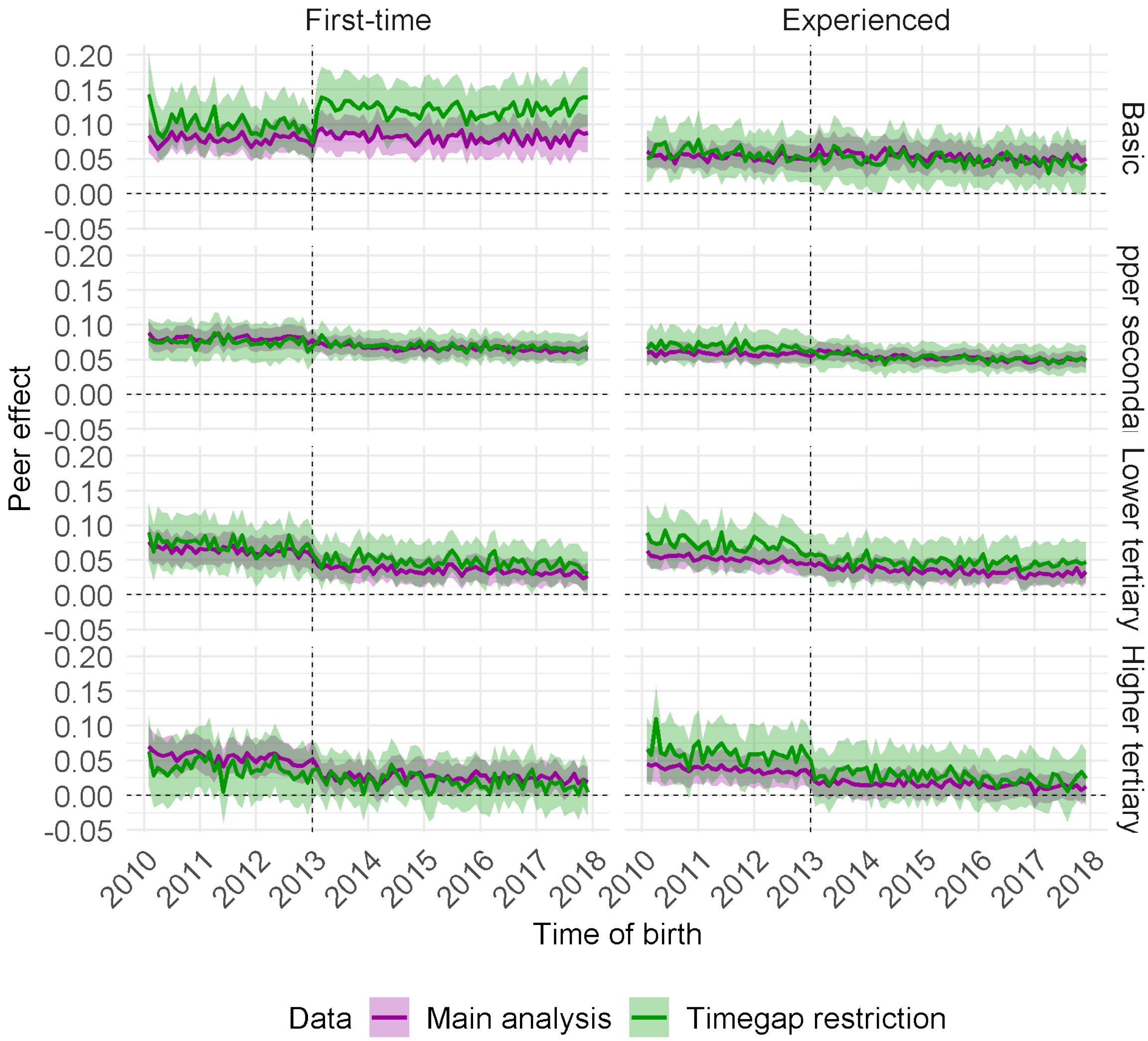

Figure S5. Peer effects of using father's quota of parental leave by focal father's education level, experience, and time of birth of the focal father's child. Showing posterior means and 95 percent posterior intervals from the main analysis and using only fathers with time gap over 12 months as responses.

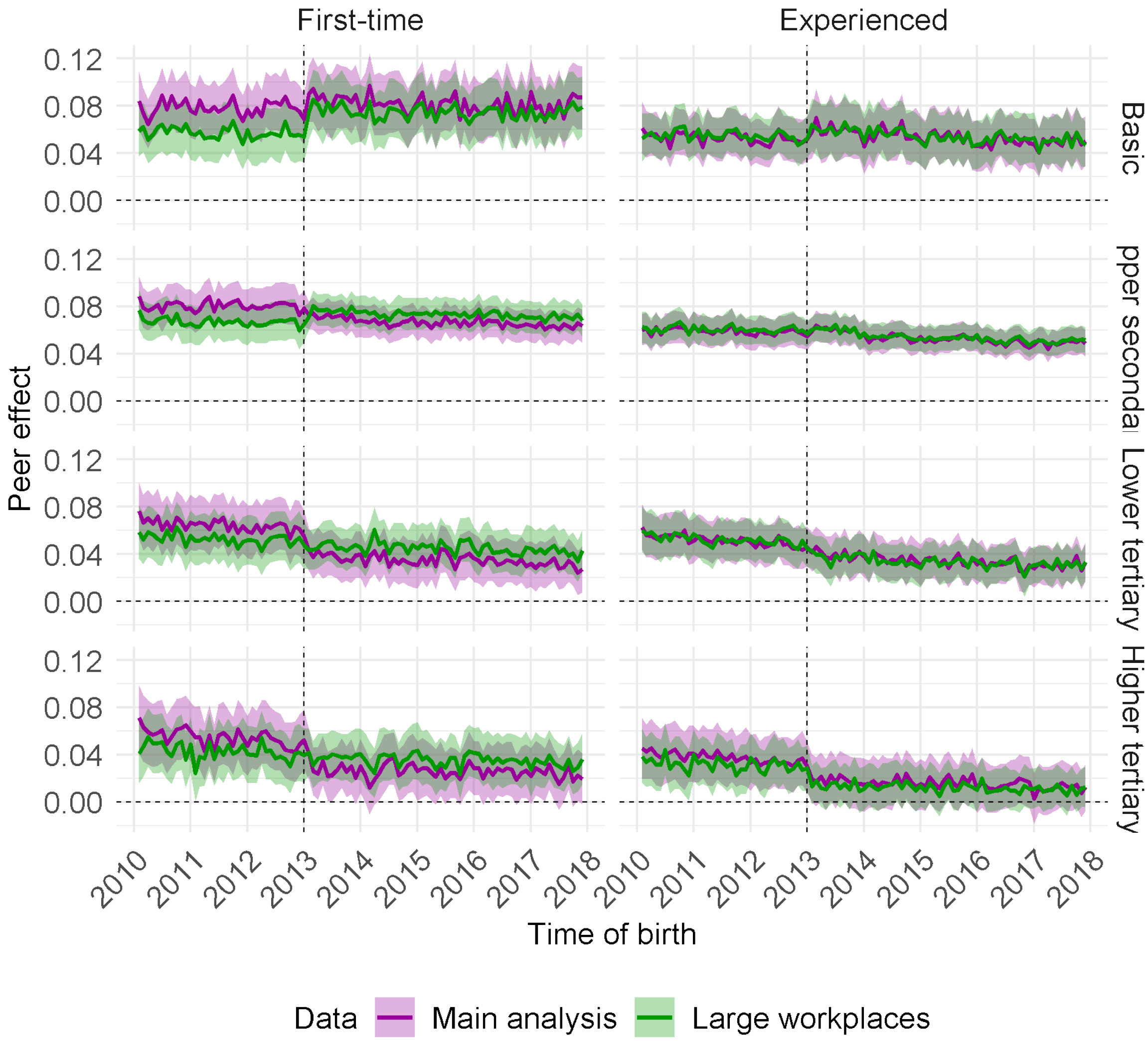

Figure S6. Peer effects of using father's quota of parental leave by focal father's education level, experience, and time of birth of the focal father's child. Showing posterior means and 95 percent posterior intervals from the main analysis and data without workplace size restriction but using only workplaces in private sector.

References

Bürkner, P.-C., & Charpentier, E. (2020). Modelling monotonic effects of ordinal predictors in Bayesian regression models. *British Journal of Mathematical and Statistical Psychology*, *73*(3), 420–451. https://doi.org/https://doi.org/10.1111/bmsp.12195

Eilers, P. H. C., & Marx, B. D. (1996). Flexible smoothing with *B*-splines and penalties. *Statistical Science*, *11*(2), 89–102. https://doi.org/10.1214/ss/1038425655

Hernán, M. A., & Robins, J. M. (2020). *Causal inference: What if*. Boca Raton: Chapman & Hall/CRC.

Lang, S., & Brezger, A. (2004). Bayesian P-splines. *Journal of Computational and Graphical Statistics*, *13*(1), 183–212. https://doi.org/10.1198/1061860043010

Pearl, J. (2009). *Causality: Models, reasoning, and inference* (2nd ed.). Cambridge University Press.

Tikka, S., Helske, J., & Karvanen, J. (2023). Clustering and structural robustness in causal diagrams. *Journal of Machine Learning Research*, *24*(195), 1–32. http://jmlr.org/papers/v24/21-1322.html

Wilkinson, G. N., & Rogers, C. E. (1973). Symbolic description of factorial models for analysis of variance. *Journal of the Royal Statistical Society. Series C*, *22*(3), 392–399. http://www.jstor.org/stable/2346786