Intergenerational Effects of Sick Leave on Child Human Capital

Julie Riise (UiB), Barton Willage (Uni Colorado, Denver), Alexander Willén (NHH)
Research question(s)

• Is the human capital development of children affected by parental take-up of employment protection and income replacement programs?

• More concretely: How does certified, paid sick leave affect school outcomes of children, at the extensive and intensive margins?

• Which mechanisms are at play?
Paper in short:

• We create a sick leave leniency measure using conditional exogenous GP swaps
  – and find large variation especially related to hard-to-verify conditions with unclear benefit from sick leave

• We estimate the effect of a parental swap to a more lenient GP on the child’s human capital development

• We investigate whether the timing of the parental swap (age of the child) matters

• We examine an arguably important channel: the effect on the parent’s attachment to the labour market and take-up of welfare services

• We conclude that the total effect on children’s human capital is negative – both on quality and quantity
Literature

• No(?) literature on possible intergenerational impact of certified sick leave

• Some literature on direct effect of sick leave on workers
  – e.g. Markussen et al. (2012), Fevang et al. (2014), Markussen and Røed (2017), Pichler and Ziebarth (2020), Godøy and Dale-Olsen (2018)

• A number of observational studies of the effect of parental welfare utilization on children

• Small but interesting literature on intergenerational transmission of dependence of welfare programs
  – e.g. Dahl et al. (2014), Dahl and Gielen (2021), Hartley et al. (2017)
The GP system and Norwegian sick leave - essentials

• GPs are the first point of contact with the health care system
  – Initial examinations, diagnoses, treatments, prescription of medications, referral to specialists, and sick leave certification

• You will need to get your sick leave certified by a GP if you are away from work more than 3 (8) days

• Sick leaves are 100% compensated from day one
  – Up to 1 year, cap of around 60000 £ per year

• Every GP has a list of patients, every Norwegian has the right to be assigned to a GP’s list
GP assignments

• When a GP quits, retires, moves or reduces his/her patient list
  – Often, the entire list is transferred (we don’t use these swaps), but when not:
  – Patients are randomly assigned to a new GP in the municipality, conditional on availability

• There are two important aspects of this process:
  – In the event of list reductions, patients to be removed are randomly drawn
  – When reassigning patients, which patient goes to which new GPs are randomly drawn

• We use this randomization as our source of exogenous variation
  – Also, we provide extensive balance tests to show that this happens in practice

• Patients are allowed to endogenously change GP twice a year.
  – We don’t use these swaps.
Empirical approach

1. Estimate coefficients of new GP dummy variables - #sickdays 1 year after swap
   — Controlling for previous GP, age at swap, time of swap, gender and sick leave in previous year

2. Construct a continuous standardized measure of leniency (mean:0, SD 1)

3. Regress child/parental outcomes of interest on the standardised leniency measure
   — Controlling for previous GP, age at swap, time of swap, gender and sick leave in previous year

• Leave-one-out design to avoid mechanical effects

• Based on linked administrative register data
Leniency measure

- Raw variation in sick leave and \textit{pre-standardized} leniency

\begin{itemize}
  \item \textbf{A: Sick Leave} \quad \textbf{B: Leniency}

  \textbf{Median:} 90 days  \quad \textbf{Mean:} 0.5  \\
  \textbf{SD:} 10.8 days
\end{itemize}

- More heterogeneity related to hard to verify causes
Identification

- Identifying assumption: GP leniency is not correlated with patient characteristics that can affect outcomes of interest

- We regress the GP leniency measure on 20+ different pre-characteristics
  - Health, labour market, education, family situation, partner outcomes
  - Small and non-significant

- We regress the GP leniency measure on all simultaneously
  - Non-significant

- Child outcomes are measured only once, but for parental outcomes we have multiple observations over time

- => apply a diff-in-diff model using within individual variation
  - Gives both qualitatively and quantitatively similar results

- => use this variation in an event study set-up to look at trends in parental outcomes
  - No differences in pre-trends

- Placebo on those 21-25 when shock hits
  - No effects (small and insign.)
Could we be picking up something else about the GPs?

- We correlate the GP leniency measure with:
  - Short- and long-term mortality at the patient level
  - Other GP practice characteristics at the doctor level
  - GP value added
  - Likelihood that the GP conducts check-ups with the patient
  - Inpatient visits and ER visits of the patient

- No correlation => confident that we measure effect of getting assigned a GP that is more lenient in certifying sick leave
## Child outcomes

### Table 4: Effect on Childhood Educational Outcomes

<table>
<thead>
<tr>
<th>(1) GPA, Gr 8-10</th>
<th>(2) GPA, Gr 11-13</th>
<th>(3) Academic Track</th>
<th>(4) HS Grad</th>
<th>(5) Start College</th>
<th>(6) Years of Ed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leniency SD</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.013** (0.004)</td>
<td>-0.014*** (0.003)</td>
<td>0.000 (0.002)</td>
<td>-0.008*** (0.002)</td>
<td>-0.008*** (0.002)</td>
</tr>
<tr>
<td>Dep Mean</td>
<td>4.139</td>
<td>3.988</td>
<td>0.743</td>
<td>0.653</td>
<td>0.614</td>
</tr>
<tr>
<td>N</td>
<td>312,357</td>
<td>459,004</td>
<td>256,157</td>
<td>322,395</td>
<td>451,122</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: * p<0.05, ** p<0.01, *** p<0.001.

The table presents the OLS estimates of the effect of GP sick note leniency. Estimating equation: $w_{ijkt} = \beta L_{eniencySD_j} + \pi_k + \theta_{it} + \epsilon_{ijkt}$, where $w_{ijkt}$ is the outcome at the top of the column, $L_{eniencySD_j}$ is a standardized continuous measure of GP sick note leniency, $\pi_k$ are previous GP FE, and $\theta_{it}$ is a vector of controls (sick leave days the year before swap, patient age, and patient sex). Displayed estimates are the coefficient $\beta$, the effect of a 1 SD increase in GP sick note leniency. Standard errors in parentheses clustered at GP level.
### Child outcomes, variation by age of exposure (swap)

Table 5: Effect Variation by Age of Exposure, Lower Secondary GPA and Start College

#### Panel A: Lower Secondary GPA

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age 3-8</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Leniency SD</td>
<td>-0.011</td>
<td>-0.016*</td>
<td>-0.012</td>
<td>-0.020**</td>
</tr>
<tr>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Dep Mean</td>
<td>4.225</td>
<td>4.159</td>
<td>4.125</td>
<td>4.094</td>
</tr>
<tr>
<td>N</td>
<td>52,297</td>
<td>72,823</td>
<td>101,885</td>
<td>83,452</td>
</tr>
</tbody>
</table>

#### Panel B: Start College

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
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<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age 3-8</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Leniency SD</td>
<td>-0.010</td>
<td>-0.011*</td>
<td>-0.012**</td>
<td>-0.013**</td>
</tr>
<tr>
<td>(0.007)</td>
<td>(0.005)</td>
<td>(0.004)</td>
<td>(0.005)</td>
<td></td>
</tr>
<tr>
<td>Dep Mean</td>
<td>0.504</td>
<td>0.529</td>
<td>0.558</td>
<td>0.571</td>
</tr>
<tr>
<td>N</td>
<td>13,759</td>
<td>47,065</td>
<td>78,829</td>
<td>69,166</td>
</tr>
</tbody>
</table>

Note: * p<0.05, ** p<0.01, *** p<0.001.

The table presents the OLS estimates of the effect of GP sick note leniency. Estimating equation:

$$ w_{ijkt} = \beta \text{Leniency}_{SD} + \pi_k + \theta_{it} + \epsilon_{ijkt}, $$

where $w_{ijkt}$ is the outcome at the top of the column, \text{Leniency}_{SD} is a standardized continuous measure of GP sick note leniency, $\pi_k$ are previous GP FE, and $\theta_{it}$ is a vector of controls (sick leave days the year before swap, patient age, and patient sex). Displayed estimates are the coefficient $\beta$, the effect of a 1 SD increase in GP sick note leniency. Standard errors in parentheses clustered at GP level.
### Parental outcomes 2 years after swap

Table 8: Effect on Own Labor Market and Safety Net Outcomes, 2 Year Post Exposure

#### Panel A: Labor Market

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employed Leniency SD</td>
<td>-0.000</td>
<td>-5052.7***</td>
</tr>
<tr>
<td>(0.001)</td>
<td>(1499.6)</td>
<td></td>
</tr>
<tr>
<td>Dep Mean</td>
<td>0.970</td>
<td>537203.7</td>
</tr>
<tr>
<td>N</td>
<td>205,991</td>
<td>205,991</td>
</tr>
</tbody>
</table>

Note: * p<0.05, ** p<0.01, *** p<0.001.

The table presents the OLS estimates of the effect of GP sick note leniency. Estimating equation: $w_{ijkt} = \beta\text{Leniency}_{SD} + \pi_k + \theta_t + \epsilon_{ijkt}$, where $w_{ijkt}$ is the outcome at the top of the column, $\text{Leniency}_{SD}$ is a standardized continuous measure of GP sick note leniency, $\pi_k$ are previous GP FE, and $\theta_t$ is a vector of controls (sick leave days the year before swap, patient age, and patient sex). Displayed estimates are the coefficient $\beta$, the effect of a 1 SD increase in GP sick note leniency. Standard errors in parentheses clustered at GP level.

#### Panel B: Safety Net

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Any UI</td>
<td>0.003*</td>
<td>284.364</td>
<td>0.001</td>
<td>235.056</td>
<td>0.006**</td>
<td>2270.762***</td>
</tr>
<tr>
<td>(0.001)</td>
<td>(145.127)</td>
<td>(0.001)</td>
<td>(138.278)</td>
<td>(0.002)</td>
<td>(487.125)</td>
<td></td>
</tr>
<tr>
<td>Any DI Level</td>
<td>0.046</td>
<td>3375.965</td>
<td>0.021</td>
<td>3722.960</td>
<td>0.675</td>
<td>54832.837</td>
</tr>
<tr>
<td>N</td>
<td>205,991</td>
<td>205,991</td>
<td>205,991</td>
<td>205,991</td>
<td>205,991</td>
<td>205,991</td>
</tr>
</tbody>
</table>
Parental outcomes 5 years after swap

Table 9: Long-Run Earnings and Welfare, 5 Year Post Exposure

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Earnings</td>
<td>Total Benefits</td>
</tr>
<tr>
<td>Leniency SD</td>
<td>-4893.167*</td>
<td>983.469*</td>
</tr>
<tr>
<td></td>
<td>(1925.122)</td>
<td>(490.540)</td>
</tr>
<tr>
<td>Dep Mean</td>
<td>551023.858</td>
<td>51786.526</td>
</tr>
<tr>
<td>N</td>
<td>175,967</td>
<td>175,967</td>
</tr>
</tbody>
</table>

Note: * p<0.05, ** p<0.01, *** p<0.001.
The table presents the OLS estimates of the effect of GP sick note leniency. 
Estimating equation: $w_{ijkt} = \beta \text{LeniencySD}_j + \pi_k + \theta_{it} + \epsilon_{ijkt}$, where $w_{ijkt}$ is the outcome at the top of the column, $\text{LeniencySD}_j$ is a standardized continuous measure of GP sick note leniency, $\pi_k$ are previous GP FE, and $\theta_{it}$ is a vector of controls (sick leave days the year before swap, patient age, and patient sex). Displayed estimates are the coefficient $\beta$, the effect of a 1 SD increase in GP sick note leniency.
Standard errors in parentheses clustered at GP level.
Discussion of mechanisms

- Reduced labour market attachment and income + increased take-up of other welfare services
  - In sum: Negative effects on parent’s economic resources

- BUT, the timing of the shock matters – shocks in early years do not seem to give clear/as big negative effects on human capital (measured at age 16+)

- Would expect the effect of reduced labour market attachment and economic resources to be stronger the longer exposed, but no clear signs of this

- Stress, worrying, role modelling - something like that - around the critical measurement time (end of lower secondary school) does likely also play a role
Robustness/sample checks

- Adjustment with shrinkage factor
  - To adjust for potential measurement error
  - Effects increase slightly

- Dropping children with same exogenous swap as parent
  - No difference

- Restrict to parents using sick leave the year before swap
  - To avoid results being affected by never-takers
  - Larger effects

Specification checks

- Leave out each of the controls in turn
- PSM common support
- Random inference P-values
- Leave out one year at the time
- Leave out one county at the time
- Dropping GPs with very few new assigned patients
- => everything seems solid :(
Concluding remarks I

• Employment protection and income replacement programs play an important role not only for the focal workers, but also in their children’s lives.

• We find sizable negative effects of parental sick leave on the child’s human capital development – and that the timing matters.

• Sick leave induces parents to be more likely to find themselves outside the workforce, earn lower wages, and become more dependent on the social safety net.

• Also probably a story of increased stress and/or change of role models.
Concluding remarks II

• Conventional social protection policies designed to help individual workers can generate important spillovers to their children.

• In our study negative spillovers were bigger than potential positive spillovers
  – Important to investigate the mechanisms and their relative magnitude further

• Our results imply that the cost of these policies is likely larger than previously thought
Thank you!

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