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ISSN: 2365-9793

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ABSTRACT

Children in the Aftermath of the Great Recession*

In this paper we study effects of mass layoffs on parents and their children in the aftermath of the Great Recession using staggered difference-in-differences (DiD). We exploit quasi-experimental variation in announcements of mass layoffs in Danish firms in 2008-2019. We document that parents exposed to a mass layoff during and immediately after the Great Recession are negatively affected 6 years after the event; more so and for a longer period of time for parents at high risk of long term unemployment. Perhaps surprisingly, we find no overall significant negative effects of parental mass layoffs on children; neither academic achievement, absenteeism nor well-being are affected. We even find some positive effects for the children of parents who were more adversely affected by the layoff, consistent with an increase in parental time investment following unemployment. This last finding would not have appeared using a traditional two-way fixed effects approach, which appears to be biased towards zero in our setting.

JEL Classification: I20, J63

Keywords: mass layoff, unemployment, school outcomes, academic achievement, wellbeing

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* We acknowledge financial support from the Independent Research Fund Denmark. We appreciate comments from an anonymous referee. The authors declare that they have no relevant or material financial interests that relate to the research described in this paper.

1. Introduction

The Danish economy was greatly affected by the Great Recession. The employment rate of unskilled workers declined by ten percentage points and the number of foreclosures and arrears multiplied quickly (DEC, 2016, 2019; ECLM, 2018). Thus, the Great Recession led to job loss, less income stability and more financial strain for especially socially disadvantaged families. In this paper we ask how the Great Recession affected children, while focusing on effects going through parental job loss.

Our paper speaks to two strands of literature; an interdisciplinary literature concerned with the consequences of the Great Recession on children and a voluminous economics literature on job loss exploiting plausibly exogenous variation due to mass layoffs and workplace closures.

The first strand of literature comprises a number of cross-country comparisons of how the Great Recession affected children. Chzhen et al. (2017) focuses on the impact of the crisis on children in rich countries including Denmark. They show that the GDP deterioration in Denmark was approximately like the average rich country, while unemployment and youth unemployment increased less than in other rich countries. As regards child poverty and deprivation, Danish children were in a very good position before and after the crisis in an international comparison. Social spending on family-related benefits declined in absolute terms after the crisis in most rich countries including Denmark, while spending on the elderly increased. Jenkins et al. (2013) also study the impact of the Great Recession across developed countries. They focus on real income, poverty and inequality primarily in the period 2007-2009 and base their analysis on the same data material as Chzhen et al. (OECD, Eurostat and World Development Indicators). As regards children, Jenkins et al. (2013) show various poverty measures across age groups and confirm the picture from Chzhen et al. that the elderly gained and average households and children lost a bit. Relatedly, Garfinkel et al. (2016) study the fragile families data following a cohort born 1998-2000 in twenty large cities in the US. They find that the Great Recession increased the already large divide between high- and low-SES families. While families in which the mother had a college education were characterized by near immunity to the crisis, effects on those without a college education were harsh in terms of economic well-being, relationship stability and parents' health.

We take away two points from this strand of literature. The Great Recession affected the rich countries, including Denmark, though less severely than other countries, and children, in particular children from low-SES families, were disproportionally affected.

The second strand of literature has exploited mass layoffs to better understand causal effects of unemployment on individuals themselves (e.g. Andersen et al., 2021 and Bennett & Ouazad, 2020 for Denmark) and to a lesser extent also to understand effects on children of laid off parents (e.g. Mörk, Sjögren & Svaleryd, 2020 for Sweden; Huttunen & Riukula, 2019 for Finland; Rege, Telle & Votruba, 2011 for Norway), see literature review by Mörk et al. 2020 (in their Table A1). Kalil (2013) argues that job loss is among the most obvious phenomena induced by the Great Recession, which may have negative effects on child development, and summarizes results of the empirical literature as supportive of detrimental effects of job loss on children.[2] For the Nordic countries, however, results are less clear. All the studies for Nordic countries agree that there are negative effects of job loss on parents' labour market outcomes. And, in those cases where there are also detrimental effects on child outcomes, the authors agree that these effects do not go through disposable incomes as the welfare state appears to counteract negative income effects (Sjögren et al. 2020; Huttunen & Riukula, 2019; Rege et al., 2011).

Rege et al. (2011) study Norwegian fathers' and mothers' job loss immediately before their children's graduation. They find that paternal job loss just before graduation reduces graduation year grade point average (GPA), whereas maternal job loss increases GPA. They point at the gender difference in mental distress after job loss as a potential explanation for the disparate results. Huttunen and Riukula (2019) focus on job loss in the deep recession in Finland in the 90's, and find that paternal job loss reduces the probability that children choose the same field of study as their fathers, and furthermore, it leads to lower wage earnings of children in adulthood. Their analyses indicate that job loss influences the longer-term intergenerational transmission of human capital. Mörk, Sjögren and Svaleryd (2020) find that effects of work place closure on children are very limited even though detrimental effects on parental health, labour market outcomes and separation are found.

We exploit plausibly exogenous variation in the timing of mass layoffs during the Great Recession and in its aftermath. Using the staggered DiD framework proposed in Callaway and Sant'Anna (2021), we obtain estimates which are robust to heterogeneous treatment effects and can be aggregated into different parameters of interest. We study effects on parental outcomes

[2] A recent review by Ruiz-Valenzuela (2021) summarizes the evidence. Examples of evidence suggesting that parental job loss adversely affects children's educational attainment are: Oreopoulos, Page and Stevens (2008) and Coelli (2011) for Canada; Kalil and Wightman (2011) for the US, and Kertesi and Kezdi (2007) for Hungary. In contrast, Hilger (2016) finds limited long-term effects from a study based on US data.

(unemployment and log disposable income) and children's school outcomes (GPA, national reading tests, absence and well-being).

We find substantial and long-lasting effects of mass layoffs on parents but no detectable overall negative effects on child outcomes. Exposure to mass layoff increases unemployment by 4-5 percentage points and reduces disposable income by 6-8 percent. The average and the dynamic treatment effects on child outcomes are insignificant across outcomes. When focusing on parents at high risk of becoming long-term unemployed, we find larger and longer lasting effects on parents. However, perhaps surprisingly, the effects on their children's school outcomes (GPA and absence) tend to be positive indicating a favorable effect of increased parental time investment. In contrast, when focusing on parents at low risk of becoming long-term unemployed, we find smaller effects on parents, but signs of negative effects on their children's national reading test scores indicating financial or psychological distress.

The remainder of the paper is organized as follows: Section 2 presents the data sources, measures and descriptive statistics. Section 3 presents the empirical strategy, whereas section 4 presents the results. Section 5 discusses and concludes the study.

2. Data

2.1. Data sources

We obtain information on mass layoffs from the Danish Agency for Labour Market and Recruitment in the register on announced layoffs (VARSLINGSSAGER). It includes announced mass layoffs in the period 2008-2019, which is during and in the aftermath of the Great Recession. A Danish workplace is mandated by law to announce a planned layoff if it involves at least 30 (10) individuals in a firm with at least (no more than) 300 employees. Some workplaces also alert about the layoff even if they are not required to do so.

We match the announced mass layoffs to individual workers using the Integrated Database for Labour Market Research (IDA), which contains an encrypted unique identifier for all Danish firms. We thus append workplaces and define layoffs at the firm level. We further augment the dataset with basic background information obtained from administrative population and socioeconomic registries (hosted by Statistics Denmark), which can be matched at the individual level through a personal id number.

We match individual workers to their children and collect child outcomes from the basic school grade register (UDFK) and registries added from Danish Agency for IT and Learning (STIL), which can again be matched to the rest of the data using the personal id number.

2.2. Treatment definition

We define a mass layoff as an event where at least 25% of employees at a firm are announced to be laid off. We impose this to ensure that the event is as exogenous as possible from the individual perspective. Individuals are considered treated, i.e. exposed to a mass layoff, in the announcement period and all subsequent periods. This is because the event we are interested in is experiencing a mass layoff, not unemployment per se. We abstract from individuals experiencing several mass layoffs, which rarely happens.

We define a child as exposed to parental mass layoff if either the mother or the father of the child is exposed to a mass layoff. Again, children are considered treated in the announcement period and all subsequent periods.

2.3. Sample description

Our gross sample consists of individuals who are exposed to a mass layoff during the period 2008-2019 and who have children born between 1987-2010. This leaves a sample of 23,797 parents; 15,230 fathers and 8,567 mothers. Our estimation samples are drawn from this gross sample and vary from outcome to outcome due to varying observation windows across child outcome variables. We construct corresponding child and parent estimation samples for each child outcome in order to understand underlying mechanisms and get closer to understanding how the first stage (parent results) drives the second stage (child results).

In Table 1 we summarize exposure to mass layoff for the gross sample. As expected, most of the individuals who experience a mass layoff do so during the beginning of the period comprising the Great Recession and the immediate aftermath of the Great Recession. More than 50% of those exposed to mass layoff are exposed in 2008-2010, and then there is a decline afterwards with minor upticks in 2012 and 2015-2016.

Table 1. Distribution of parents exposed to mass layoff by year

Year	Frequency	Percent
2008	2,487	10.45
2009	7,361	30.93
2010	2,807	11.80
2011	1,811	7.61
2012	2,626	11.04
2013	1,029	4.32
2014	724	3.04
2015	1,248	5.24
2016	1,513	6.36
2017	826	3.47
2018	905	3.80
2019	460	1.93
	23,797	100

Note: Table shows the distribution of individuals by year of first exposure to a mass layoff. Sample consists of parents of children born 1987-2010, who are exposed to a mass layoff in 2008-2019. Mass layoff is defined as an announcement of at least 25% employees being laid off.

Table 2 displays descriptive statistics for individuals exposed to mass layoff at some point during the period 2008-2019 along with a comparison sample of 5% of parents/individuals at all other workplaces. Our sample of parents exposed to mass layoff includes more fathers and fewer immigrants and is positively selected on prior income and unemployment history. For instance, only 3% were unemployed more than 20% in 2007 and 6% were poor as compared to 6% and 16% in the comparison population.

In order to distinguish parents who are potentially more vulnerable and more at high risk of becoming long-term unemployed, we identify four factors that are predictive of long-term unemployment: immigrant background (i.e. parent is an immigrant or descendant of immigrant), low education (i.e. no education beyond compulsory education), poor (i.e. parent's income was less than 50% of the median in 2007), and high unemployment (i.e. unemployed more than 20% of year 2007). We define a subgroup at (relatively) "high risk" if the parent is included in one or more of those groups. In our sample 31% are considered at high risk.

Table 2. Means of background variables

	Exposed to mass layoff	Not exposed to mass layoff
Age (years)	38.1	37.8
Father	0.640	0.470
High risk	0.310	0.370
Immigrant	0.100	0.120
Low education	0.190	0.200
Poor	0.060	0.160
Unemployed>20%	0.030	0.060
Observations	23,797	125,959

Note: All variables are measured in 2007. All variables but age are indicator variables defined in the main text. Not exposed to mass layoff is a 5% random comparison sample.

2.4. Outcome variables

While our main interest is in child outcomes, we also consider effects of exposure to mass layoff on parents' unemployment degree (i.e. percent unemployed during a calendar year) and log disposable income (i.e. log of earnings plus transfers minus taxes). Effects on these parental outcomes can be regarded as a first stage in that the extent to which children are affected likely depends on the extent to which parents are affected. Unemployment and disposable income thus represent two possible channels through which children may also be affected.

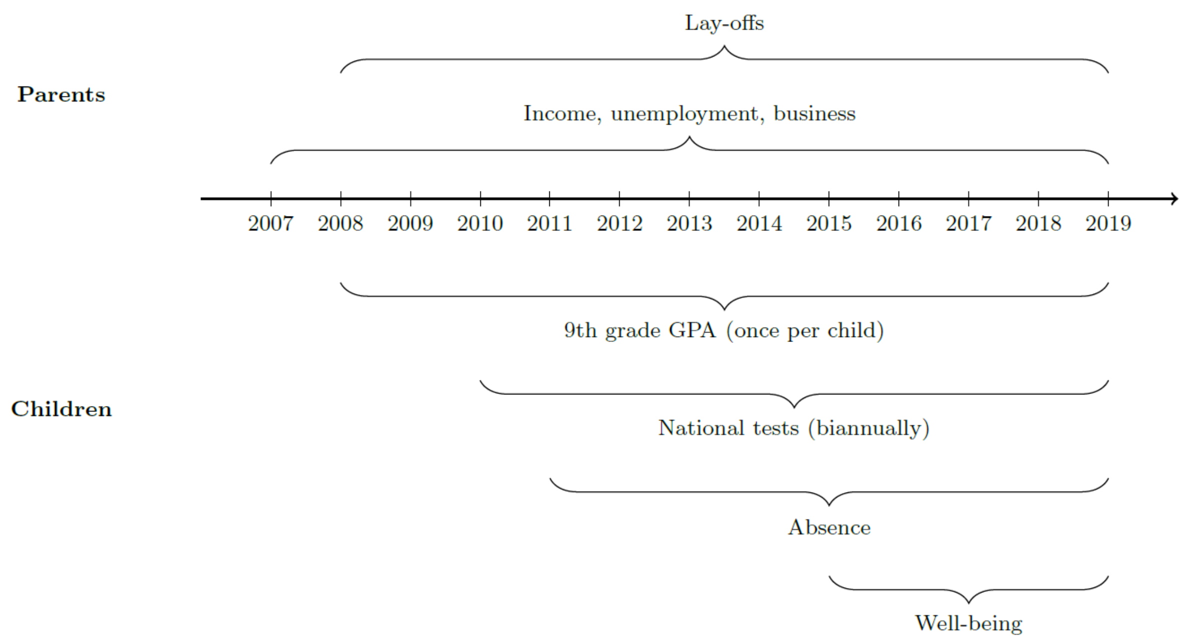
Four sets of child outcomes are studied. First, we observe 9th grade exit exam grades and teacher-assessed grades for all children in the entire period 2008-2019. Second, we observe national reading tests for children in public school from 2010 onwards. Reading tests are administered in 2nd, 4th, 6th and 8th grade, and thus we have one or more tests scores for children hitting the relevant age window. To ease interpretation, we standardize all grades and test scores to have mean zero and a standard deviation of one. Third, we observe days of absence for all children in grades 0 through 9 from 2011 onwards. In our empirical analyses we simply consider the fraction of the year absent (including legal and illegal absence as well as sickness).[3] Finally, we observe responses from the annual well-being survey for all public school children from 2015 onwards. We construct a standardized well-being measure by first standardizing each of the items

[3] A low level of absenteeism is generally regarded as a beneficial school outcome indicating good mental and physical health. However, some families go on vacation during the school year, which would increase absenteeism without having detrimental effects on children.

“Do you like your school?” and “Do you like your class?”, which are 5 point Likert items (3 point in grades 0-3), and then averaging over the items and standardizing again.

Figure 1 summarizes our data sources and the years of data used for the empirical analyses.

Figure 1. Overview of Data Sources



Note: Table summarizes data used in the empirical analyses. Announced mass layoffs are observed in 2008-2019. Parental background is observed in 2007 and parent outcomes are observed in 2008-2019. Child outcomes are observed in 2008-2019 (GPA), 2010-2019 (national test scores), 2011-2019 (absence) and 2015-2019 (well-being).

3. Empirical Strategy

Our empirical strategy revolves around exploiting plausibly exogenous variation in the timing of announced mass layoffs. The strategy follows the logic of a standard difference-in-differences (DiD) estimator where some individuals are exposed to a mass layoff in a specific period. The change in the outcomes of these individuals between the pre- and post-period is then contrasted with that of a group of individuals not exposed to a layoff in either period. Identification is achieved under the "parallel trends" and "no anticipation" assumptions, in which case the not (yet) exposed individuals may serve as valid counterfactuals.

However, to fully exploit the variation in announced mass layoffs taking place throughout our observation period, we apply a staggered DiD framework that allows us to aggregate the individual estimates into a single average treatment effect (ATE) estimate, as well as a set of ATEs that are allowed to vary with the treatment timing or with the length of exposure to treatment (denoted group-time average treatment effects). The latter is akin to the standard two-way fixed effects (TWFE) approach typically used in event studies. However, a recent literature has developed around the limitations of classical event studies (Chaisemartin and D'Haultfoeuille, 2020; Callaway and Sant'Anna, 2021). In particular, the standard TWFE estimator will generally not yield unbiased estimates when the treatment effects are heterogeneous (across units or over time). In fact, this bias can even lead to sign reversal resulting from the fact that the TWFE may attach negative weights to certain comparisons between earlier- and later-treated units (see Goodman-Bacon, 2021, for more details).[4]

Heterogeneity is very likely to be present in the case of the effects of layoffs. For example, low-SES households may be more vulnerable to a negative income shock, or a layoff may be more likely to lead to long-term unemployment if it happens during a recession. To account for this, we apply the staggered DiD estimator introduced by Callaway and Sant'Anna (2021). Like the TWFE estimator, this estimator is a weighted average of group- and period-specific treatment effects (canonical DiD estimators), but unlike TWFE, the applied weights ensure that the ATE is identified also under heterogeneous treatment effects. The estimator is specifically suited to our setting because it is based on a binary treatment where units remain permanently treated (so-called staggered adoption). While individuals exposed to a layoff may of course find new employment,

[4] Also without negative weights, the TWFE may be substantially biased. For example, if weights are significantly correlated with time, and at the same time, treatment effects are heterogeneous over time.

their exposure to the layoff in the first place is never undone. The effect we are estimating is thus not that of losing a job, but that of experiencing a mass layoff.

Specifically, our effects of interest are different aggregated versions of the following disaggregated DiD estimates:

$$ATT(g,t) = E\left[Y_t - Y_{g-1} \,|G_g = 1\right] - E\left[Y_t - Y_{g-1}|D_t = 0\right], \qquad (1)$$

where $ATT(g,t)$ is the effect at time t of experiencing a layoff at time g. Under the standard DiD assumptions, the ATT identifies the effect of the layoff by comparing the average change in the outcomes between periods t and $g\text{-}1$ for individuals who experience a layoff in period g ($G_g=1$) to individuals who have not yet experienced a layoff in period t ($D_t=0$). In our analysis, the control group consists of individuals who do eventually experience a layoff in some later period. Although this limits the size of the control group, it also arguably makes it more similar to the group that experience the layoff in a particular period. This makes the parallel trends assumption more plausible than if we had used a never-treated group as the counterfactual.

We then aggregate the ATTs into the effects that we are interested in based on Callaway and Sant'Anna (2021) in the following ways:

$$\theta_{es}(e) = \sum_{g \in G} 1\{g + e \leq T\} \cdot P(G = g|G + e \leq T) \cdot ATT(g, g + e) \qquad (2)$$

$$\theta_{sel}(\tilde{g}) = \frac{1}{T - \tilde{g} + 1} \sum_{t=\tilde{g}}^{T} ATT(\tilde{g}, t) \qquad (3)$$

$$\theta_{sel}^{O} = \sum_{g \in G_{sel}^{\theta}} \theta_{sel}(g) \cdot P(G = g|G \leq T) \qquad (4)$$

where G is the time period that a particular individual is treated and T is the last period observed. $\theta_{es}(e)$ is then the average effect of experiencing a layoff *e* periods after the layoff, θ_{sel}(g) is the average effect of experiencing a layoff in period *g* (across all post-treatment periods), and θ_{sel}^{O} is the "total" average effect of a layoff across all post-treatment periods and across all individuals that ever experience a layoff. For our main results, we focus on the total aggregated effects (θ_{sel}^{O}) and graphical illustrations of $\theta_{es}(e)$ as is commonly done in event studies. Furthermore, we show heterogeneous subgroup effects, and in the appendix, we also consider the θ_{sel}(g) average effects, which will reveal whether effects across the state of the Danish economy .

4. Results

First we present the main results, then we present results by subgroup and finally we present dynamic treatment effects, where effects are estimated year-by-year after the exposure to mass layoff.

4.1. Main results

Table 3 shows the overall average treatment effects for each of the five child outcomes as well as corresponding parent samples. Looking first at the parent outcomes, which can be regarded as a first stage, we see strong and substantial effects of exposure to a mass layoff on parental outcomes. For all but the well-being sample, the effect of exposure to a mass layoff is an increase in the unemployment rate of 4-5 percentage points and a decrease in disposable income by 6-8 percent. The well-being sample stands out with much smaller effects; a minor 2 percentage point increase in unemployment rate and a small and insignificant effect on log disposable income. This is because the well-being sample is more distant from the Great Recession, and thus consists of parents exposed to mass layoffs in 2015-2019, whose mean unemployment rate was 2.2 percent and mean disposable income 6 percent higher than the other samples (12.67 versus 12-60-12.61). This difference across samples reflects that the impact of exposure to mass layoff was more substantial and/or lasting during and immediately after the Great Recession than in the subsequent boom period.

Now turning to results for the children, the average treatment effects point in different directions and they are never statistically significant. For GPA (exam) and GPA (teacher), point estimates are positive (around 0.1 SD) and borderline significant. If anything, this suggest that parental exposure to mass layoff improves children's results at the end of 9th grade, which would be consistent with positive effects of job loss stemming from increases in parental time investments. For national reading tests, the point estimate is negative (-0.058 SD) and borderline significant. If anything, this indicates that parental exposure to mass layoff reduces reading performance as measured in 2nd, 4th, 6th and 8th grade, which could be due to increased financial or psychological distress.

Table 3. Effects of parental job loss on child and parent outcomes

	GPA (exam)	GPA (teacher)	National tests	Absence	Well-being
Sample period:	2008-2019	2008-2019	2010-2019	2011-2019	2015-2019
Child effect	0.107	0.088	-0.058	0.023	-0.015
	(0.066)	(0.065)	(0.040)	(0.154)	(0.062)
Mean dependent variable	0.089	0.028	0.019	5.187	0.017
Observations	15,541	n.r.	44,443	97,625	29,569
Parent effect					
Unemployment rate	4.665***	4.584***	4.769***	4.246***	1.995***
	(0.557)	(0.552)	(0.384)	(0.322)	(0.616)
Mean dependent variable	3.429	3.463	3.594	3.426	2.150
Log disp. Income	-0.065**	-0.058*	-0.083***	-0.073***	-0.020
	(0.033)	(0.033)	(0.025)	(0.016)	(0.019)
Mean dependent variable	12.617	12.616	12.612	12.602	12.671
Observations	7,376	n.r.	21,069	47,754	14,254

Note: Table shows estimates of the total average treatment effect for children (top panel) and the corresponding samples of parents (bottom panel). Each column uses a different sample defined by the years where child observations are available for the child outcome of that specific column. The top panel reports child effects, whereas the bottom panel reports effects for the corresponding unique parents to those children. Coefficient estimates corresponds to the parameter denoted θ_{sel}^{O} in the main text. Number of observations for GPA (teacher) is similar to GPA (exam). Exact number is not reported in order to preserve anonymity (cells with less than five observations may not be reported, and the difference between the number of observations for GPA (teacher) and GPA (exam) is less than five in some instances).***, ** and * indicate significance at 1%, 5% and 10%-level.

4.2. Subgroup analyses

Table 4 replicates the analysis for mothers and fathers, respectively. While there are some differences in parent effects between mothers and fathers, there is absolutely no clear patterns as regards the children. Effects are quite similar no matter whether the exposure to parental mass layoff comes from the mother or the father.[5]

Table 5 presents results when the samples are split by risk status. Parent effects are overwhelmingly driven by parents at (relatively) high risk of long-term unemployment. For the GPA samples, the effects of exposure to a mass layoff are nil for parents at low risk, while effects for parents at high risk are large. Exposure to mass layoff increases unemployment by 6.6-6.7 percentage points and reduces disposable income by 14-16 percent. These differences across parents at high risk and parents at low risk carries over to children. Parental exposure to mass layoff increases grades by 0.213 SD for the exam results and 0.295 SD for the teacher-assessed grades for children at high risk, while there are no effects for children of parents at low risk. For absence, while the effects are not significant, they again suggest that, if anything, children of parents at high risk are more positively affected (in terms of lower absence) than children of parents at low risk.

For the national test samples, the parent effects are again more unfavorable for parents at high risk, but the child effects are driven by the sample at low risk. Parental exposure to mass layoff reduces national test results by 0.123 SD for children at low risk.[6]

To sum up, the results in this subsection indicate different potential mechanisms for children at high versus low risk. For children of parents at high risk of becoming long-term unemployed, exposure to mass layoff appears to *improve* their school outcomes as measured by grades at the end of 9$^{\text{th}}$ grade[7], which suggests that the *time investment* channel is important. For children of parents at low risk of becoming long-term unemployed, exposure to mass layoff appears to *reduce* their school outcomes as measured by national test results, which suggests that the *financial or psychological distress* channel is potentially important.

[5] In Tables A1-A3 we show results by year of parental exposure to mass layoff, which do not reveal a systematic pattern of results. In particular, the results for GPA and national reading tests do not in any systematic fashion stem from layoffs during the deeper recession at the beginning of the period.

[6] An alternative measure of risk status is home ownership status. On the one hand, home ownership reflects wealth (i.e. low risk). On the other hand, home owners were exposed to distress due to the crash of the housing market (i.e. high risk). In Table A4 we split the sample by home ownership status as of 2007. For the GPA samples, parents who own their home are more negatively affected by exposure to mass layoff, and their children are the ones experiencing favorable GPA effects. For the other samples, parents who are renters are more negatively affected than owners, but still there are no detectable effects on the children.

[7] Point estimates for national tests and absence also point in the direction of improved school outcomes, but effects are not statistically significant.

Table 4. Effects of parental job loss on child and parent outcomes by parent gender

Sample period:	GPA (exam) 2008-2019	GPA (teacher) 2008-2019	National tests 2010-2019	Absence 2011-2019	Well-being 2015-2019
Child effect					
Mothers	0.105	0.088	-0.052	-0.167	-0.070
	(0.082)	(0.081)	(0.052)	(0.170)	(0.080)
Mean dep.var.	0.123	0.060	0.049	4.748	0.014
Observations	8,329	n.r.	22,740	49,064	14,596
Fathers	0.084	0.115*	-0.066*	-0.010	-0.014
	(0.068)	(0.067)	(0.040)	(0.152)	(0.065)
Mean dep.var.	0.099	0.037	0.022	5.157	0.022
Observations	15,051	n.r.	43,478	95,234	29,103
Parent effect - unemployment					
Mothers	3.585***	3.586***	4.930***	5.258***	3.851***
	(0.555)	(0.562)	(0.431)	(0.449)	(0.956)
Mean dep.var.	3.246	3.281	3.395	3.548	2.501
Observations	4,041	n.r.	11,195	24,375	7,113
Fathers	4.543***	4.614***	4.609***	4.056***	1.900***
	(0.570)	(0.575)	(0.391)	(0.319)	(0.607)
Mean dep.var.	3.326	3.347	3.549	3.347	2.088
Observations	7,108	n.r.	21,007	46,313	13,986
Parent effect - log disposable income					
Mothers	-0.113***	-0.119***	-0.080***	-0.038***	-0.014
	(0.040)	(0.040)	(0.024)	(0.008)	(0.014)
Mean dep.var.	12.553	12.552	12.552	12.544	12.605
Observations	4,041	n.r.	11,195	24,375	7,113
Fathers	-0.065**	-0.066**	-0.080***	-0.073***	-0.021
	(0.032)	(0.032)	(0.025)	(0.016)	(0.019)
Mean dep.var.	12.621	12.620	12.615	12.607	12.675
Observations	7,108	n.r.	21,007	46,313	13,986

Note: see Table 3.

Table 5. Effects of parental job loss on child and parent outcomes by risk status

Sample period:	GPA (exam) 2008-2019	GPA (teacher) 2008-2019	National tests 2010-2019	Absence 2011-2019	Well-being 2015-2019
Child effect					
High risk	0.213*	0.295**	0.079	-0.276	0.017
	(0.114)	(0.117)	(0.074)	(0.319)	(0.138)
Mean dep.var.	-0.189	-0.266	-0.203	5.800	-0.049
Observations	4,405	n.r.	12,539	28,298	8,193
Low risk	0.052	0.065	-0.123***	0.160	-0.014
	(0.075)	(0.075)	(0.047)	(0.171)	(0.074)
Mean dep.var.	0.205	0.152	0.115	4.911	0.044
Observations	10,932	n.r.	31,194	67,675	20,927
Parent effect - unemployment					
High risk	6.717***	6.563***	8.525***	7.468***	1.988**
	(0.901)	(0.898)	(0.864)	(0.858)	(0.822)
Mean dep.var.	5.653	5.709	5.849	5.518	3.292
Observations	2,051	n.r.	6,034	13,816	3,817
Low risk	4.043***	4.130***	3.361***	2.951***	2.035***
	(0.655)	(0.665)	(0.414)	(0.290)	(0.758)
Mean dep.var.	2.544	2.580	2.625	2.476	1.667
Observations	5,223	n.r.	15,237	33,208	10,227
Parent effect - log disposable income					
High risk	-0.141***	-0.165***	-0.137***	-0.105***	-0.009
	(0.048)	(0.046)	(0.036)	(0.017)	(0.039)
Mean dep.var.	12.420	12.419	12.412	12.408	12.464
Observations	2,051	n.r.	6,034	13,816	3,817
Low risk	0.010	0.006	-0.077***	-0.060***	-0.027
	(0.038)	(0.038)	(0.029)	(0.021)	(0.021)
Mean dep.var.	12.695	12.695	12.695	12.687	12.752
Observations	5,223	n.r.	15,237	33,208	10,227

Note: see Table 3.

4.3. Dynamic treatment effects

In this section we present dynamic treatment effects for GPA (exam) and national tests, where we saw borderline significant average effects.[8] Figure 2 shows effects for the full samples year by year after exposure to mass layoff. Panels D and F (for GPA) and E and G (for national tests) indicate that the effects of exposure to mass layoff on parental outcomes are long-lasting. The effects on unemployment peak at 6-8 percentage points after one year, whereas the reduction in disposable income persists at roughly 10 percent two to six years after exposure. Panels A and B show no effects on children.

Figures 3 and 4 show results on GPA (exam) and national tests, respectively, by risk status. Figure 3 shows large and persistent effects on parents at high risk as well as positive effects on GPA (exam) of about 0.2 SD for children taking the exam 0-5 years after the event and roughly 0.5 SD for children taking the exam 6-9 years after the event. The fact that effects on parents are so persistent, means that children who take the exam several years after the event are persistently exposed to the home environment affected by exposure to mass layoff. Figure 4 again shows large and persistent effects on parents at high risk and smaller effects on parents at low risk. Effects on children at high risk are miniscule and insignificant, whereas effects on children at low risk are larger and often significantly negative. Again, the effects appear to build up and become larger the more distant the event of mass layoff is.

To sum up, dynamic treatment effects reveal a pattern of effects, where the unfavorable effect on unemployment peaks immediately after the event, whereas the negative effect on disposable income is more persistent; perhaps because parents get a new job quite quickly - before the UIB runs out - but at a lower pay. The dynamic treatment graphs confirm the previous result that effects are larger for parents at high risk even though this does not have negative spillover effects on their children. If anything, the patterns for the child outcomes suggest that these children are more positively affected, possibly because they have a higher marginal benefit of additional time investments and/or because the psychological distress channel has a more adverse effect in families where parents would not typically be at high risk of losing their job.

It is also worth noting that the differences by risk groups would not have been evident, had we instead used the classical event study (TWFE) approach. For example, the dynamic TWFE

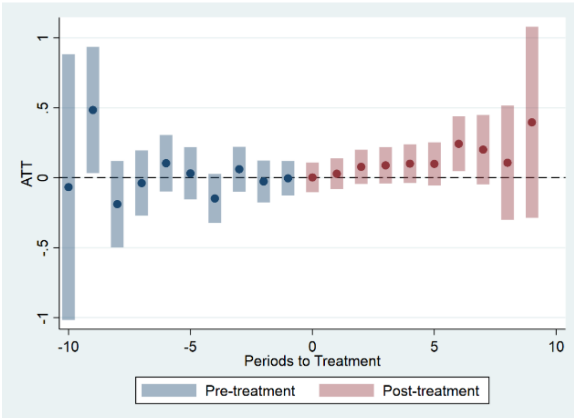
[8] Remaining results are available upon request. Coefficient estimates are noisy and confidence bands are wide.

effects on child national test scores are all close to zero and not statistically distinguishable between the high and low risk groups, see Panel B in Figure A1 in the appendix. TWFE estimates also tend to underestimate the effects on the parental outcomes. For unemployment, the effect is estimated to be 1-2 percentage points lower in the years following the layoff (e.g., a 4 percent rather than a 5-6 percent increase in unemployment two years after the layoff), see Panel A in Figure A1 in the appendix. In our setting, the traditional approach thus seems to bias the estimates towards zero. This is not a general feature of the different approaches, but depends on the heterogeneities that are present in the particular setting. In our setting, the TWFE estimates appear to put too much weight on groups that are relatively unaffected.[9]

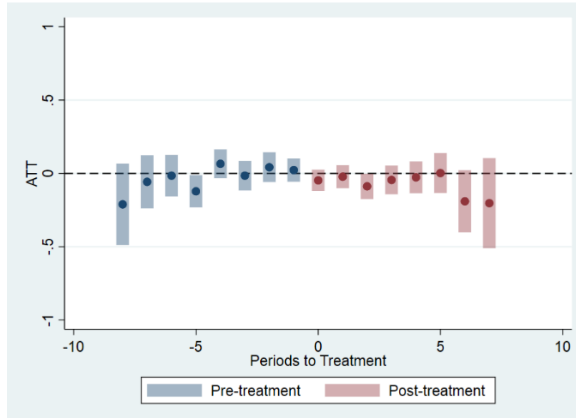
[9] If we suspect a specific type of heterogeneity, we can test whether it would lead to a bias like this. For example, we observe that the TWFE weights are positively correlated with the year of the layoff. This means that if layoffs happening towards the end of the observed period tend to have effects that are closer to zero, the estimates would in general be biased towards zero. By a similar logic, other heterogeneities could also cause this.

Figure 2. Dynamic treatment effects on child and parent outcomes

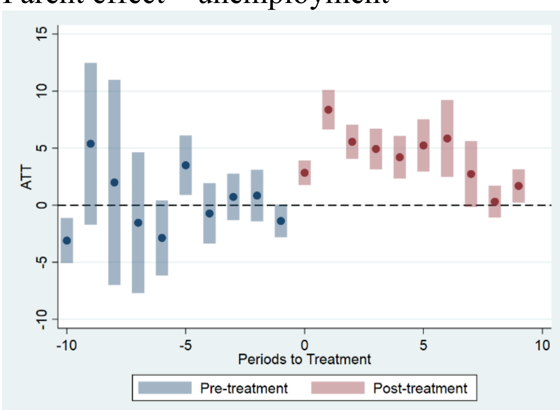
A: GPA (exam)
Child effect



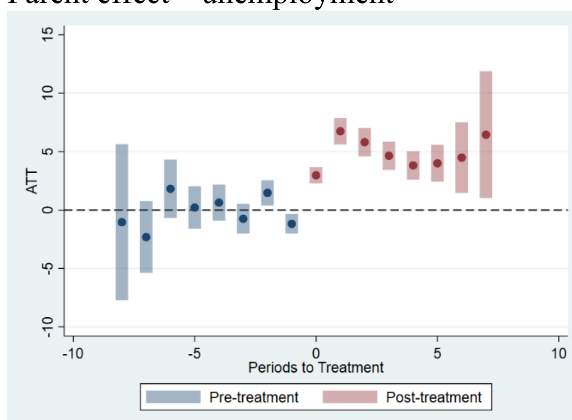
B: National tests
Child effect



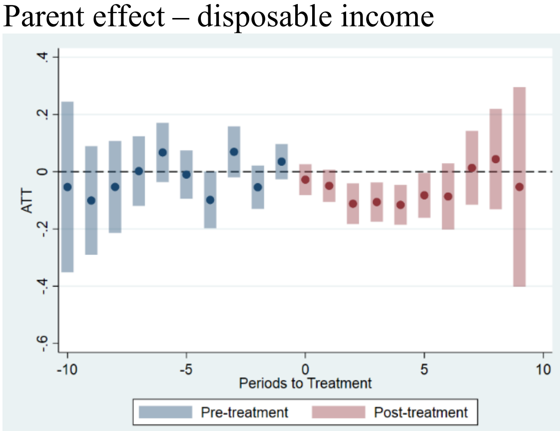
C: GPA (exam)
Parent effect – unemployment



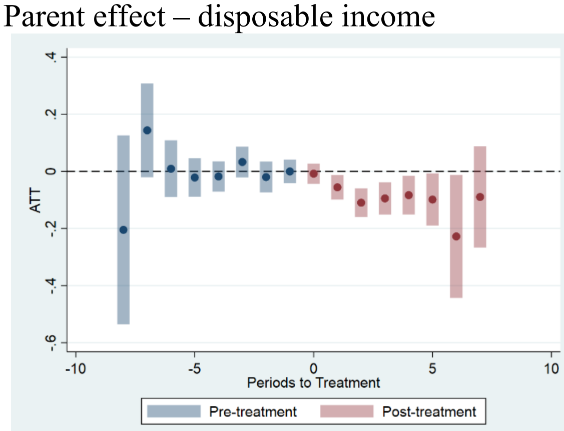
D: National tests
Parent effect – unemployment



E: GPA (exam)
Parent effect – disposable income



F: National tests
Parent effect – disposable income

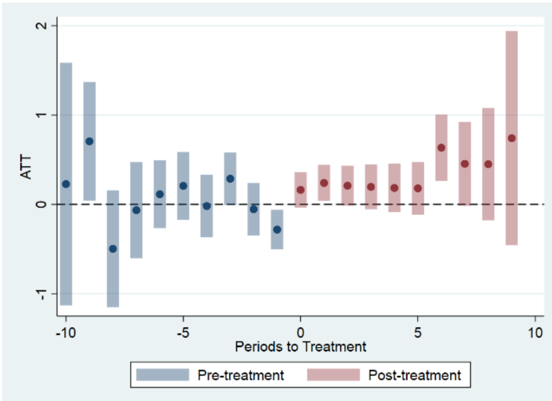


Note: Figure illustrates the average effect of experiencing a mass layoff before and after exposure to the event, i.e. the parameter denoted $\theta_{es}(e)$ in the main text. Panels A-B show child effects and D-F show parent effects for the corresponding unique parents to the children. Sample period is

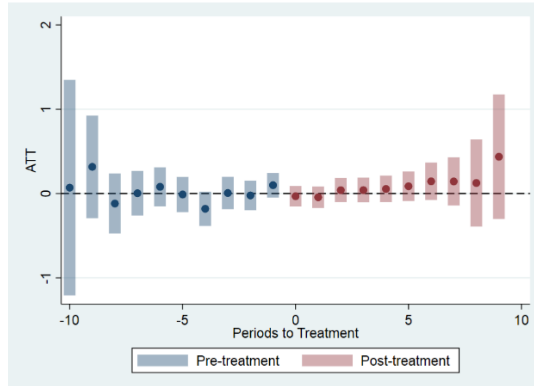
2008-2019 for GPA (exam) and 2010-2019 for national tests corresponding to the years where child observations are available for GPA and national tests. Columns indicate 95%-confidence bands.

Figure 3. Dynamic treatment effects on GPA (exam) by risk status

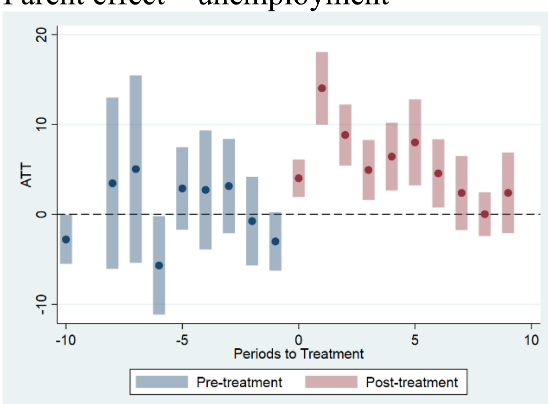
A: High risk
Child effect



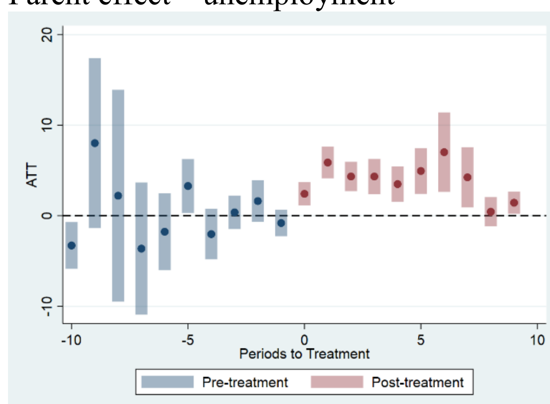
B: Low risk
Child effect



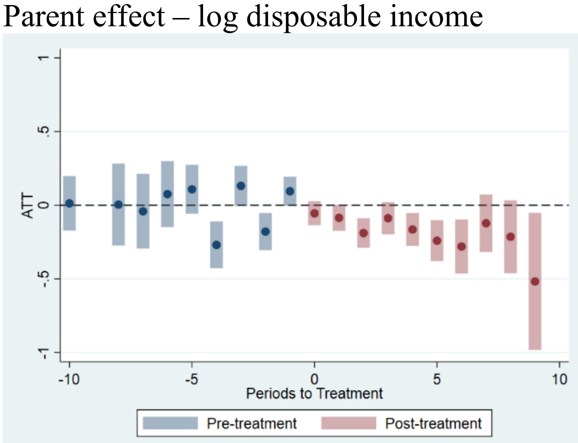
C: High risk
Parent effect – unemployment



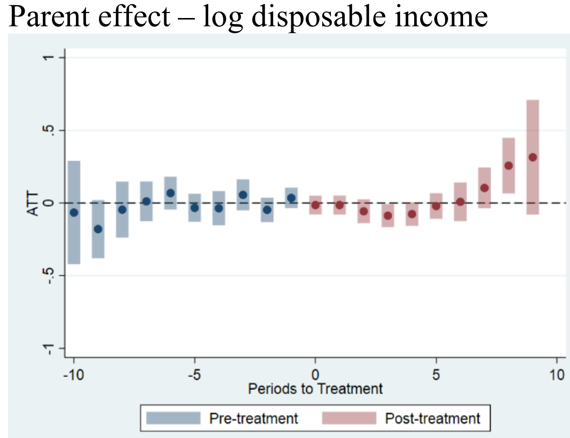
D: Low risk
Parent effect – unemployment



E: High risk
Parent effect – log disposable income



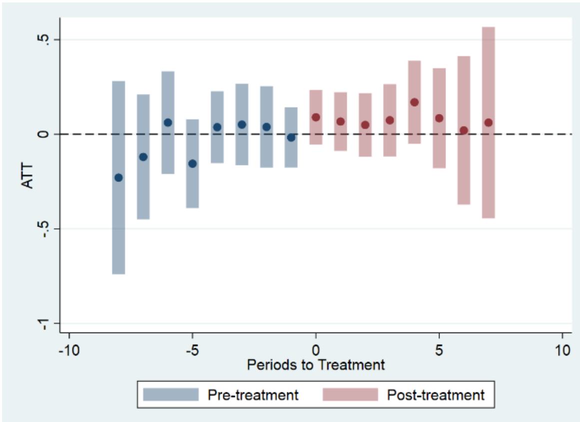
F: Low risk
Parent effect – log disposable income



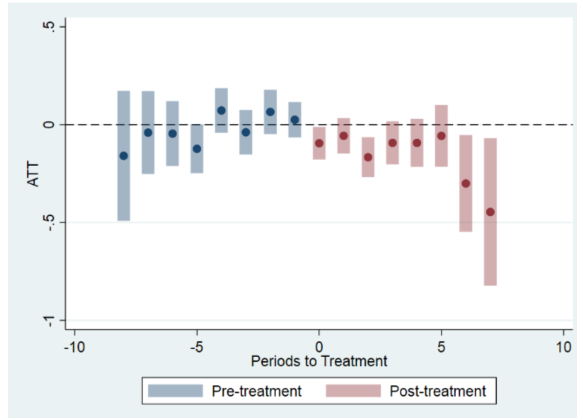
Note: see Figure 2.

Figure 4. Dynamic treatment effects on national tests by risk status

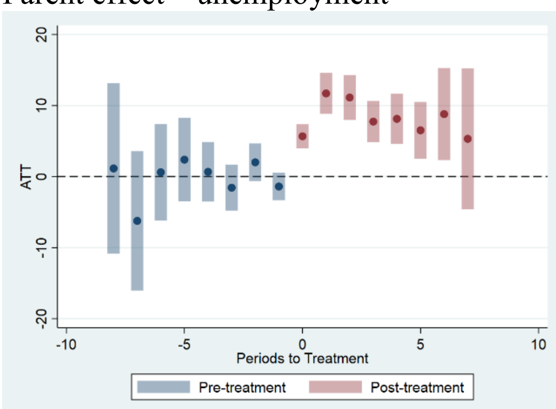
A: High risk
Child effect



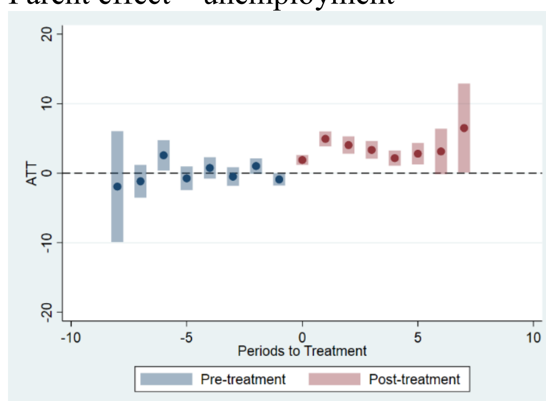
B: Low risk
Child effect



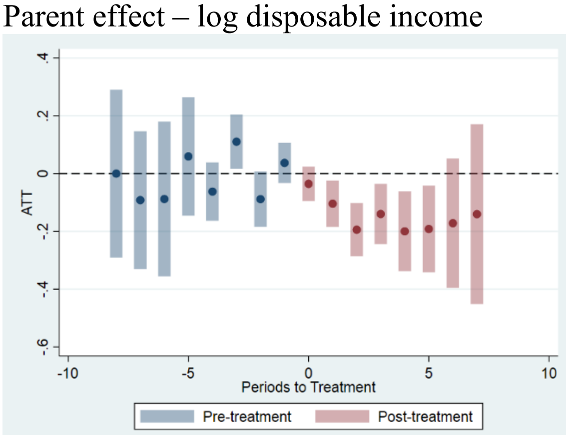
C: High risk
Parent effect – unemployment



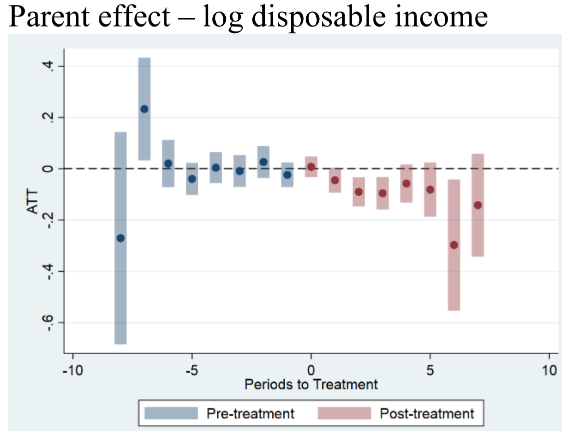
D: Low risk
Parent effect – unemployment



E: High risk
Parent effect – log disposable income



F: Low risk
Parent effect – log disposable income



Note: See Figure 2.

5. Discussion and conclusion

We use a staggered difference-in-differences approach to examine effects of mass layoffs on parents and their children during and after the Great Recession. We use announcements of mass layoffs in Danish firms in 2008-2019 and show that parents exposed to a mass layoff during and immediately after the Great Recession are negatively affected up to 6 years after the event; more so and for a longer period of time for parents at high risk. Perhaps surprisingly, we find no overall significant negative effects of parental mass layoffs on children; neither academic achievement, absenteeism nor well-being are affected.

Our overall null findings are consistent with the previous literature. It is consistent with the strand of literature studying how the Great Recession affected children across countries. Chzhen et al. (2017) and Jenkins et al. (2013) show that the GDP deterioration in Denmark was approximately like the average rich country, while Danish children were in a very good position before and after the crisis as concerns child poverty and deprivation. It is also consistent with the literature studying the impact of parental job loss on children in the Nordic countries, which typically finds limited or mixed effects on children (e.g. Mörk et al. 2020; Rege et al. 2011).

When focusing on parents at high risk of becoming long-term unemployed, we find larger and longer lasting effects on parents. However, perhaps surprisingly, we find positive effects on their children's 9th grade GPA (and effects on their other school outcomes that also tend to be positive, though not significantly). First of all, this indicates that if financial and psychological distress is present, either families are able to shield their children from this distress, or it is not devastating enough to spillover on to the children. Secondly, this also indicates that increased parental time investment has a favorable effect on child outcomes. A positive effect of job loss on children is also found by Rege et al. (2011) for Norwegian mothers (but not for fathers). However, Rege et al. argue based on the gender difference of their results, and explain why children benefit more from mothers having more time available compared to fathers. They draw on studies on mental distress, social roles and time use, and argue that a positive effect for mothers is related to job loss leading to limited mental distress, social norms that allow women to appreciate child rearing and mothers devoting more time to child care after job loss in contrast to fathers.

In contrast, when focusing on parents at low risk of becoming long-term unemployed, we find smaller effects on parents, but signs of negative effects on their children's national reading test scores. This indicates that even though the increase in the unemployment rate and the drop in disposable income is less compared to families at high risk, the consequences for children may be more severe. First of all, this indicates that the family is not able to shield their children from the consequences of job loss even though those consequences are less than for families at high risk. The financial consequences may be harsher if the family has higher fixed costs or more expensive homes, or the psychological distress may be higher if preferences or social norms are not consistent with appreciating full-time child rearing or are such that the job loss itself is felt as more distressful (perhaps because it is more unexpected). Secondly, job loss may not lead to increased time investment, for instance, if parents suffer from mental distress or spend all their time searching for a new job. Finally, children in low-risk families may have more to lose, whereas children in high-risk families face a "floor effect" because their outcomes are already very bad or their family situation is already so poor that further unemployment has no further consequences.

We use the staggered DiD approach, which is the-state-of-the-arts event-study design. This approach renders our estimates robust to heterogeneous treatment effects, which is almost unavoidable in the context of mass layoffs. While estimation results do not vary systematically with calendar year of the mass layoff, they do vary systematically with risk status and with distance to the event, either of which emphasizes that the approach should be robust to this kind of heterogeneity. In our particular case, the weights of the classical event study design (TWFE) are indeed significantly correlated with time, which biases the estimated effects on parental unemployment from the classical event study approach downwards by approximately two percentage point. Our study thus seconds the recent econometrics development on event study designs, underlining that the classical approach should be replaced by the new robust approaches.

References

Andersen, Asger L., Amalie S. Jensen, Niels Johannesen, Claus T. Kreiner, Søren Leth-Petersen & Adam Sheridan (2021) How Do Households Respond to Job Loss? Lessons from Multiple High-Frequency Data Sets. Draft, University of Copenhagen.

ECLM (2018) Krisens skygger trækker stadig spor. Tema: 10 år efter krisen. Economic Council of the Labour Movement / Arbejderbevægelsens Erhvervsråd, October 2018.

Bennett, Patrick & Amine Ouazad (2020) Job Displacement, Unemployment, and Crime: Evidence from Danish Microdata and Reforms. *Journal of the European Economic Association* 18 (5): 2182-2220.

Callaway, Brantly & Pedro H. C. Sant'Anna (2021) Difference-in-Differences with multiple time periods. *Journal of Econometrics* 225: 200-230.

Chzhen, Yekaterina, Brian Nolan, Bea Cantillon & Sudhanshu Handa (2017) "Impact of the Economic Crisis on Children in Rich Countries." Chapter 2 in (eds.) Cantillon, Bea, Yekaterina Chzhen, Sudhanshu Handa & Brian Nolan (2017), *Children of Austerity: Impact of the Great Recession on Child Poverty in Rich Countries*. UNICEF, Oxford University Scholarship.

Chaisemartin, Clement de & Xavier D'Haultfoeuille (2020) Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects. *American Economic Review* 110(9): 2964-96.

Coelli, Michael (2011) Parental job loss and the education enrolment of youth. *Labour Economics* 18 (1): 25–35.

DEC (2016) Dansk Økonomi Forår 2016. Danish Economic Councils/De Økonomiske Råd.

DEC (2019) Dansk Økonomi Efterår 2019. Danish Economic Councils/De Økonomiske Råd.

Garfinkel, Irwin, Sara S Mclanahan & Christopher Wimer (eds.) (2016) *Children of the Great Recession*. Russell Sage Foundation.

Goodman-Bacon, Andrew (2021) Difference-in-differences with variation in treatment timing. *Journal of Econometrics* 225(2): 254-277.

Hilger, Nathaniel (2016) Parental Job Loss and Children's Long-Term Outcomes: Evidence from 7 Million Fathers' Layoffs.*American Economic Journal: Applied Economics* 8(3): 247–283.

Huttunen, Kristiina & Krista Riukula (2019) Parental Job Loss and Children's Careers, IZA DP No. 12788.

Jenkins, Stephen P., Andrea Bandolini, John Micklewright & Brian Nolan (eds.) (2013) *The Great Recession and the Distribution of Household Income*. Oxford University Press.

Kalil, Ariel & Patrick Wightman (2011) Parental job loss and children's educational attainment in black and white middle-class families. *Social Science Quarterly* 92 (1): 57–78.

Kalil, Ariel (2013) Effects of the Great Recession on Child Development. *Annals of the American Academy of Political and Social Science* 650: 232-249.

Kertesi, Gabor & Gabor Kezdi (2007) Children of the post-communist transition: Age at the time of the parents' job loss and dropping out of secondary school. *B. E. Journal of Economic Analysis and Policy:Contributions to Economic Analysis and Policy* 7 (2): 1–25.

Mörk, Eva, Anna Sjögren & Helena Svaleryd (2020) Consequences of parental job loss on the family environment and on human capital formation-Evidence from workplace closures. *Labour Economics* 67: 101911.

Oreopoulos, Philip, Marianne Page & Ann Huff Stevens (2008) The intergenerational effect of worker displacement. *Journal of Labor Economics* 26 (3): 455–83.

Rege, Mari, Kjetil Telle & Mark Votruba (2011) Parental Job Loss and Children's School Performance. *Review of Economic Studies* 78: 1462–1489.

Ruiz-Valenzuela, Jenifer (2021) The Effects of Parental Job Loss on Children's Outcomes. *Oxford Research Encyclopedia in Economics and Finance*. https://doi.org/10.1093/acrefore/9780190625979.013.654

Appendix: Additional tables and figures

Table A1. Effects of parental job loss on child outcomes by year of mass layoff

	GPA (exam)	GPA (teacher)	National tests	Absence	Well-being
Sample period:	2008-2019	2008-2019	2010-2019	2011-2019	2015-2019
Child effect					
2009	-0.034	-0.065			
	(0.107)	(0.109)	0	0	0
2010	0.164	0.167			
	(0.135)	(0.136)	0	0	0
2011	0.255**	0.255**	0.008		
	(0.124)	(0.120)	(0.063)	0	0
2012	0.354***	0.303***	-0.107*	-0.038	
	(0.114)	(0.119)	(0.060)	(0.242)	0
2013	-0.065	-0.034	-0.045	-0.410	
	(0.177)	(0.171)	(0.082)	(0.285)	0
2014	0.508**	0.498**	-0.098	-0.240	
	(0.222)	(0.236)	(0.119)	(0.335)	0
2015	0.083	0.144	0.002	-0.256	
	(0.174)	(0.179)	(0.091)	(0.340)	0
2016	-0.032	-0.090	-0.096	-0.466	-0.227**
	(0.187)	(0.196)	(0.098)	(0.361)	(0.106)
2017	0.057	-0.064	-0.031	0.225	0.141
	(0.264)	(0.280)	(0.141)	(0.479)	(0.137)
2018	-0.034	-0.051	-0.229	0.625	0.096
	(0.348)	(0.280)	(0.200)	(0.540)	(0.166)
Mean dep.var.	0.089	0.028	0.019	5.187	0.017
Observations	15,541	n.r.	44,443	97,625	29,569

Note: Table shows estimates of $\theta_{sel}(g)$, which is the treatment effect of events in year g. Table shows effects on five child outcomes. '0' indicates that observation window of outcome has not started. Number of observations for GPA (teacher) is similar to GPA (exam). Exact number is not reported in order to preserve anonymity. ***, ** and * indicate significance at 1%, 5% and 10%-level.

Table A2. Effect of job loss on unemployment by year of mass layoff

	GPA (exam)	GPA (teacher)	National tests	Absence	Well-being
Sample period:	2008-2019	2008-2019	2010-2019	2011-2019	2015-2019
Parent effect - unemployment					
2009	2.733***	2.868***			
	(0.560)	(0.564)	0	0	0
2010	8.638***	8.782***			
	(2.277)	(2.278)	0	0	0
2011	5.018***	5.040***	5.815***		
	(1.252)	(1.254)	(0.933)	0	0
2012	4.146***	4.309***	4.498***	5.093***	
	(1.611)	(1.671)	(0.717)	(0.781)	0
2013	6.106**	5.362**	5.010***	5.219***	
	(2.954)	(2.771)	(0.807)	(1.072)	0
2014	5.565***	5.517***	7.111***	6.595***	
	(1.881)	(1.877)	(1.206)	(1.180)	0
2015	6.822***	6.790***	4.401***	5.661***	
	(2.465)	(2.462)	(0.984)	(1.260)	0
2016	0.984	0.929	2.285***	4.874***	3.286***
	(0.866)	(0.863)	(0.720)	(1.149)	(1.106)
2017	5.701	5.638	3.090***	5.271***	4.841**
	(4.522)	(4.522)	(0.865)	(1.560)	(1.899)
2018	5.701**	5.774**	3.583**	1.836***	4.040
	(3.058)	(3.009)	(1.863)	(0.695)	(2.764)
Mean dep.var.	3.429	3.463	3.594	3.426	2.150
Observations	15,541	n.r.	44,443	97,625	29,569

Note: Table shows estimates of $\theta_{sel}(g)$, which is the treatment effect of events in year g. Table shows effects on parental unemployment for the five samples corresponding to the five child outcomes reported in Table A1. '0' indicates that observation window of outcome has not started. Number of observations for GPA (teacher) is similar to GPA (exam). Exact number is not reported in order to preserve anonymity. ***, ** and * indicate significance at 1%, 5% and 10%-level.

Table A3. Effects of job loss on disposable income by year of mass layoff

	GPA (exam)	GPA (teacher)	National tests	Absence	Well-being
Sample period:	2008-2019	2008-2019	2010-2019	2011-2019	2015-2019
Parent effect – log disposable income					
2009	-0.039	-0.049			
	(0.051)	(0.051)	0	0	0
2010	-0.162***	-0.163***			
	(0.054)	(0.053)	0	0	0
2011	0.018	0.013	-0.077**		
	(0.059)	(0.059)	(0.037)	0	0
2012	-0.004	-0.013	-0.080	-0.058***	
	(0.053)	(0.053)	(0.049)	(0.014)	0
2013	-0.271**	-0.272**	-0.103**	-0.060**	
	(0.127)	(0.126)	(0.050)	(0.024)	0
2014	0.024	-0.027	-0.091	-0.062***	
	(0.134)	(0.130)	(0.064)	(0.016)	0
2015	-0.081	-0.076	-0.109**	-0.002	
	(0.070)	(0.069)	(0.047)	(0.014)	0
2016	-0.021	-0.036	-0.053	-0.010	-0.029
	(0.123)	(0.124)	(0.050)	(0.013)	(0.019)
2017	-0.047	-0.048	-0.068	-0.007	0.004
	(0.129)	(0.128)	(0.071)	(0.017)	(0.024)
2018	-0.305*	-0.291	-0.099	0.055	0.004
	(0.183)	(0.181)	(0.099)	(0.037)	(0.019)
Mean dep.var.	12.617	12.616	12.612	12.602	12.671
Observations	15,541	n.r.	44,443	97,625	29,569

Note: Table shows estimates of $\theta_{sel}(g)$, which is the treatment effect of events in year g. Table shows effects on log disposable income for the five samples corresponding to the five child outcomes reported in Table A1. '0' indicates that observation window of outcome has not started. Number of observations for GPA (teacher) is similar to GPA (exam). Exact number is not reported in order to preserve anonymity. ***, ** and * indicate significance at 1%, 5% and 10%-level.

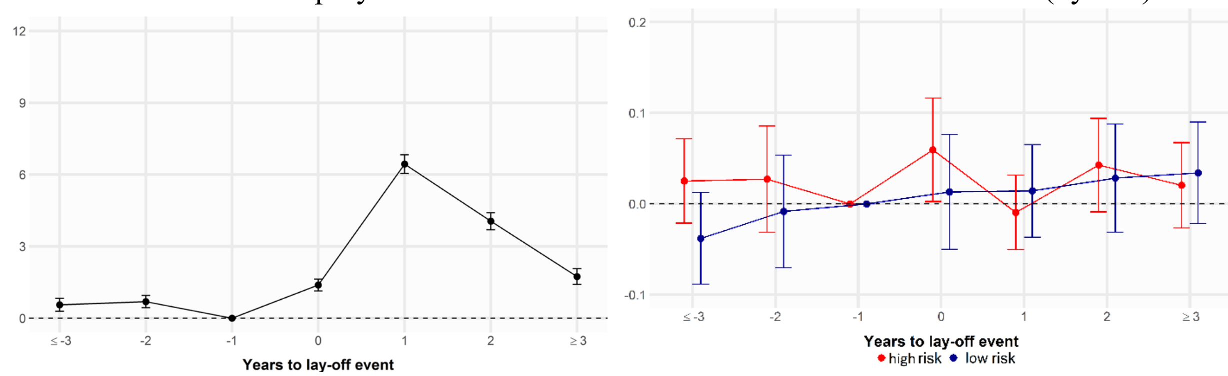
Table A4. Effects of parental job loss on child and parent outcomes by home ownership status

Sample period:	GPA (exam) 2008-2019	GPA (teacher) 2008-2019	National tests 2010-2019	Absence 2011-2019	Well-being 2015-2019
Child effect					
Owner	0.180*	0.171*	-0.036	0.047	-0.041
	(0.102)	(0.104)	(0.063)	(0.208)	(0.099)
Mean dep.var.	0.181	0.124	0.086	4.966	0.038
Observations	6,428	n.r.	17,999	38,777	12,108
Renter	0.054	0.025	-0.065	-0.012	0.014
	(0.084)	(0.082)	(0.051)	(0.212)	(0.086)
Mean dep.var.	0.023	-0.039	-0.026	5.333	0.003
Observations	9,113	n.r.	26,444	58,848	17,461
Parent effect - unemployment					
Owner	5.314***	5.295***	3.131***	3.137***	1.528**
	(1.050)	(1.048)	(0.418)	(0.495)	(0.693)
Mean dep.var.	2.879	2.919	2.619	2.500	1.540
Observations	2,999	n.r.	8,391	18,097	5,632
Renter	4.639***	4.454***	5.899***	4.982***	2.378***
	(0.627)	(0.618)	(0.572)	(0.421)	(0.914)
Mean dep.var.	3.807	3.837	4.213	3.991	2.550
Observations	4,370	n.r.	13,218	29,712	8,611
Parent effect - log disposable income					
Owner	-0.079*	-0.077	-0.028	-0.033***	-0.001
	(0.048)	(0.048)	(0.031)	(0.010)	(0.021)
Mean dep.var.	12.685	12.683	12.690	12.684	12.753
Observations	2,999	n.r.	8,391	18,097	5,632
Renter	-0.052	-0.040	-0.124***	-0.101***	-0.032
	(0.045)	(0.045)	(0.035)	(0.026)	(0.029)
Mean dep.var.	12.570	12.570	12.562	12.552	12.618
Observations	4,370	n.r.	13,218	29,712	8,611

Note: see Table 3.

Figure A1. Effects of parental job loss estimated by a traditional (TWFE) event study

A: Parent effect - unemployment B: Child effect – National tests (by risk)



Note: Figure illustrates the average effect of experiencing a mass layoff on parental and child outcomes, relative to the baseline year (-1). Estimated using a two-way fixed effects model.