Family-level stress and children's educational choice: Evidence from parent layoffs*

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Abstract

We analyse the effect of a parent's layoff on the educational outcomes of their children. We use administrative data on layoffs caused by shocks to labor demand and variation in child age at the time a parent is laid off to estimate the age-specific impact on high school graduation rates. We find that parent layoff may have a large impact on high school completion rates, but the effect is restricted to children who are about to apply to high school. A parent layoff in the month before the school choice deadline decreases the likelihood that the child will finish high school on time by 9 percentage points relative to a layoff in the same school semester, but after the deadline. The effect is higher for low-information families, consistent with the hypothesis that making optimal education decisions may be costly, even if there are no financial constraints on access to education.

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1 Introduction

Educational attainment is highly correlated with parental income in a range of different settings.[1] This correlation reflects either the optimal return to schooling for families with different earnings potential, or the economic constraints which prohibit poorer households from optimally investing in education. Traditionally, economic constraints are modeled as credit constraints - credit markets are incomplete with respect to future earnings (Lochner and Monge-Naranjo, 2012). The evidence of credit constraints as a major impediment for poor families to invest in education is, however, limited (Francesconi and Heckman, 2016; Lovenheim, 2011).

Family income can have a negative effect on child skill formation beyond credit constraints. Heckman and Mosso (2014) emphasize the empirical role of parenting in skill formation. Economic insecurity can, for example, affect parents' ability to make optimal long-term decisions or restrict parental time available for involvement in their child's education, both of which are crucial for educational outcomes.[2] To identify a causal link between parenting decisions and economic constraints in the real world is not straightforward, as parenting skills may be correlated with skills affecting parent earnings. In this paper, we attempt to do just that.

We consider a setting where education is free, but where the role of parental

[1]For US colleges, income has become increasingly predictive of college enrollment for men in a way that can not be explained by ability or college tuition (Lovenheim and Reynolds, 2011). Admission of middle-class students would be substantially higher if admissions were based on SAT alone (Chetty et al., 2020). Belley and Lochner (2007) Describe how the correlation between family income and college enrollment has increased over time.

[2]Sapolsky (2018) documents the increasing body of research in neurology on how the increased level of stress associated with lower socio-economic status can lead to reduced function in the pre-frontal cortex, associated with executive function and long-term planning. Another factor highlighted in research on education and child psychology points to the causal effect of parent involvement in children's education on educational outcomes from pre-school to high school graduation (see See and Gorard, 2015, for a review).

involvement in the child's education is large and the ability to make a complex choice with delayed rewards is crucial. This setting is the choice of upper secondary school track in Sweden. As in most OECD countries, Swedish families choose whether their children should pursue a vocational or theoretical education at an early age. We estimate the effect of parental economic stress during this choice on children's long-term educational outcomes. This allows us to capture any non-financial constraints on low-income parents' ability to provide optimal levels of education for their children.

We estimate the impact of family-level economic insecurity caused by a parent getting laid off. Our data includes the exact timing of the layoff, which allows us to use variation in the age of the child at the time the shock hits to estimate the impact of economic insecurity independent of the marginal returns to schooling for the student. The register data on layoffs include all firms laying off five or more workers due to reductions in demand such as plant closures, reduced production, firm restructuring, etc. This guarantees that all layoffs in our data set are initiated by a firm-level shock, which makes the timing of the layoff plausibly exogenous to the age of the child at the time, even if selection on unobserved parent characteristics is present.

For layoffs that coincide with the time when children transition to upper secondary school, we find a significant decrease in the likelihood of ever completing high school. The estimated likelihood of completing high school on time reduces from 64 percent to 54 percent for children whose parents are laid off up to 7 months before the school choice. Some of the loss is compensated by later graduation, but at age 21 (when 98 percent of all graduates have already completed their schooling) this group are still 10 percentage points less likely to have obtained their degree. A delay in high school graduation is associated with a 16 percent gap in earnings compared to on-time high school graduates, while never completing have a 48 percent lower income on average.

The effect of layoff is larger for families where the expected investment cost of the high school choice is higher and for parents where a layoff will lead to more economic insecurity. The primary costs to parent involvement in the school choice are information costs and travel costs. We use siblings as a proxy for the information level of the family at the time of the event. If the shock affects the school choice of the oldest child, the estimated effect on graduation is large, but for younger siblings, the estimated impact is not statistically different from 0. Younger siblings have the advantage of more family-level information about the choice prior to age 15, therefore she will not be as adversely affected by a reduction of parent investment at the time. Similarly, we find that the effect is larger for families who live far from the closest high school, increasing cost of attendance and information gathering. Layoffs of single-earner parents, parents with lower pre-layoff earnings and parents who receive UI following the layoff are all associated with larger effects on children.

This paper contributes to the literature on the scarring effects of layoffs as well as to understanding the role of parent income in education. The evidence on the intergenerational effects of parent layoff is mixed (see Mörk et al., 2019, Appendix A, for an overview). Earlier studies on education outcomes show a decrease in graduation year GPA after parent job loss Rege et al. (2011). Oreopoulos et al. (2008) show that Canadian children whose fathers are displaced by firm closures have 9% lower annual earnings in their late-20s/early-30s, while Mörk et al. (2019) (Sweden), Huttunen et al. (2019) (Finland) and Hilger (2016) (US) only find small early-career earnings losses for children. Huttunen et al. (2019) find a shift away from the parent's industry in early employment. We highlight the importance of the exact timing of the layoff event in a child's life.

The remainder of the paper is structured as follows. In section 2 we discuss the Swedish Administrative data and describe the school system. In section 3 we discuss the empirical strategy, section 4 describes the results on high school graduation rates of children and section 5 concludes.

1.1 Introduction: Layoffs

Layoffs are known to have scarring effects on individuals, including reduced long term earnings (Jacobson et al., 1993), worse mental health (Eliason and Storrie, 2009; Browning and Heinesen, 2012) and increased divorce rates (Charles and Melvin Stephens, 2004).

In economic downturns, labor market policy can either focus on firm retention of workers, or generous unemployment insurance. Worker layoff may be necessary for creative destruction, but there may be individual consequences from layoff that justifies retention schemes such as guaranteed paycheck protection loans in the CARES act of 2020. Beyond the known effects of layoff to long term earnings and mental health, the layoff of an individual may impact their family as well.

In this paper, we study family-level impacts by looking at the effect on child education when a parent looses their job. We find that the timing of the layoff matters, and if the event happens to coincide with the transition from primary to secondary school, the child is 10 percentage points less likely to complete high school on time than a peer who didn't experience a parent layoff. Children who are about to make a choice about their future education are much more sensitive than children who are currently enrolled in a program at the time of layoff.

The high school choice determines whether the student gets a vocational degree or prepares for further studies at university. An understanding of how this choice is impacted by increased family-level stress may be useful to understand why it appears that families with less resources do not take full advantage of increased freedom of choice in school settings (see e.g. Hastings and Weinstein, 2008; Gorard et al., 2013; Skolverket, 2003 for discussion).

We use Swedish administrative data individuals in combination with administrative data on education and layoffs. A layoff is defined as a shock to the family that occurs because the firm where a parent is employed is reducing production. We observe all events where a firm notifies least 5 employees at a single location. The use of notification data ensures that the timing of the separation is due to demand factors facing the firm, rather than a bad employer-employee match.

We match families with layoff events to survivor families based on observable demographic characteristics as well as income and industry to match families who experience layoff to families who survive layoff events, either because the firm only does a partial layoff, or because the notification at their firm happened in a different year. Data on all employer-employee matches in Sweden 1986-2015 allows us to identify individuals who are ever connected to a firm that appears in the notification data. We further use data on demographics as well as earnings and unemployment histories to match the control sample to families who experience layoff.

Our empirical approach further adjusts for selection on observables by using the outcomes of older children. Under the assumption that the mean selection effect doesn't vary by the age of the child at the time of parent layoff, we can use the average difference between treatment and control groups of older children to estimate the average selection effect. Consider the high school completion rate at age 19. The treatment effect for children age 20 at the time of parent layoff will be 0, as the event happens after the outcome is realized, and any difference between treatment and control group will be due to selection of families into layoff. As long as the unobservables that drive selection into layoff are constant over child age in the range of interest, this is an unbiased measure of the average selection effect.

We find a significant decrease in the likelihood to finish high school on time, and a decrease in the overall likelihood of ever completing high school. The effect is concentrated to children of age 15, who have not yet started high school at the time of layoff. For 15 year olds, the estimated likelihood of completing high school on time reduces from 64 percent to 54 percent. Some of the loss is compensated by later graduation, but at age 21 (when 98 percent of all graduates have already completed their schooling) this group are still 6 percentage points less likely to have obtained their degree.A delay in high school graduation is associated with a 16 percent gap in earnings compared to on-time high school graduates, while never completing have a 33 percent lower income on average. (Make appendix table from JTB1 01 Sumstats edu)

Several of our results indicate that the layoff interfere with the high school choice itself. The effect is concentrated to families where the job separation occur 1-4 months before the high school choice deadline. The high school applications are due in mid-February of grade 9 (age 16). We find that the effect is the largest for children whose parents' separation date is right before this date. *We also find that the effect is concentrated to the oldest sibling in the family, for whom parental support in education choice might be more important. Effects are* *larger in areas with no local high school, which increases the cost of attendance by requiring longer travel or that the child moves.*

We [will] also describe how the effect varies by the size of the parent's income shock here.

This paper contributes to the literature on intergenerational mobility and the literature on the effect of labor markets on educational choice. First, we add to the mixed evidence on the intergenerational effects of parent layoff (see Mörk et al., 2019, Appendix A, for an overview). Earlier studies on education outcomes show a decrease in graduation year GPA after parent job loss Rege et al. (2011). Oreopoulos et al. (2008) show that Canadian children whose fathers are displaced by firm closures have 9% lower annual earnings in their late-20s/early-30s, while Mörk et al. (2019) (Sweden), Huttunen et al. (2019) (Finland) and Hilger (2016) (US) only find small early-career earnings losses for children. Huttunen et al. (2019) find a shift away from the parent's industry in early employment. Second, the family link adds to our understanding of how educational choice is impacted by the labor market (Oreopoulos et al., 2012; Blom et al., 2015), especially going beyond the binary college enrollment choice (Acton, 2020).

The remainder of the paper is structured as follows. In section 2 we discuss the Swedish Administrative data and describe the school system. In section 3 we discuss the empirical strategy, section 4 describes the results, section 5 makes a fancy selection model and section 6 concludes.

2 Background

2.1 School choice

Upper secondary school in Sweden, like many OECD countries, offer vocational and theoretical programs for children age 16-18 (OECD, 2019). This section describes the details around the choice of high school program.

Figure 1 illustrates the Swedish school system. There are 18 nationally standardized programs which can be either theoretical or vocational. A vocational program provides education in "core" subjects as well as occupation-specific skills, but does not ensure university-level qualifications. Around 30 percent vocational high school graduates do attend at least one year of higher education, compared to 70 percent of graduates with a theoretical degree (XX table).

The choice environment changes across location and over time. Since the school reform in 1992, establishment of privately run schools have changed the market. 53 percent of 15 year-olds in 2000 had access to most[3] nationally standardized programs, 71 percent had this full access in 2010. The average number of schools per market has increased from 9 to 12.5. At the same time, the markets are fewer, meaning more students commute across municipalities to their high school (Fjellman et al., 2019) and the share of potential students who live in a municipality with no school at all has grown from 33 percent to 42 percent (see table 4).

The application to high school programs is due in February, the last semester of primary school (The exact deadline varies by year and municipality, usually between February 1st and February 15th). Students usually apply to 2-4 programs,

[3] 15 out of 18

ranked by preference. Most students who passed the minimum requirement for passing compulsory school are accepted to their first choice, but in the case of limited slots, allocation is based on grades. The preliminary admittance is based on grades in the fall semester of year 9, the final admittance is based on the final grade. National exams, which are important for final grade setting, are administered in Late April and early May, the final semester of grade 9, when students are 16 years old.[4]

A failure to pass necessary subjects in primary school will require the student to finish those subjects before entering high school; an individual program is set up for the student, which may take more than the standard three years (Skolverket, 2020).

2.2 Data

This section describes the Swedish administrative data we use in this paper. We combine individual data with data on family connections and a detail registry of all layoffs.

The notification registry includes ~~data on~~ firm notifications of five or more workers between 2005-2013. By law (Lag (1974:13)), all firms ~~that are~~ at risk of laying off more than five full-time employees in the region must notify the local unemployment agency office 6 weeks to 6 months before termination of employment. The exact timing of the notification depends on the size of the layoff and observe date of notification for the firm as well as termination date for the individuals who are laid off. Firms must report the reason for the layoff at the initial notification date. After negotiation with the union or application of current labor

[4]School classes are based on year of birth, and the academic year runs from August to June. In the rest of the paper we discuss child age in years since birth, abstracting from school grade, as the two definitions overlap

law, the firm also reports the identity of the individuals who are to be laid off, and their termination dates.

Layoffs are driven by a reduction in labor demand. Stated reasons for notifications include plant closure, bankruptcy, reduction in production or changes in the production process. Separations due to worker misbehaviour are not included in this dataset, see appendix section A.2 for a detailed description of the layoff and unemployment process.. While employees facing layoffs are still negatively selected based on observables, the restriction to firm-induced layoffs allows us to argue that the exact timing of the layoff is exogenous to employee characteristics. Figure 16 shows the variation over time in total number of layoffs and the characteristics of the affected employees. Pre-layoff income increases for layoffs after the great recession, while the share of layoffs in manufacturing decreases.

These layoffs are due to firm reductions in production, which is arguably less related to the unobserved characteristics of the marginal laid off employee than unemployment spells observed in the data where the cause is unknown. Furthermore, the exact layoff date and the variation in time between notification and termination gives additional variation in treatment. Table XX shows characteristics of the sample of laid off employees, notified employees and employees who work for a firm with at least one notification event.

Our population of interest are children who may be affected by parents' layoff. Given the time covered by the notification data, we focus on families with children born 1980-1992. This ensures that we can have a balanced panel of child outcomes for children aged 13-23. The panel data follows individuals from age 18 (or 16 if they are employed) and onward. We know the biological parents of the children, and can also observe the household they live in when they first appear in the data. We can also observe whether both biological parents are in the same household in any given year. We observe the highest level of education by year: high school is registered after graduation, college is registered as years of enrollment. Appendix figures XXX shows graduation rates and university enrollment by age for our sample and the population at large. We also see the field/major of the education.

For parents, we observe a longer panel of income and employment. Employer-employee match data allows us to focus on individuals who are employed at a firm with layoff risk. We focus on parent income and industry of employment as matching characteristics, as well as demographic characteristics. Table XXX shows the characteristics of the parents in our sample, as well as in the population at large. This table also shows the matching procedure, which we turn to next.

3 Empirical strategy

To identify the effect of a parent layoff on children's educational outcomes, we rely variation in the child's age at the time of layoff, as well as matching to families who are connected to vulnerable firms. As many educational outcomes are observed only once, we use the panel structure of our data to find variation in time of treatment, not variation in outcomes over time.[5]. Our approach therefore differs from more conventional typical settings where event study methods are used, such as the literature that studies earnings losses from job loss.

This section first describes the empirical setup and the identifying assumptions.

[5]See XXX [Add here references using variation in time of treatment, look at Hilger's paper and find other papers]

Second, we discuss the exact matching procedure and variables used.

We estimate the effect on outcome y_i at child age a_O as a function of the event year of layoff, t_E, a matched set of family characteristics, $\beta X_{i,c,t_E}$, and a set of age-at-treatment fixed effects. *The age-at treatment effect are estimated for intervals of 0.5 (to represent a school semester).*

$$y_{i,a_O} = \sum_{a_E=13.0}^{a_E=25.5} \delta_{a_E} \mathbf{1}_{[age_i=a_E]} \mathbf{1}_{[Layoff_{i,t_E}]} + \tau_c + \gamma_{t_E} + \beta X_{i,c,t_E} + \varepsilon_{i,c,t_E} \quad (1)$$

Equation 1 may look familiar, but we want to emphasize that this is a crossectional regression. The outcome y_{i,a_O} does not vary over time relative to treatment, but is fixed in the outcome age a_O. In order to observe how stable the outcome is overtime we estimate separate regressions with different y_{i,a_O}s. The δ_a estimates are normalized to 0 at age $a_E = a_O + 1$, but the age estimates vary over a_E, the age at which the event occurred.

If $a_E > a_O$, the impact of the event on the outcome must be 0, as the cause precedes effect. We use this to argue that any observable difference between the treatment and control group for $a_E > a_O$ must be driven by selection into treatment.[6] The older children therefore serves as an additional control, accounting for any potential selection on unobservables. Under the assumption that any unknown family traits which affect selection into layoff are unrelated to the age of the child at the time a potential layoff occurs, the average difference between treatment and control will be constant over age. Hence, we can estimate

[6] In this respect, our setting is therefore similar to Chetty and Hendren (2018), who estimate the effects on children's outcomes of being exposed to a better neighborhood by exploiting variation in the age at which families move between commuting zones. Similarly to our setting, they can use children whose families move *after* the age at which outcomes are measured to gauge selection on unobservables (see Chetty and Hendren, 2018, Section III).

the average selection effect from the older cohorts.

$$\sum_{T_0}^{26}(\delta_{a\ \text{Layoff=1}} - \delta_{a\ \text{Layoff=0}}) = \bar{\xi}$$

This approach is symmetric to normalizing the difference between the treatment and control group to 0 in $t-1$ in order to control for any time-invariant unobservable differences between the groups in a difference-in-difference approach. The adaption of the classical assumption in this case is that any unobservable difference between treated and control families are constant across child age.

3.1 Matching

We currently do an exact matching over family characteristics. In addition to matching on the gender and birth year of the child, the variables included are parent age (in 5-year groups) gender, parent income ventile and 2-digit industry group. The sample which is used to find the exact matching is only based on individuals who are employed in a firm which has at least one layoff event 2004-2013. This adds an additional variable to the matching, as all individuals in the sample face some layoff risk.

We are currently matching on parent characteristics when children are 13 in order to avoid any match in post-treatment age. This means matches are likely to be worse for children who are older at the event date. I will check the robustness of my result by matching based on a fixed time relative to the layoff event.

Table 1 Shows the summary statistics of the layoff group and control group without matches, with our current match (match 3) and with some additional characteristics (match 7) We are currently revisiting our matching variables.

3.2 Fixed effects

The time fixed effects capture the changing composition of the laid off population by year. The average unobserved quality of the laid off worker is higher in recession-time layoffs than in layoffs which occur when the economy is stable (Hilger, 2016). The inclusion of families with older children allows us to capture the year effect. The cohort fixed effects capture the change in educational attainment by cohort.

3.3 Identifying Assumptions

Our empirical strategy exploits variation in children's age at the time of their parents' layoff. More formally, our identification requires that be orthogonal to XXX conditional on XXX, or

4 Results

- Main figure
  - This figure shows the estimated difference between treatment and control group.
  - Effect for students in the three semesters leading up to the transition
  - Students already enrolled in high school are not less likely to complete after parent layoff shock.
  - Test joint significance of all high school years - refer to table
  - long-term robust
- The drop is caused by a modest reduction in parent earnings

- First stage figure
- Impact including UI benefits
- Size of effect is constant across child age at the time of layoff

- The effect is sizable, but limited in time
  - the expected earnings of high school graduates after graduations are XX percent higher per year in ages 20-30
  - 48 percent higher for the relevant sample during the first four years after graduation.
  - Alternative cost of schooling negative.
  - Selection. Alternatively internship opportunities for vocationally-affiliated schools. Informal employment unobserved.
  - Elasticity of children's earnings to parents earnings
  - Again, this is only in a particular age band
- Mechanism: Transition to upper secondary school
- School choice
  - The application deadline to high schools is in February, age 16.
  - Use variation in the exact timing of layoff to identify differential impact of stress at time of high returns to parent involvement - school choice.
  - Figure xx shows drop in long-term outcome for treat relative to control for layoffs 4 to 0 months before application deadline
  - Inconsistent with updated information on labor market - everyone pre-application would change behaviour.
- Grades

- We do not observe grades directly.
- Grades could be affected (Rege et al., 2011).
- We do not find evidence that grades matter in the long run, no effect of layoffs close to final exams.
- Passing grades: matter for time to completion,
- Choices not competitive in grades: figure on distribution of grades over options, beyond passing grades.
- Timing of grades: Final exams in April and May, age 16.

Intro section. 1 describes the first stage - the impact on la

4.1 Parental layoff and earnings

The first stage in the inter-generational transmission of a layoff shock is to understand how parents are affected. In this section, we document the short and medium term effects of layoff on individual earnings and unemployment. We show that insecurity about the future earnings increase, and we interpret a higher level of uncertainty as an important effect of the layoff. The effects on parents do not vary by the age of the child.

Labor earnings for parents experiencing layoff drop by 20 percent relative to the control group, and the gap remains economically significant even 7 years after the layoff, see figure 2a. As explained in section 2.2, we define a layoff as a termination of employment induced by the employer due to a reduction in labor demand at the firm. Layoffs do not necessarily lead to unemployment, as there may be sufficient time between notification and termination date for the employee to find a new job. Figure 2b shows that only 50 percent of parents affected by layoff register as unemployed in the following year.

Conditional on unemployment, annual labor income falls by almost one third in the year after layoff, see figure 2c. Unemployment insurance covers up to 80 percent of pre-unemployment income, which is reflected in the disposable income in figure 2d. Unemployment insurance coverage is not automatic, and the coverage ceiling is fixed in nominal terms over the entire period of interest. See appendix A.2 for an explanation of UI benefits and severance pay.

In addition to a decrease in expected disposable income due to unemployment or a worse match with the next employer, the variability of earnings increase at the time of layoff. Appendix figure XX shows the increased range of income after layoff. Two years after the employment shock, disposable income is lower than pre-layoff for 75 percent of the sample, and the spread between the 25th and 75th percentile increase by 50 percent 7 years after layoff, compared to 2 years before.

We will refer to this combination of a spike in probability of unemployment, a moderate drop in expected future earnings in both the short and the long run and an increase in variability of earnings as economic insecurity. As with other papers on employment XXXXXXXXXX, we expect this to increase stress and decrease time devoted to childrens'education. XXX paper on mental health and inequality - relative positions

This increase in economic insecurity does not vary with the age of the child. As discussed in section 3, this is a key assumption for identification. Figure XXX shows the layoff probability over child age, controlling for event year and parent age. A linear specification fails to reject the null hypothesis that the age of the child is uncorrelated with the likelihood of parental layoff. Given layoff, the income paths of parents do not vary by the age of the child at layoff (see appendix figure XX)

4.2 Effect on child high school graduation rates

The impact of parent layoff on child graduation rates are concentrated to layoffs that occur up to three semesters before the transition to high school. Figure 4 shows the estimated age-semester effect on the graduation rate of children with family layoffs relative to children in survivor families in the same age-semester. The x axis is reversed, showing the age at time of layoff by semester from age 25 to age 13. Children who are younger than 20 (white region) at the time of parent layoff experience the family shock when they are still enrolled in high school or primary school. Children who are 20 or older (grey region) have already completed high school by the time their family is hit by the shock, serving as an additional control group. Parental layoff prior to child high school enrollment have a significantly negative effect on the eventual graduation rates of the children. The impact on high school graduation rates for students in the semester prior to compulsory school graduation is large, decreasing the expected on-time graduation rate from 73 percent for students with no family shock to 58 percent for students who experienced a parent layoff at this time in their school life. Students already enrolled in high school at the time of parent layoff (age 16.5 to age 19) were not significantly less likely to complete high school than their peers, see table 2 for the joint significance test for students of high-school age.

To drop out of education without a completed high school degree is associated with large, long-term negative effects on earnings. In our sample, earnings are up to 48 percent lower for dropouts compared to high school graduates in the first years out of high school, see table 2. Earnings of dropouts in the population follow a parallel income path to high school graduates at 60 to 75 percent of earnings up until at least age 30, and never catches up completely (See appendix section A.1 for a detailed description of earnings by education level).

Children who did not graduate at age 19 may still be able to graduate high school later, in which case the economic impact would not be as severe. Our estimates, however, are robust to looking at graduations as of age 21, allowing for two years of repeat grade or complementary education to finish primary school. Figure XX shows graduation rates by age 21, when 98 percent of all individuals who will ever complete high school have graduated. Even here, we find a drop in graduation rates of 9 percentage points for students in the last two semesters of compulsory school. Even a delay in graduation age (i.e. someone who has finished by age 21 but not by age 19) signals lower educational achievement than on-schedule graduation.

There is no effect on the graduation rate from academically challenging degrees. Figure XX shows the graduation rates for scientific degrees unaffected by parent layoff for all ages. This degree is usually attended by highly motivated students.[7] Panel B shows a small drop in graduation from theoretical degrees for children affected at age 15, but the variation is large. Graduation rates from vocational degrees are depressed for students who are about to start their high school and already enrolled students (see panel c). XX parental involvement and motivation is more important for students on the margin, BRITTS XX.

In addition to student variation in sensitivity to parent involvement, we also observe that the effect is larger for households who are already experiencing more economic insecurity. We find that the effect is concentrated to households with more pre-layoff economic insecurity. The estimates are larger for children in below-median household income XXX FIG XXX and for households where the laid off father is the single earner XXX. No monotonic relationship

[7] Note that we do not observe grade enrollment in real time, only after graduation. Hence, we do not know which program dropouts enrolled in, if any.

between estimates and size of earnings loss, which is consistent with the idea that uncertainty is the driver.

We do not find any evidence that children drop out of school to find employment to support family income. In addition to the lower expected earnings later in life, children who do not graduate high school are not earning more than their peers in age 16-19.[8] Figure XX shows the estimated effect on the cumulative earnings in the late teens by parent layoff. We find no significant impact, but point estimates are noisy due to the low share of teenagers with observable income in our sample. In the population, those who will not get a high school degree by age 19 earn less from age 16 than those who will. Employment during high school can be facilitated through vocational program internships, increasing the teenage earnings of students in vocational relative to theoretical high school tracks. See appendix A.1 for more details.

summarize: large effects, big consequence. Economic uncertainty at the time of layoff, not the realized effect on earnings. Note: we do not observe short-term shocks (income at annual level)

4.3 Transition to high school: Mechanisms

Despite the modest impact of layoffs on parental income, we find large effects on high school graduation rates for children who have not yet entered high school at the time of parental layoff. We find that the impact doesn't vary by the size of the income shock, but that academically strong students are insulated from the shock. Now, we turn to the driver of the sizable effect for this particular

[8] Note that high school dropout is defined as the absence of high school graduation, therefore students who are still attempting to complete their degree but fail to ever pass the minimum number of classes required will be considered dropouts. This will not allow for time to seek outside employment.

age group.

There are two potential reasons why the transition between compulsory school and high school can be a vulnerable time in the student's education path. First, consider the effect of enrollment on completion rates. Schools are incentivized to help struggling students in their programs to completion, but not to take on new students who do not appear to meat their academic standard. Hence, a shock to academic performance prior to high school enrollment may lead to students not getting into their preferred school or re-take requirements prior to enrollment. Second, consider the high school choice. As described in section 2, the choice of high school requires knowledge of the expected labor market return to at least 15 different education tracks as well as individual schools. This is a family-level decision with a high degree of parental involvement (kalla XX). Not having sufficient information and parental support can lead to a suboptimal school choice which decreases the child's likelihood of graduation. As high school is not mandated by law, teenagers with a higher discount factor may even take this opportunity to not apply to any schools at all.

We first differentiate between these two channels by considering the exact timing of the parental layoff relative to the child's school calendar. We focus on two important dates in the last semester of compulsory school: the high school application deadline in early February and national exams in the second week of May.[9] The February and May deadlines correspond to the school choice and academic shock channels, respectively.

Figure 7 shows the difference in high school graduation rates between families with and without parental layoff by the exact termination date associated with

[9]The exact test dates and application dates vary by school year. We use February 1st as the application deadline, as the historical application dates have varied between February 1st and Feruary 16th. Similarly, we use May 1st as the relevant cutoff for national tests, which are an important factor in final grades.

the layoff. We fit a nonparametric estimate of the change in outcome by age at time of layoff, allowing for an interruption in the time series in February (panel a) and May (panel b) respectively. Layoffs right before the school choice deadline in February lead to significantly lower graduation probabilities for children than layoffs with termination deadlines after February, see panel 7a. The estimated effect is robust to a wide range of bandwidths for the nonparametric estimate, see appendix figure. The nonparametric specification and optimal bandwidth follows Calonico et al. (2014).

There is no significant effect around the national exams. Rege et al. (2011) finds a negative effect on final grades at age 16 in a similar setting in Norway. As we do not observe grades directly, we cannot reject any effects on grades following layoffs around May in the last semester of compulsory school, but we do not find any medium run effects of shocks close to the final exams, which partially determine grades.

The significant effect of layoffs before February suggest that increased economic insecurity in the family affects children's graduation rate by diverting parent attention at the time of school choice. The point estimate at the February cutoff is robust to a wide selection of bandwidths (see appendix figure 18) and inclusion of controls (see table 3). We also find that the density and distribution of layoff characteristics and pre-layoff covariates is smooth over the cutoff, see appendix B.1.

We find that the estimated difference at the cutoff is larger for parents with a binding termination date. As the time between the first individual notification and the termination date can be several months, it is not necessarily binding for all parents. If you have already managed to secure a new job prior to your termination date, you might actually have more time to help your child with their education than in the absence of a layoff. Figure fig: 8 shows the result for parents who transition from the employer who laid them off to registered as unemployed. For this sample, we know the termination date is binding, as they have not found new employment before termination. The estimated effect for families with their first unemployment date the day before the high school application deadline is 16 percentage points, similar to the aggregate effect for students with a parent laid off at age 15.5.

~~What can we say about temporary distraction relative to parent change in fundamentals~~

~~Neil: parents who are unemployed in pre layoff period up until deadline?~~

~~4.4 Not ITS mechanism sketch~~

The results from figure 7 are consistent with a model of limited parental time with differential returns to parent involvement depending on the school activity. After the layoff is announced, the parent will need to devote more of her leisure time to job search, which will decrease the time available to engage with children's schooling. Increased stress due to the economic insecurity may also have a negative impact on the quality of parent involvement, holding time constraints fixed. See and Gorard (2015) Identifies two mechanisms through which parent involvement affect children's educational outcomes: improved learning and aligned expectations. Involved parents can function as teachers to directly improve learning. They may also reinforce the school's message about the expectations about for example student behavior and the importance of going to school. In our case, parental involvement in the high school choice may be important to communicate the importance to go on to high school (which is voluntary), as well as expectations about what kind of track would be acceptable. Parents may be better suited than teachers to help students understand their individual return to different schooling options. In order to credibly be involved, parents need to be informed about the current state of the high school market.

Information costs for the high school choice are high (Skolverket, 2003). In the average high school market, there are 10 different schools to choose from in 2005, 16 different schools in 2013 (see appendix table 4). Schools advertise themselves to prospective students and their families primarily through visiting days outside of regular office hours - meaning unemployed parents have no time advantage.

We proxy for the family's knowledge about the high school choice using the sibling order of the child whose high school choice is impacted. Given the nature of knowledge, the cost of gathering information is going to be highest the first time a choice is made. Repeat choices may require some updating, but we assume that families don't unlearn over time (Chetty et al., 2013). Therefore, the cost of parent involvement in the high school choice of the oldest sibling is going to be higher than the cost for younger siblings.

Figure XX shows the estimated effects for the oldest (or only) child in the family (panel xxa) and younger siblings (panel b). For older siblings, we estimate a clear negative effect of parental layoff prior to high school choice. For younger siblings, the estimates are more noisy, but the point estimate at age 15 is only 1/3 of that for older siblings, and not statistically different from 0. They are XXX different.

We know school choice is important - why is this costly to parents? Investigate information costs and actial costs

Proxy for information - siblings

sibings figure - separate

test joint significance for each 16, 15.5 15 variable.

real costs - commuting costs/moving costs. Approximate with no school in muni in year

re-visit number of schools - inverse u-shape nice. other information cost.

5 Old results

This version of the paper only discusses the outcome of high school completion. For more details on the next steps of the paper, please refer to the slide deck *Tanndal Aug 24*.

5.1 High school results

Figure 4 shows the estimated effect of parent layoff on on-time high school completion. The x axis is reversed, showing the age at time of layoff by semester from age 25 to age 13. Children who are younger than 20 (white region) at the time of parent layoff experience the family shock when they are still enrolled in high school or primary school. Children who are 20 or older (grey region) have already completed high school by the time their family is hit by the shock, so they serve as an additional control group.

If treatment occurs at age 20 or above, there can be no effect on high school completion by age 19. Any difference in age 19 high school completion between children who experience parent layoff when they are in their 20s and children who don't is attributable to selection, and we normalize the difference to be 0 at age 20. For children who are older than 20 at the time of layoff, we do not observe any significant difference or age trend. The children who are older at time of layoff serve as an additional control, similar to a pre-treatment trend in a difference in difference approach.

The effect of parent layoff on high school completion depend on the exact timing of the layoff relative to the child's school career. While children who are already well enrolled in high school (age 17-18 at time of layoff) do not seem to be affected, children who are in the transition from compulsory schooling to high school (age 15-16) are significantly less likely to complete their degree on time than their peers whose families don't experience a layoff.

A parent layoff that happens when their child is age 15 decreases the likelihood of on-time high school completion by 10 percentage points, or from 75 to 65 percent. *Discuss size.*

The same pattern holds if we look at a more robust measure of high school completion. 84 percent of all high school graduates finish on-time at age 19. There are several reasons a student may finish at a later age, such as grade retention, foreign exchanges and gap years, or having to attend an individual (longer) program in order to obtain complete primary school degree. By age 21, 98 percent of all graduates have finished (appendix table/figure 10). Figure 5 shows the estimated likelihood of having at least a high school degree by age 21. Even in the long run, we observe a significantly lower likelihood of finishing high school for children who experience family layoff at age 15.

Daughters appear to be more negatively impacted than sons, see table 2.

The transition between compulsory and high school changes the nature of schooling in three different dimensions. First, the student now has to make a choice about what school and what program she wants to attend. Second, the grades from primary school matter, lower grades may prevent you from getting into your most preferred school or program. Third, schooling is no longer compulsory, allowing the student to drop out completely. See section 2 for a detailed explanation of the high school choice. The exact timing of the layoff may be informative about the mechanism through which parent layoff affect children's high school performance. Figure 7 plot the outcomes the exact date of layoff. Grades reflect the performance throughout grades 8 and 9, so any layoff in this time period (between the dotted lines in the figure) could impact this. The high school application is due around February 15[10], the solid line in the figures.

We estimate the high school completion by parent layoff date nonparametrically, allowing for a time series interruption at the high school application deadline. We follow Calonico et al. (2014) to find the optimal bandwidth, treating the application deadline as a regression discontinuity. Appendix figure 18 shows robustness to different bandwidths. The estimated immediate impact of an after-deadline layoff is similar to the estimate for 15-yaer-olds in the baseline specification. This suggests the family shock impacts the high school choice, not final grade. We will investigate this directly.

This is it so far. Please refer to the slide deck Tanndal Aug 24 for an update on the work in progress and next steps.

High-commitment high school programs are not affected. Figure 6a and 6b contrast the change in completion rate for theoretical, scientific programs, where

[10]The exact date vary by municipality and year

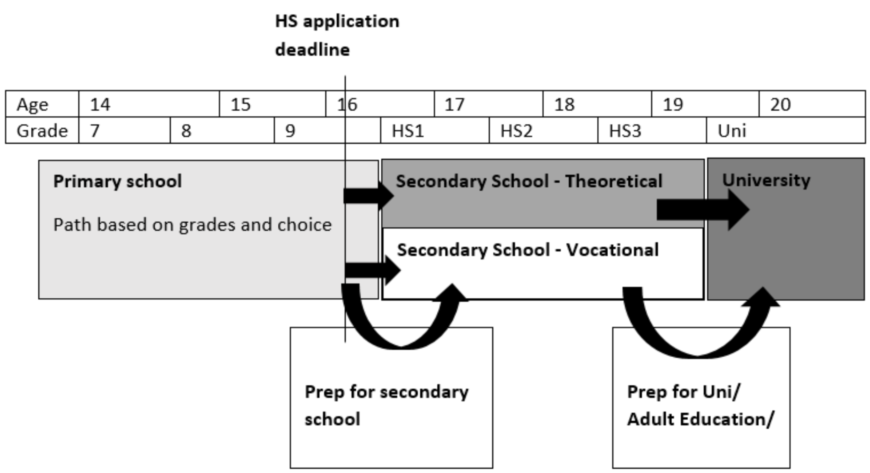
we do not see any change, to the significant drop for vocational programs. *XXX Stats that Scientific programs are more likely to lead to uni, and have higher entry GPA requirements.*

Things to add

- Correct RD stuff for ITS figure
  - Econometrics: Calculate the correct approach to re-weight in ITS
  - Alternative, nearest neighbor
  - Balance table
  - Robustness with respect to bandwidth and number of
- Single- earner vs two-earner households (have done in bix at some point)
- Pre-layoff earnings: below/above median
- Information: Sibling comparison
- test if age 15 significantly different between siblings? Jointly different
- Cost: better measure of travelling cost? include?

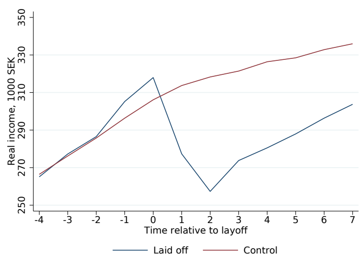
6 Figures

Figure 1: Schooling in Sweden

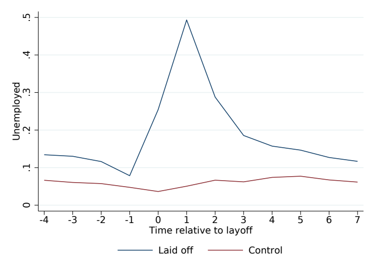


Notes:

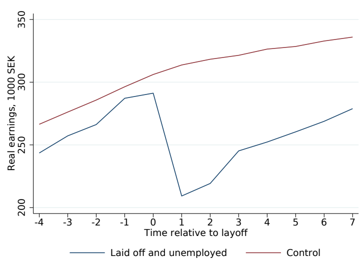
Figure 2: Layoff and Parent outcomes



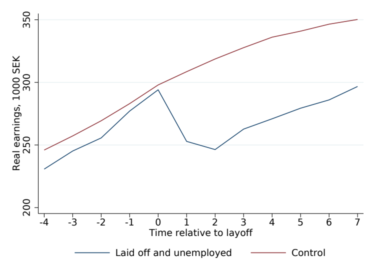
(a) Labor income, time to layoff



(b) Unemployment , time to layoff



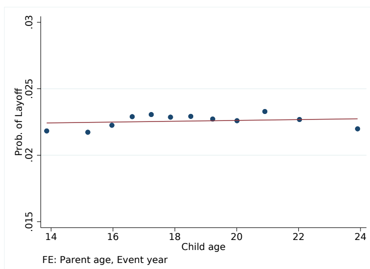
(c) Labor income - conditional on unemployment



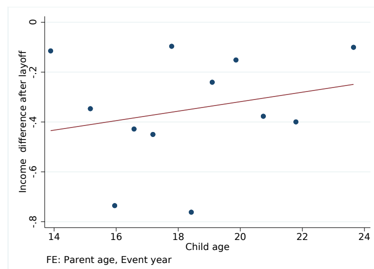
(d) Disposable income - conditional on unemployment

The treatment group is defined as individuals who appear in the layoff data with a termination date in year 0. In panel (c) and (d) the layoff group includes only individuals who experience unemployment following layoff. The control group is weighted according to the procedure described in section 2.2. Disposable income includes unemployment benefits and labor income. Income is measured annually in 1000s of 2010 SEK.

Figure 3: Parental outcomes by the age of child at time of potential layoff



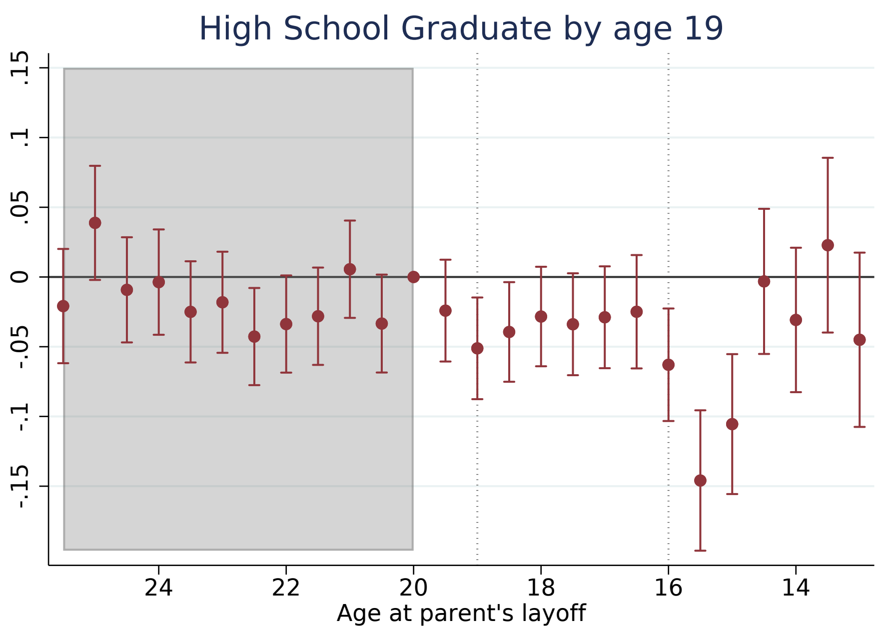
(a) Likelihood of parental layoff by child age



(b) Parental income shock conditional on layoff, by child age

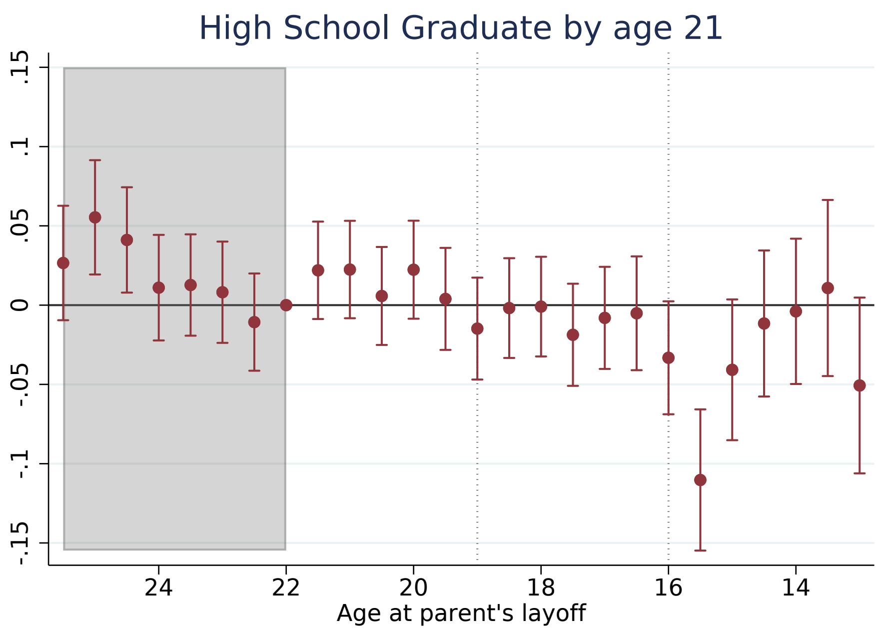
Panel (a) shows a binscatter of the likelihood of unemployment in the sample of parents connected to firms in the notification register. Conditional on parent age and year of layoff, twe cannot reject the null hypothesis that there is no linear relation between child age and parent layoff probability. The 95 percent confidence interval on the linear coefficient is (-.0000458 .0001079) with a p-value of 0.428.
In panel (b) the outcome of interest is parental earnings loss after layoff. Earnings loss is measured as the average share of income earned in the two years folowing layoff, relative to pre-layoff income. Again, the binscatter shows no significant correlation between the size of the income shock and child age, conditional on parent age and event year. The 95 percent confidence interval on the linear coefficient is (-.0693986 .031357) with a p-value of 0.459.
See appendix table XX for the full specification

Figure 4: High school completion by age 19



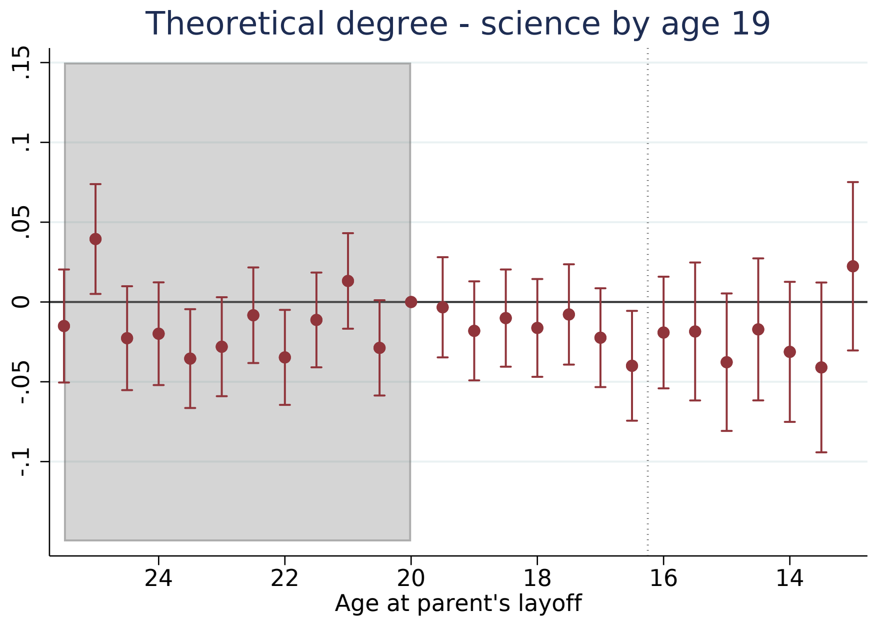
Notes: This figure shows the estimated impact of parent layoff on child on-time high school graduation rate by the age of the child at the time of parent separation. The parameter estimates are $\delta_{a\ \text{Layoff}=1} - \delta_{a\ \text{Layoff}=0}$ from equation 1 for age at parent layoff $a \in (13, 25)$ normalized to 0 at $a = 20$. The regression include cohort and event year fixed effects and are run on the matched sample. The outcome, high school graduation at age 19, is measured as 1 if the child's highest education 19 years after birth is a completed 2- or 3-year high school degree or higher, and 0 otherwise. 84 percent of all students who will graduate high school have graduated by age 19.

Figure 5: High school completion by age 21



Notes: This figure shows the estimated impact of parent layoff on child high school graduation rate by the age of the child at the time of parent separation. The parameter estimates are $\delta_{a\ \text{Layoff}=1} - \delta_{a\ \text{Layoff}=0}$ from equation 1 for age at parent layoff $a \in (13, 25)$ normalized to 0 at $a = 22$. The regression include cohort and event year fixed effects and are run on the matched sample. The outcome, high school graduation at age 21, is measured as 1 if the child's highest education 21 years after birth is a completed 2- or 3-year high school degree or higher, and 0 otherwise. 98 percent of all high school graduates have graduated by age 21.

(a) Scientific grade completion by age 19



(b) Scientific grade completion by age 19

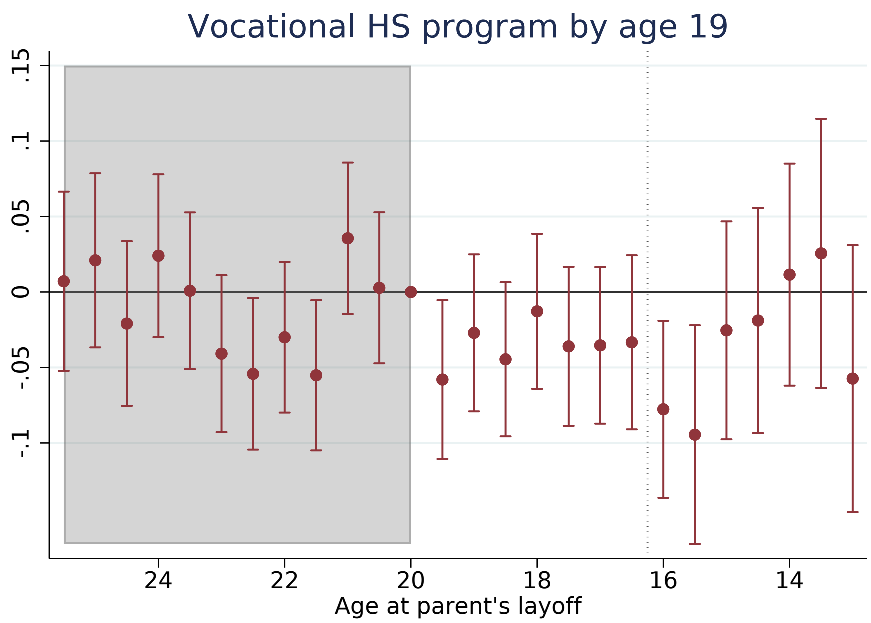
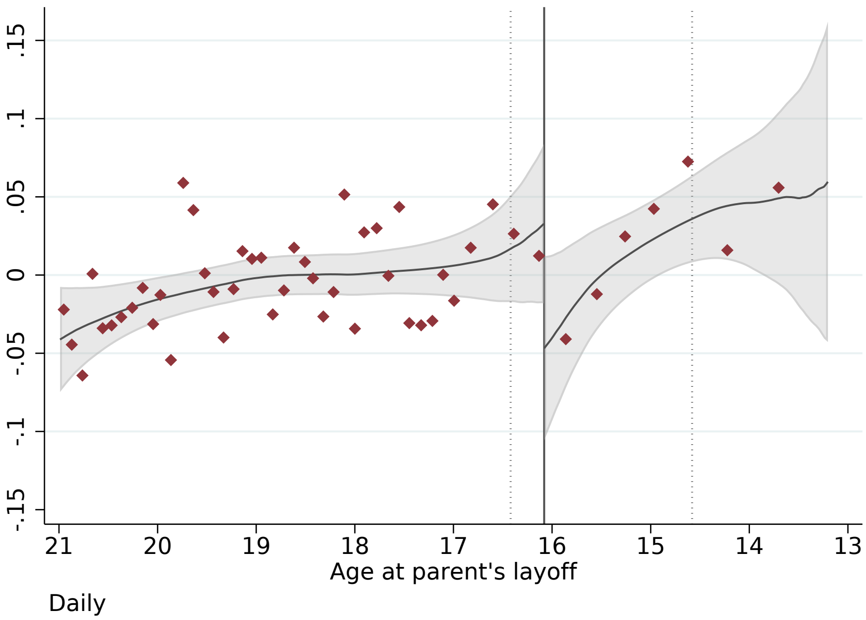
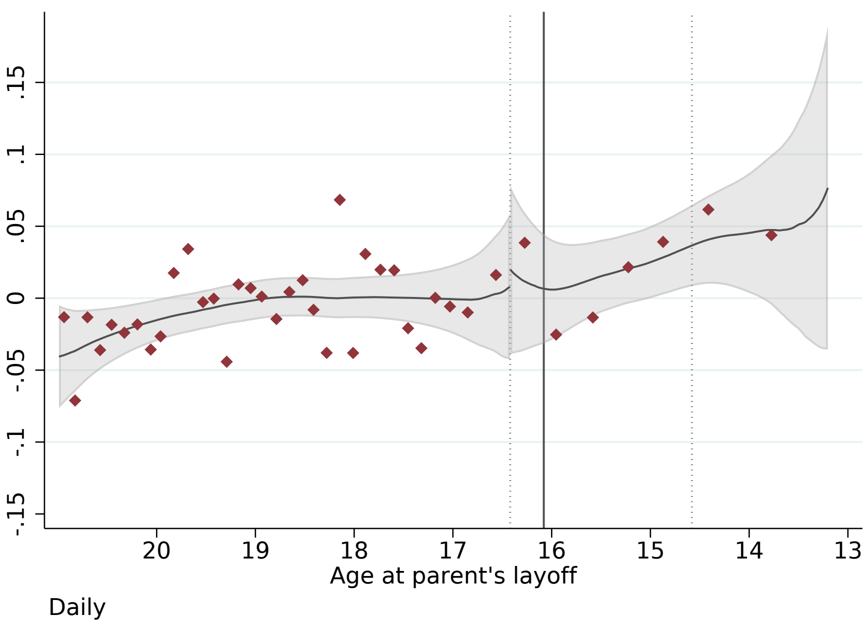


Figure 7: High school graduation rate by separation date



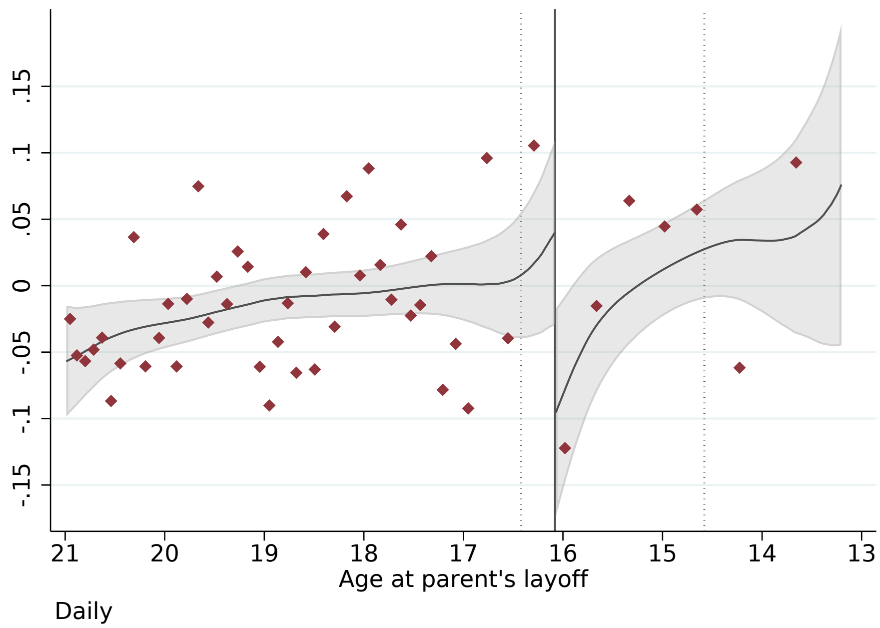
(a) Time series break at high school application deadline



(b) Time series break at Primary school final exams

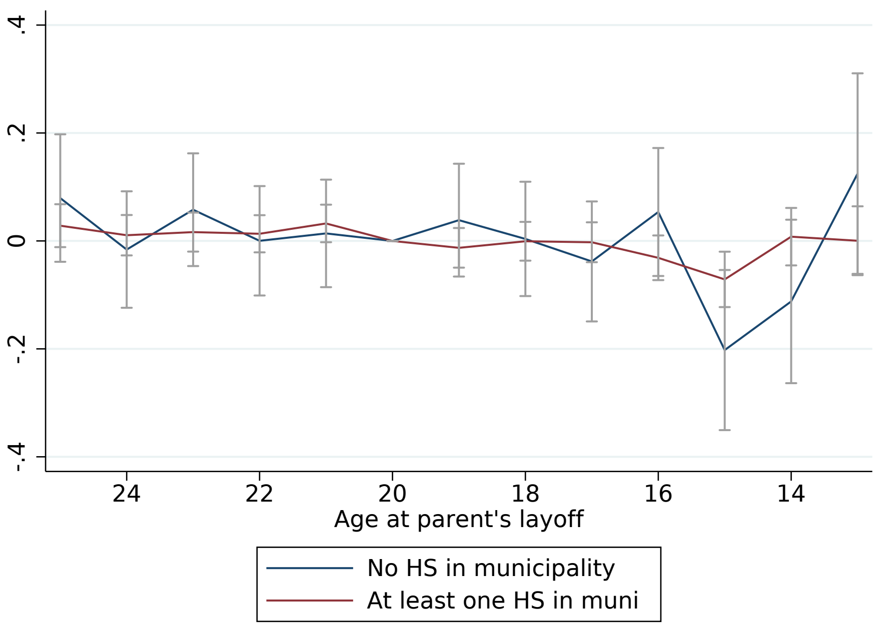
Notes: This figure shows the differential impact of parent layoffs around the time of high school applications (panel a) and compulsory school final exams (panel b). The estimated effect at the cutoff is robust to a wide selection of bandwidths, see appendix figure 18.

Figure 8: High school graduation rate by first day of parent unemployment



Notes: This figure shows the differential impact of parent layoffs around the time of high school applications for parents who experience unemployment subsequent to their termination date. The bandwidth is chosen to be MSE optimal at the interruption time using the method of Calonico et al. (2014), following the standard for regression discontinuity designs.

Figure 9: Local school availability



Notes:

7 Tables

Table 1: Summary Statistics

	(1) Layoff	(2) Control group	(3) Layoff weight 3	(4) Control weight 3	(5) Layoff weight 7	(6) Control weight 7	(7) Pop. >30yo
Female	0.285	0.282	0.237	0.237	0.176	0.167	0.485
	(0.451)	(0.450)	(0.425)	(0.425)	(0.381)	(0.373)	(0.500)
Income	2603.7	2999.4	2832.9	2864.3	3165.7	3203.8	2364.5
	(1636.3)	(2088.3)	(1714.8)	(2022.4)	(1914.5)	(2193.4)	(2072.6)
Household	3946.3	4481.5	4134.0	4255.9	4442.2	4555.2	3529.5
income	(2373.4)	(2815.5)	(2369.1)	(2664.8)	(2513.6)	(2808.5)	(2880.9)
Age	40.92	41.47	40.93	40.95	41.00	41.01	39.40
	(5.000)	(4.912)	(4.509)	(4.470)	(4.197)	(4.147)	(6.712)
Married	0.620	0.656	0.622	0.638	0.640	0.640	0.526
	(0.485)	(0.475)	(0.485)	(0.481)	(0.480)	(0.480)	(0.499)
Unemployed	0.115	0.0467	0.0888	0.0558	0.0546	0.0358	0.104
	(0.318)	(0.211)	(0.284)	(0.230)	(0.227)	(0.186)	(0.305)
Highest ed:	0.535	0.511	0.540	0.549	0.577	0.592	0.392
High school	(0.499)	(0.500)	(0.498)	(0.498)	(0.494)	(0.491)	(0.488)
Highest ed:	0.135	0.176	0.140	0.135	0.0953	0.0928	0.325
University	(0.341)	(0.381)	(0.347)	(0.342)	(0.294)	(0.290)	(0.468)
Manu.	0.431	0.476	0.433	0.433	0.467	0.470	0.211
	(0.495)	(0.499)	(0.495)	(0.495)	(0.499)	(0.499)	(0.408)
N	29032	868136	19704	89471	8239	13260	7835166

Table 2: Results for population subsets - gender

	Baseline	Men	Women	Fathers	Mothers
layoff_event = 1	0.00668	-0.00387	0.0205***	0.00247	0.0226*
	(0.00542)	(0.00724)	(0.00784)	(0.00615)	(0.0116)
In Grade 8 or 9	-0.0602***	-0.0400*	-0.0857***	-0.0605***	-0.0585**
(Age 14.5-16)	(0.0152)	(0.0207)	(0.0215)	(0.018)	(0.0286)
In High school	-0.0162*	-0.018	-0.0148	-0.0200*	-0.00649
(Age 16.5-19)	(0.00905)	(0.0122)	(0.0129)	(0.0104)	(0.0186)
Constant	0.637***	0.599***	0.686***	0.645***	0.609***
	(0.00427)	(0.00574)	(0.00611)	(0.00483)	(0.00903)
Observations	223,119	126,664	96,455	135,247	87,872
R-squared	0.011	0.016	0.018	0.012	0.03
FE:	cohort-year	cohort-year	cohort-year	cohort-year	cohort-year

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Binary outcome - younger than 14.5 dropped

Table 3: Interrupted time series estimates of effect of layoff pre application deadline

VARIABLES	(1) Graduation	(2) Graduation	(3) Graduation	(4) Graduation Parental unemployment
RD_Estimate	0.10504**	0.09568*	0.09566*	0.235***
	(0.0431)	(0.05172)	(0.05171)	(0.0829)
Effective Observations Pre	703	473	473	289
Effective Observations Post	1218	663	663	375
Bandwith (MSR)	1.20	0.747	0.747	0.815
Cohort-year FE	No	Yes	Yes	No
Control weights	No	No	Yes	No

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: We follow Calonico et al. (2019) to estimate the optimal bandwith and robust confidence interval for the point estimate at the time series interruption as if it was an RD with controls. We use cohort-year dummys as controls. In the third column we include the control group to be able to allow for re-weighting, but this only has a marginal impact on the estimate. Column 4 is specified as column 1, but only for parents who experience inemployment after layoffs.

A Data

Here we can put details about data and summary statistics.

A.1 Earnings by education level

Individuals with less than a high school degree in our data earn significantly less than graduates. Figures 12 (a) to (h) show the income paths for selected cohorts by highest degree in 2015 (the last year of observation). The sample is restricted to native-born individuals with a known level of education. The earnings path for high school dropouts is parallel to the path for high school graduates for all cohorts, both in mean and median earnings, until at least age 30. Dropouts earn on average less than 70 percent of a high school graduate's earnings up to the age of 30.

Figure 13 shows the earnings by education for the same cohorts, focused on earnings age 16-20. Dropouts earn less than in-school peers, even during the school years. Official unemployment surveys show that youth unemployment[11] in Sweden has been 15-25 percent since 2001. Among 15-19 year olds in the labor force, the unemployment rate is 22-37 percent for the same time period. This relation is driven by selection or negative opportunity costs of going to high school. A vocational school may facilitate connections to employers in their vocation, offering higher-paid job opportunities than to those who've left school. We do not observe the time of dropout, therefore it is possible that some share in the dropout group are students who attempt to graduate but fail to meet minimum requirements. Note that informal jobs will no appear in this administrative dataset.

[11] Individuals aged 15 to 24

A.2 Layoffs

The register data on layoffs in this paper comes from firms reporting notifications to the public unemployment authority (Arbetsförmedlingen). According to Swedish law (1974:13), firms that plan to lay off five or more full-time employees are required to report this to the local UI office. The minimum notification period varies by the size of the layoff. The reason for layoff needs to be specified in the report, ensuring that layoffs are initiated because of a reduction in labor demand at the firm. Initially, the firm has to report the number of individuals getting laid off. After negotiations with the unions are finished, they also need to report which employees are affected.

Who gets laid off is determined by last-in first-out laws, but can in practice be rounded by negotiations over severance pay. An employee is categorized as laid off if she is registered as subject to layoff and we observe her termination date, but we do not require her to actually register as unemployed. Hence, there may be selection into layoff, as mediated by the laws and union negotiations, but we do not condition treatment status on being unable to find a new job after the initial shock.

To receive UI (Unemployment insurance) benefits, the laid off worker needs to have been a member of a UI insurance fund (A-kassa) for at least a year prior to their termination date, and have run out of severance pay. (Any severance payment sum is calculated to wage equivalents based on the last monthly wage prior to layoff.) Hence, we do not expect all layoffs to appear at the UI office. In the data, around 50 percent of everyone experiencing layoff is registered at the UI office the year after layoff, see figure 14c. If eligible, UI benefits are 80 percent of earnings up to a ceiling. The ceiling is determined by law, holding it fixed in nominal terms 2002-2014. In 2005, the ceiling was at roughly median earnings.

The average drop in real earnings following the layoff is not very large, but has a permanent effect on earnings. Figure 14 shows the evolution of mean earnings over time relative to layoff for the treatment and control group, including 14b and excluding 14a UI benefits. Unfortunately, we cannot separately observe severance pay from labor earnings, and there appears to severance payments in the year after layoff as well as in the layoff year. Earnings drop by 15-20 percent 2 years after layoffs relative to pre-layoff earnings. 7 years after the shock (in a balanced panel), earnings are still 10 percent lower than in the control group.

Characteristics of the laid off population varies by year of layoff. This is to be expected as recession layoffs are going to be less adversely selected than layoffs in years when the business cycle is more favorable. Figure 16 shows the pre-layoff earnings, household income and share of layoffs in manufacturing over the time period.

Unemployment

B Additional results

B.1 Interrupted time series

We use the exact termination date specified in the layoff to estimate the time series - explain method.

Age in days are calculated as the difference in days between the termination date in the parental layoff and January first of the birth year of the child. As education cohorts and birth year cohorts are identical, Age at parent's layoff tells us where in the school system the child is if she followed the normal path of schooling.

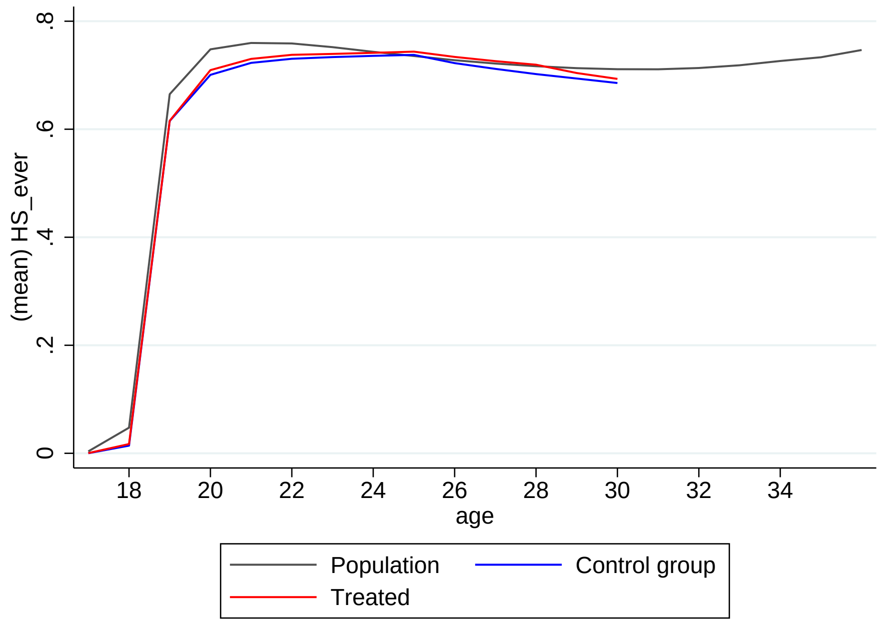
Figure 17 shows the raw data on graduation rates by time of parental layoff. Panel A groups the data into equally-sized bins over the age-date distribution, panel B shows the monthly discrete bins. The pattern is qualitatively similar to that in figure (ITS main). In order to ensure that figure (ITS main XXX) is comparable with figure **??**, we calculate the layoff probability relative to the control group within each weighting cell, and include only the treated families with valid matches.

Figure 18 shows the robustness of the point estimates with respect to the bandwidth of the nonparametric estimate. The standard errors are chosen based on the discussion of optimal bandwidths for regression discontinuity designs Imbens and Kalyanaraman, 2011; Calonico et al., 2014. The point estimate at the cutoff is robust to including or excluding controls and event year fixed effects, see table 3.

There is no change in density around the February cutoff relative to the may cutoff, but it should be noted that higher ages in calendar years can include more cohorts, and we therefore see an increase in observations for older age groups. Figure 19 shows pre-determined variables such as the birth year of the child (panel 19c) and parental pre-layoff income (panel 19a) is not different on each side of the cutoff. The unemployment spells also appear to be similar around the deadline, with an equal number of days in unemployment (panel 19d) and similar earnings in the two years after the layoff (panel 19b).

C Appendix Figures and tables

Figure 10: High school degrees by age



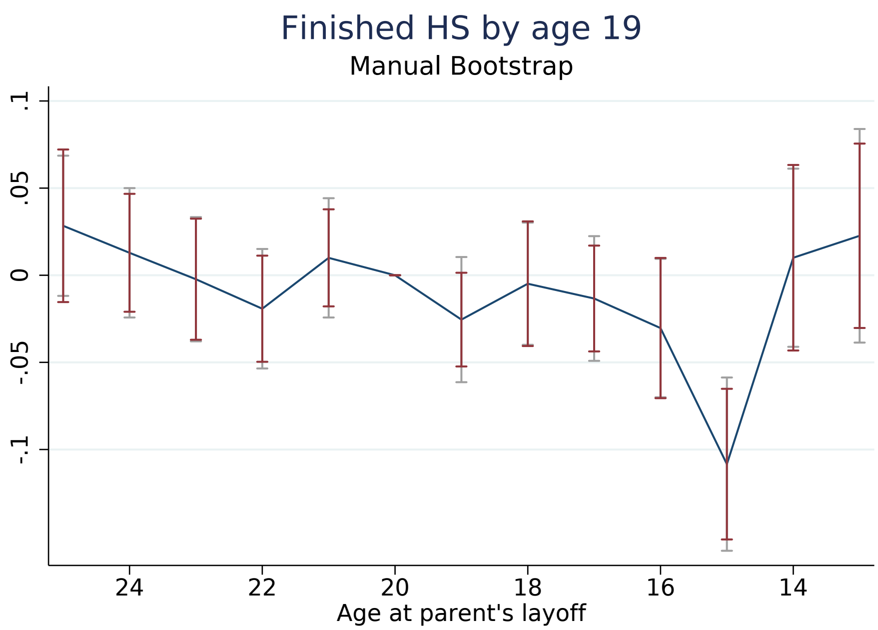
XXX Remake this figure for one cohort XXX the current drop at older ages is a cohort composition thing

Table 4: High School Choice Environment

Year	School Market level			Municipality level	
	N Schools	**N Programs**	**Programs $\geq$15**	**N Schools**	**No school**
2000 mean	8.96	14.51	0.53	1.04	0.33
sd	(14.84)	(2.26)	(0.50)	(1.08)	(0.47)
2005 mean	10.41	15.28	0.64	0.89	0.36
sd	(14.73)	(2.83)	(0.48)	(0.86)	(0.48)
2010 mean	12.46	15.65	0.71	0.84	0.42
sd	(16.32)	(2.59)	(0.46)	(0.90)	(0.49)
2013 mean	15.61	15.75	0.69	1.55	0.38
sd	(19.02)	(2.76)	(0.46)	(1.80)	(0.48)

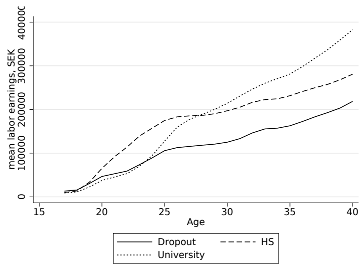
The average number of schools and program a student making a high school choice will face in her school market* or municipality.
* School markets are defined based on 2010 commuting patterns defined by Skolverket (2011).
Source: Skolverket

Figure 11: High school completion by age 19, SE

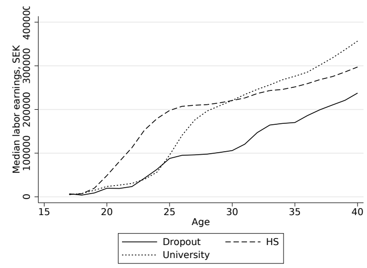


A comparison between bootstrapped and analytical standard errors. Bootstrapped confidence intervals are in red and analytical confidence intervals in gray.

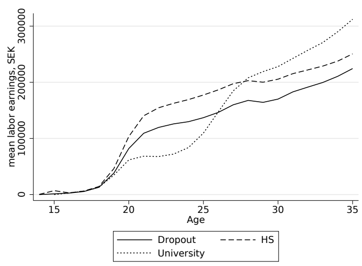
Figure 12: Income paths by education level - selected cohorts



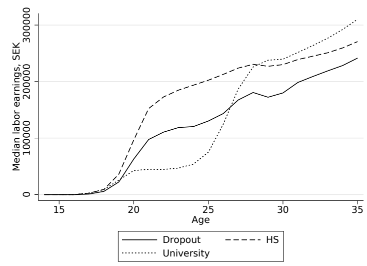
(a) Mean earnings, 1975 cohort



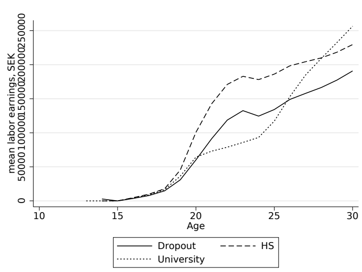
(b) Median earnings, 1975 cohort



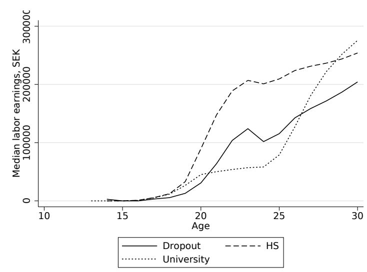
(c) Mean earnings, 1980 cohort



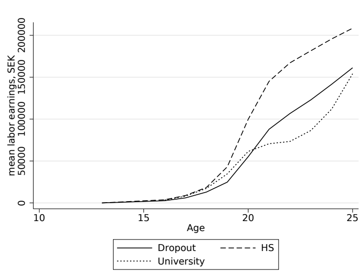
(d) Median earnings, 1980 cohort



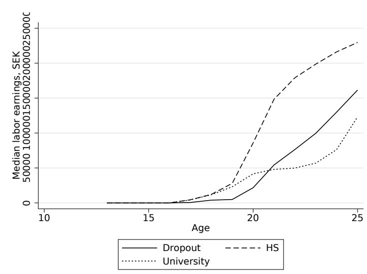
(e) Mean earnings, 1985 cohort



(f) Median earnings, 1985 cohort

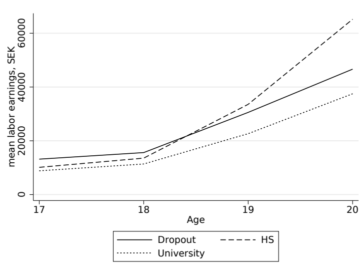


(g) Mean earnings, 1990 cohort

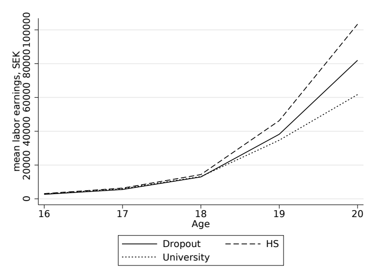


(h) Median earnings, 1990 cohort

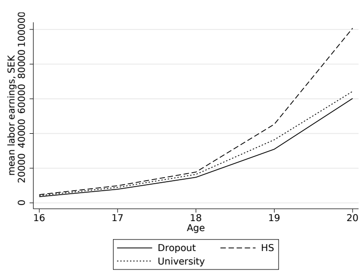
Figure 13: Income paths by education level age 16-20 - selected cohorts



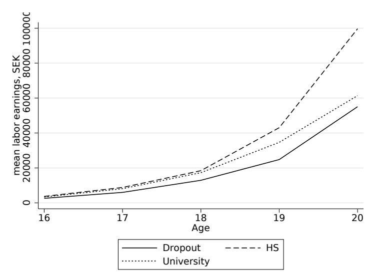
(a) Mean earnings, 1975 cohort



(b) Mean earnings, 1980 cohort

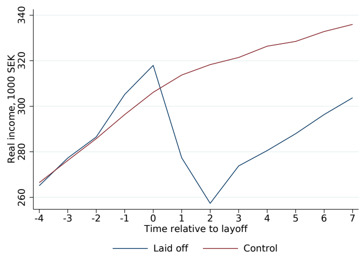


(c) Mean earnings, 1985 cohort

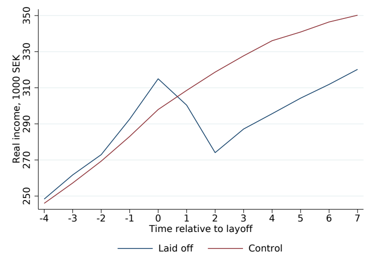


(d) Mean earnings, 1990 cohort

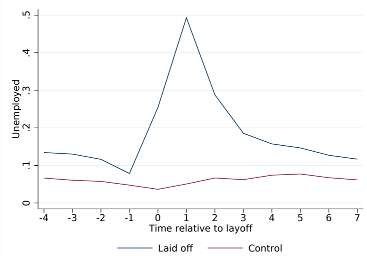
Figure 14: Layoff and Parent outcomes



(a) Labor income, time to layoff



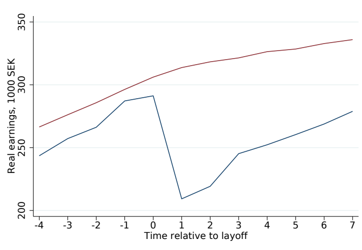
(b) Disposable income, time to layoff



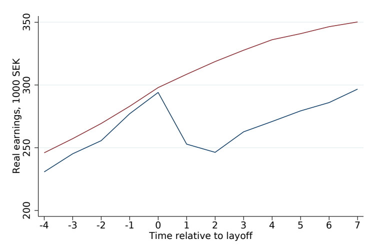
(c) Unemployment relative to layoff year

The treatment group is defined as individuals who appear in the layoff data with a ternination date in year 0. The control group is weighted according to the procedure described in section XX. Disposable income includes unemployment benefits and labor income. Income is measured annually in 1000s of 2010 SEK.

Figure 15: Parent outcomes if Layoff leads to unemployment



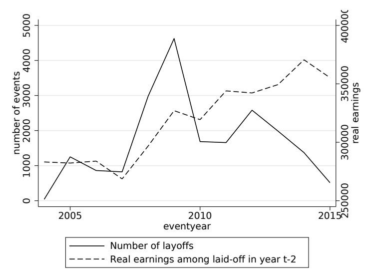
(a) Labor income, time to layoff



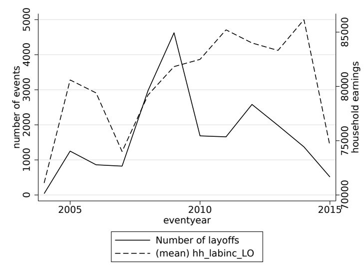
(b) Disposable income, time to layoff

Here the treatment group is restricted to individuals with a layoff date who appear in the UI office data in the year of layoff or the year after. The control group are not laid off and are not unemployed in time 0 or 1. Disposable income includes unemployment benefits and labor income. Income is measured annually in 1000s of 2010 SEK.

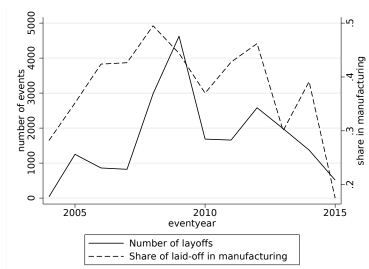
Figure 16: Characteristics of laid off employees by year



(a) Pre-layoff earnings by layoff year



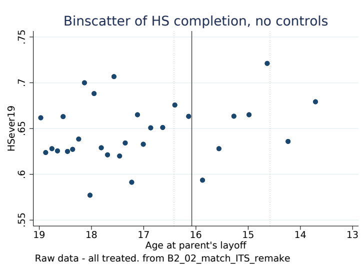
(b) Pre-layoff household earnings by layoff year



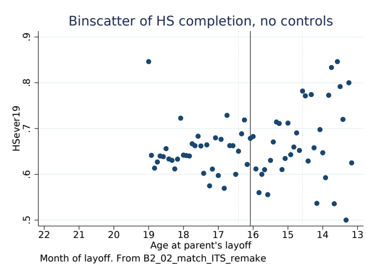
(c) Pre-layoff employment in manufacturing sector by layoff year

The characteristics of the unemployed population can be expected to vary by the time of unemployment.

Figure 17: Graduation rates for children with parental layoff only



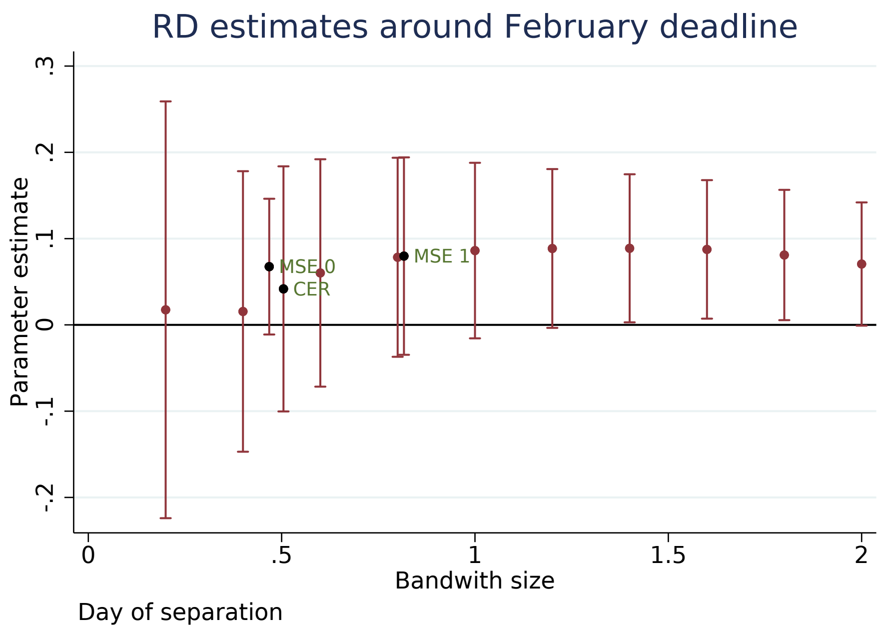
(a) Date of parent layoff



(b) EMonth of parent layoff

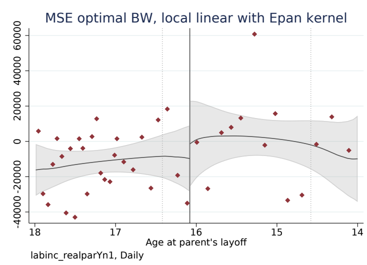
Raw data: Binscatter of the high school completion by day (panel a) and month (panel b) of separation. No controls, only data from familoies with a parental layoff. Panel a is approximated by equalliy sized bins across the distribution of layoffs. In panel B, each scatter is a calendar month-age bin.

Figure 18: Robustness of ITS - different bandwidths

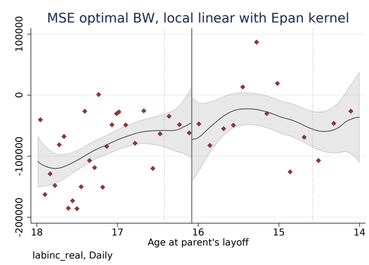


[12]ote: The MSE optimal bandwith follows Imbens and Kalyanaraman (2011) and the CER optimal bandiwth follows Calonico et al. (2014), in line with the literature on regression discontinuity designs.

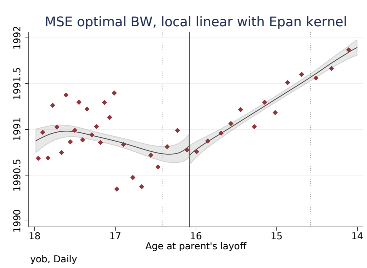
Figure 19: Placebo test of time series interruption



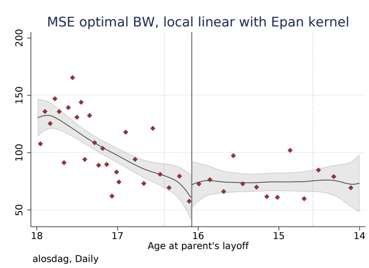
(a) Parent pre-layoff earnings around application deadline



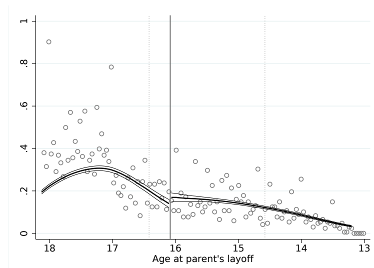
(b) Parent post-layoff earnings around application deadline



(c) Child cohort around application deadline



(d) Parent days of unemployment around application deadline



(e) Density around application deadline

Figure notes: The non-parametric fit is estimated by a local linear estimator (polynomial of degree 1) with an MSE-optimal bandwidth following Calonico et al. (2014)

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