Job Loss at Home: Children's Grades during the Great Recession in Spain

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Abstract: This paper studies the effect of father's job loss on children's school performance during the Great Recession in Spain. Conditioning on student fixed effects and observed covariates, the Great Recession in Spain generates exogeneous variation in job loss analogous to that provided by randomization. Using original panel data for students observed since the beginning of the crisis in a school in the province of Barcelona, I find that father's job loss has a negative and significant effect on school performance of about 13 to 19% of a standard deviation. Moreover, the effect of father's job loss appears to be largely concentrated among children of already disadvantaged families. Finally, school performance prior to father's job loss is not affected by future job losses, suggesting a causal link between father's job loss and children's educational outcomes.

JEL Classification: $I20$, $I24$, $J63$, $J65$

Keywords: parental job loss, school performance, Great Recession, fixed effects.

1 Introduction

The available evidence on the effects of job loss indicates that job loss has negative effects for the affected worker. According to the literature, among these negative consequences we can find short-run earning losses that persist in the long-rung (Jacobson et al., 1993), lower re-employment probabilities (Kletzer, 1998; Huttunen et al., 2011), prevalent feelings of job insecurity (Barling et al., 1999b), worse physical and mental health (Eliason and Storrie, 2009b,a)

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and an excess risk of divorce (Eliason, 2012; Charles and Stephens, 2004). A recent and rapidly growing literature has addressed the question of whether parental job loss has detrimental effects on their offspring. The majority of these papers show a negative effect of parental job loss on different educational outcomes. This paper studies the impact of father's job loss on children's school performance during the Great Recession in Spain.

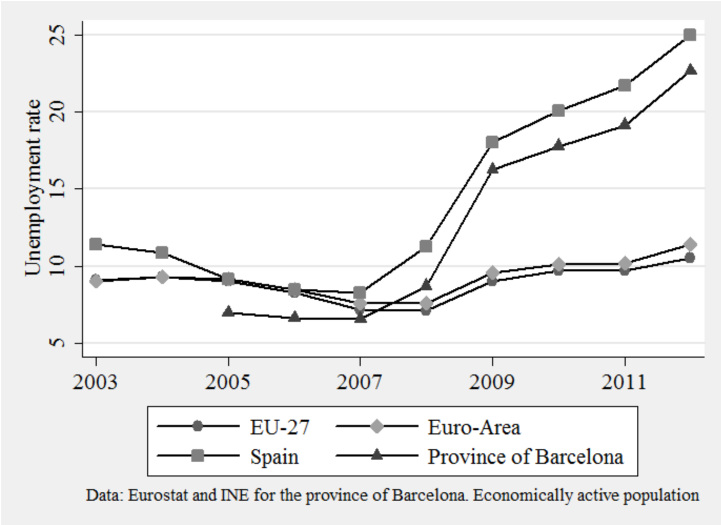
According to the evidence mentioned above, parents experiencing job loss suffer from income reduction, job uncertainty and a worse family environment. All these variables are usually seen as inputs affecting the grade production function of their children[1], and could, therefore, be suggested as mechanisms through which parental job loss would translate into a worse school performance for those affected students. On the other hand, students whose parents face an episode of job loss might change their beliefs on the relationship between effort and success. And this, in turn, might change their tastes for effort exerted while at school. In this case, though, empirical evidence on the direction of the distortion introduced by parental job loss does not seem to be as clear. Evidence coming from the Social Psychology field suggests that children whose parents suffer job loss develop negative work beliefs (Barling et al., 1998). Moreover, Giuliano and Spilimbergo (2009) find that those individuals that experienced an economic recession during their teenager years are more inclined to believe that luck, rather than effort, is the fundamental driver of success. However, there is also evidence that would suggest a positive impact on the tastes for effort. For instance, Betts and McFarland (1995) show that children choose more education when the labor market is weak.

In a simple one period static model in which children decide the level of effort they exert at school each academic year, and effort positively influences school performance, parental job loss is assumed to affect both the marginal returns and marginal costs of effort, by making children more or less productive while studying, and altering their incentives to study. The data collected and the estimation strategy followed in this paper will allow me to estimate the total effect of an exogenous change in parental job loss on the educational performance of their offspring. That is, not holding other inputs constant.

As Rege et al. (2011) point out, estimating a causal relationship between parental job loss and child outcomes faces two main challenges: concerns of omitted variable data and the scarcity of appropriate data. I address both of them by exploiting the recent developments in the Spanish labor market and by using a dataset specifically designed to address this question. In particular, this paper uses original data I gathered myself on over 400 children aged 3 to 18 for the academic years 2007-2008 to 2011-2012 in a school in the province of Barcelona. Grades for all the subjects taken during each academic year are available for each children. On the parental side, a survey was designed to collect their personal data retrospectively, with a special focus on the labor situation and job characteristics at the beginning of the crisis, i.e. in January 2008,

[1] See Todd and Wolpin (2003) for a review on the specification and estimation of the production function for cognitive achievement.

Figure 1: Unemployment rates



and then later on in January 2010 and January 2012.

Starting from 2008, millions of jobs have been destroyed in Spain.[2] Figure 1 shows the unemployment rates in the EU-27, euro-area, Spain and the province of Barcelona for the economically active population. Both the Spanish unemployment rate and the unemployment rate in the province of Barcelona reach its minimum in 2007, and start increasing dramatically thereafter (unemployment rates in Spain and the province of Barcelona are 25% and 22.6%, respectively, in 2012). The same pattern is repeated if I would restrict the data to males aged 25 to 74. Under the assumption that the vast majority of employment destruction observed in this period is due to the Great Recession, job losses would be exogenous to the worker. Or as Gregg et al. (2012) put it, the recession provides an exogenous shock to employment analogous to exploring job displacement for known plant closures. However, it could be that those losing the jobs during the recent crisis have some unobserved characteristics that affect both their labor status and the school performance of their children. In order to address this last challenge, the panel nature of the data collected allows to condition for unobserved characteristics of both the student and the father by using student (worker) fixed effects. Thus, the empirical strategy followed in this article relies on the fact that, conditioning on student fixed effects and observed covariates, the Great Recession in Spain generates exogeneous variation in job loss analogous to that provided by randomization. That is, the policy effect that I will estimate in this paper corresponds to what is called in the evaluation literature as the local average treatment effect (LATE).

Fixed effect estimates of the effect of father's job loss on the average grade and the percentile

[2] According to the Labor Force Survey data provided by the Spanish National Institute of Statistics (INE) almost 4 million jobs were destroyed between 2007 and 2012.

rank (in the year and grade) are negative and statistically significant. In particular, I find that father's job loss entails an average decrease in children's average grades of about 13.2 to 16% of a population standard deviation, and a reduction of about 15.7 to 19.6% of a (population) standard deviation in the percentile rank measure. Importantly, both the percentile and the average grade prior to job loss are not affected by future job losses experienced by the father, suggesting a causal link between father's job loss and children's school performance. Moreover, the effect of father's job loss appears to be largely concentrated among children of already disadvantaged families in terms of the level of education of the father, but not in terms of the level of income of the father at the beginning of the crisis. Also, even though imprecise, the results seem to be larger for those children whose father closed his own business after 2008, and more concentrated on boys rather than on girls. Even if in the whole sample father's job loss is associated with a significant decrease in income, these differential effects do not seem to be driven by changes in income. Thus, I find no clear evidence supporting the hypothesis that income could be a mechanism behind the effect of father's job loss on school performance. I also find that the occupational status of the father or the mother, residential relocation or changes in civil status are not the main drivers of the effect of father's job loss on school performance of their offspring.

This paper is closely related to a recent emerging literature trying to assess the effects of parental job loss on several children outcomes. The first published articles focused on the effects of parental job displacements on their children's earnings later in life. Oreopoulos et al. (2008) use Canadian administrative data to find that children whose fathers were displaced had annual earnings about 9% lower than similar children whose fathers did not experience an employment shock, and that these estimates are driven by those children at the bottom of the income distribution. On the contrary, using data from Norway, Bratberg et al. (2008) find that displacement has negative effects on earnings of affected workers, but find no statistically significant effect of father's displacement on earnings of their children.

More consensus is found on the more recent literature analyzing the impact of parental job loss on different educational outcomes. Using administrative Norwegian data, Rege et al. (2011) estimate the effect of parental job loss due to plant closure[3] on a summary measure of ten subjects for a pooled cross-section of graduating secondary school children. Their estimates suggest that paternal job loss has a negative impact of a 6% of a standard deviation on children's GPA at age sixteen, whereas they find a non-significant increase in GPA associated with maternal job loss. Stevens and Schaller (2011) use SIPP data to study the relationship between parental job loss (they focus on the father unless the child lives in single-mother household) and grade retention between ages 5 to 19. Their findings indicate that the probability of children's grade retention increases by 15% after conditioning on child fixed effects. Their measure of job loss considers those that are classified as being fired, employer sold or went bankrupt, and due to slack work or business conditions. This contribution improves upon Kalil and Ziol-Guest (2008), which use the same data to explain grade retention, but concerns were raised on the exogeneity

[3]It is common to assume in the literature that job loss due to plant closure is exogenous to the worker.

of the measure used to capture parental job losses. Coelli (2011) finds that parental job loss from layoffs and business failures that occur when youth complete high school are found to be negatively related with enrollment at university and community college in Canada. A related study in this literature by Ananat et al. (2011), uses state-level US data on mass layoffs to show that job losses decrease test scores for math and reading assessments, and these effects are larger for eighth than fourth graders. Gregg et al. (2012) do not have information on job displacement for the worker itself and instead they try to identify those parents being displaced by the contractions in employment suffered by the industry in which the father was working during the recession of 1980's in the UK. They find that a child with a likely displaced father obtained lower grades, equivalent of about 2% lower wages as an adult, had a lower early labour market attachment, and no direct impact on earnings at age 30/34. Finally, instead of focusing on job losses, Pinger (2013) investigates how paternal unemployment affects children's educational attainment. She finds that paternal unemployment decreases the probability of upper secondary schooling choice by around 18 percentage points.

The contributions of this paper to this literature are threefold. First, I use an original dataset I specifically designed to address the research question. Second, the combination of job losses due to the Great Recession in Spain, together with the use of fixed effects given the panel nature of the data, make my measure of job loss more likely to fulfill the assumption of exogeneity than any other paper in the literature. Finally, a variety of heterogeneous effects and mechanisms not explored before are identified.

The structure of the paper is as follows. Section 2 describes a simple theoretical framework describing the effects of parental job loss on children's optimal effort while at school. Section 3 describes the original dataset used in the paper, and section 4 presents the empirical strategy. Finally, section 5 shows the main results and section 6 concludes.

2 The impact of parental job loss on grades. A simple theoretical framework

Consider a student in general education that every year has to choose how much effort to devote to study, e, and assume that her utility while she is in school depends directly and positively on the grades she obtains, G. In general, it's not unreasonable to think that better grades can entail a greater reward than bad grades either in the family environment (parents offering extra consumption for better grades) or later on in life by granting access to higher education, a wider choice of studies or a better job. The grade production function is determined by the level of effort supplied by the student: $G = g(e)$ and is supposed to be strictly increasing and concave in the level of effort. The effort that students devote to study entails a disutility, $d(e)$, which is supposed to be strictly increasing and convex. Thus, under this framework, the problem of the student is very similar to a static labor supply model, but here the student chooses the level of effort to maximize her utility, subject to the grade production function:

$$\max_{e} \; U(G,e) = G - d(e) \tag{1}$$

$$st \; G = g(e) \tag{2}$$

The first order condition for an interior solution is given by (3) and states that students will choose the level of effort that equates the marginal rate of return to effort with its marginal cost.

$$g'(e) = d'(e) \tag{3}$$

Under this formulation there is only one level of effort that is optimal. A simple way of introducing heterogeneity in this setting is to follow Card (1994). Card introduces heterogeneity in the Becker (1967)'s optimal schooling choice model by introducing differences in the costs of (or tastes for) schooling, and in the economic benefits of schooling. Likewise, I will assume that the marginal rate of return to effort, $g'(e)$, and the marginal cost of effort, $d'(e)$, are linear functions with person-specific intercepts and homogeneous slopes:

$$g'(e) = \beta_i(e) = b_i - k_1 e \tag{4}$$

$$d'(e) = \delta_i = r_i + k_2 e \tag{5}$$

$$k_1 \geq 0, k_2 \geq 0 \tag{6}$$

As Card (1994) states, variation in b_i can be seen as differences in ability (for the same level of effort, more able people obtain higher grades). But he also points out that changes in school quality could be parameterized in this model by shifts in b_i. At the same time, variations in b_i could also reflect differences in family background, or, in general, those inputs traditionally seen as affecting the production function for cognitive achievement (see Todd and Wolpin (2003)). Variation in r_i instead can be seen as different tastes for effort.

Parental job loss could potentially affect both the marginal benefits and costs of effort. As stated in the introduction, people experiencing job loss suffer from income reduction, worse family environment, etc. That is, empirical evidence has until now shown a negative impact on the inputs that generally are seen as affecting the production function for cognitive achievement. But it could also be that children benefit from parents being more at home after job loss. (Todd and Wolpin (2003) point out the lack of consensus of maternal employment on school achievement, for instance). Additionally, parental job loss could simply be just another input in the grade production function, that, at the same time, can have an effect on other inputs (family income, environment at home, etc.).

Parental job loss could also distort the tastes for effort of the affected student. However, the direction of the distortion could go, a priori, in any direction. Giuliano and Spilimbergo (2009) find that a recession during impressionable years (between 18 and 25 years of age) makes an individual more inclined to believe that luck, rather than effort, is the fundamental driver of success. Moreover, research in Social Psychology suggests that from as young as 5 years of age, children understand such concepts as pay, labor disputes, unemployment and welfare. (Barling et al., 1999b). Barling et al. (1999a) find that children's perceptions of their parent's job insecurity indirectly affect their grade performance through the effects of beliefs in an unjust world and negative mood. Similarly, Barling et al. (1998) postulate a model by which children who watch their parents experiencing layoffs and insecurity, develop negative work beliefs that then predict their work-related attitudes. According to these studies, parental job loss would introduce a negative distortion in the tastes for effort. On the contrary, it might be that students whose parents face job loss are more aware of the importance of education later in life, and thus receive an additional incentive to exert a higher level of effort that would lead to a better performance while at school. In this sense, the empirical evidence shows that, in general, children choose more education when the labor market is weak (see, for instance, Betts and McFarland (1995)). In this case, parental job loss would introduce a positive distortion in the tastes for effort[4].

Therefore, both b_i and r_i could potentially be affected by parental job loss, and I will express this by writing both of them as a function of parental job loss (JL): $b(JL)_i$ and $r(JL)_i$, respectively. Optimal level efforts are then determined according to[5]:

$$e_i^* = \frac{b(JL)_i - r(JL)_i}{k_1 + k_2} \tag{7}$$

Thus, the direction of the impact of parental job loss on effort (and therefore on grades) depends on the impact of parental job loss on both the marginal returns and costs of effort[6]. Given that my estimation strategy relies on the use of a natural experiment, I will not be able to identify in the estimation below any of the parameters of the grade production function or the disutility of effort. Instead, what I will uncover is a policy effect, i.e. the total effect of an exogenous change in parental job loss on grades (that is, not holding other inputs constant). I will come back to this point in the estimation strategy section, after describing in depth the dataset in the next section.

3 Data

The data used in this paper is an original dataset I collected myself, gathering data on the parental labor market situation and grades for 408 children of ages ranging from 3 to 18 in a

[4]It seems reasonable to think that if this positive distortion exists, it would be bigger the older the student is.

[5]Where a necessary condition for the equilibrium to exist with non-negative levels of effort is that $b_i \geq r_i$.

[6]Even if not included here, it might as well be that parental job loss affects the slopes (k_1, k_2) of the marginal return and marginal costs of effort. In any case, the effect will still be theoretically ambiguous.

school in the province of Barcelona.[7] In particular, for each of these children, I observe their grades in the different subjects from the academic year 2007-2008 to the academic year 2011-2012 (as long as they have been enrolled in the school since the academic year 2008)[8]. On the parental side, I designed a survey to collect personal information as well as current and past information of their labor market situation and, if the parent was employed, the characteristics of the job. The survey was supposed to be answered by both parents if they were living in the same household as the children. If only one parent was living at home at the time the survey was administered, then the survey was answered only by that parent.

Regarding the information on the labor market characteristics of the parents, I collected information on their labour market situation (and if employed, on the job characteristics) in January 2012, January 2010 and January 2008. With the information of these 3 points in time, and the dates regarding labour status changes, I have reconstructed their labor market situation for the 5 periods in which I also observe the grades of their offspring. Due to missing data for some individuals, I had to make some reasonable assumptions regarding dates of job loss. Even if I am able to use the 5 years of information by making these assumptions, they could be introducing some measurement error in the dates regarding labor status changes. Thus, even if the main results shown both in this section and in the results section use this 5 period reconstructed dataset, I perform robustness checks using only the 3 years (2008, 2010 and 2012), for which information regarding the labor status is certain and there is no need to make any assumptions.

Following the related literature, a number of exclusion criteria were applied to create the final sample. First, those kids that were not living in 2012 in a two-parent household were dropped from the analysis (30 observations dropped). In all these cases the student was living only with the mother, and therefore, I have no information on the labour characteristics of the father. Second, given that the sample does not seem to be representative of students with an immigrant backfround (see Ruiz-Valenzuela (2014)), students whose father is an immigrant were excluded (22 additional observations dropped). Third, given that students in the High-School stage ("Bachillerato") have already made the transition from compulsory to post-compulsory education and, as a result, I can only observe those that decided on continuing their studies, I am not considering them in the analysis (45 additional observations dropped). The final two exclusion criteria are important for the identification strategy. I restrict the sample to those students that I can observe for each of the 5 periods. That is, I keep the observations for which I can observe the grades at the beginning of the crisis (academic year 2008), and for every year after that. A total of 128 students are excluded after applying this restriction. Out of them, 82 students are excluded because they were too young in the academic year 2007-2008. That is,

[7]For a more detailed description of the questionnaire design, data collection, survey and item non response, and representativeness of the data, see Ruiz-Valenzuela (2014).

[8]The academic year in Spain starts in September and finishes by the end of June, with summer holidays in the months of July and August. From now on, when I refer to the academic year 2008, I will be referring to the academic year going from September 2007 to June 2008. The same applies to the other 4 additional academic years in the sample.

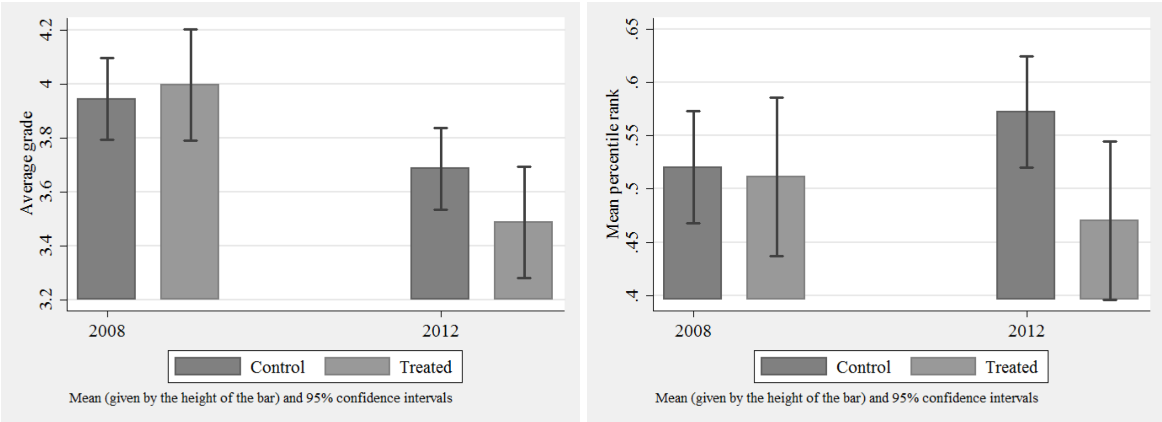
given their age, it's impossible that they would have been in the sample for 5 academic years. This affects to children that in the academic year 2012 were in the second stage of Kindergarten and those in the first grade of Primary School[9]. The remaining 46 students that are not observed for 5 years are those that entered the school in the Secondary Education stage. That is, they graduated from Primary school in another school, and enrolled in the school where the data was collected once they moved to Secondary Education. If data was available at the school where I collected the data also for grades in previous schools, then this information was incorporated in the dataset. Finally, the last and very important exclusion restriction has to do with the employment status of the fathers in the first period of observation. That is, I restrict the sample to those students whose fathers were employed in January 2008. After applying this restriction, 5 additional observations are dropped. Thus, the final sample consists of 178 students in compulsory education whose grades were observed for all the 5 academic years from 2008 to 2012 and whose father was employed at the beginning of the crisis in 2008, was present at home during all the period and had Spanish nationality. Robustness checks will be conducted by removing some of this exclusion criteria.

Information on the grades for all subjects taken in each academic year was made available by the school for those students whose parents answered the questionnaire. The grades in Secondary School have a number format ranging from 1 to 10, with 10 being the best possible grade and the passing grade being bigger or equal to 5. In Primary School instead, grades can take on 5 different values: (1) Fail, (2) Pass, (3) Good, (4) Very Good and (5) Excellent. I translated the Secondary School grades for each subject into this 5-value scale following the traditional convention in the school[10]. The student in Primary or Secondary School receives a report with her gradesheet three times during each academic year. In the second stage of Kindergarten, parents receive a report twice a year where different areas (Maths, Language, Arts and Musical Education) are evaluated with a range of short sentences. These short sentences can be clearly positive (ex: the child can count from 1 to 5, the child can write her name, the child distinguishes the colors, the child can recognize the songs studied, etc.), clearly negative (ex: the child can not count from 1 to 5, the child can not write her name, etc.), or improving-type of sentences (the child has improved when counting, writing her name, etc.). In order to translate these sentences into a numeric grade for each of the areas evaluated, I have constructed two type of measures. The first type of measure (Measure 1 from now on) assigns a value of 1 to

[9]In Spain, Kindergarten education is composed of two stages, none of them compulsory. The first stage is addressed to children from ages 0 to 3 and the second stage to children from 3 to 6 years of age. Even if it is not compulsory, 98% of the children of 3 years of age were enrolled in the second stage of Kindergarten in the academic year 2008. Compulsory education goes from the year the child turns 6 until the year the child turns 16, and is divided in two stages. Primary School, with a total of 6 grades (until the year the child turns 12, absent any repetition) and Secondary School, comprising 4 additional grades. After completing compulsory education successfully, students can choose to enrol in High-School (Bachillerato) for 2 more additional years or in Vocational Training.

[10]That is, those with grades 1 to 4 in Secondary School were assigned a grade of Fail (1). Those with a grade 5 in Secondary School were assigned a grade of Pass (2). Those with a grade 6 were assigned a grade of Good (3). Those with a grade of 7 or 8 were assigned a grade Very Good (4) and finally, those with grades 9 or 10 were assigned a grade of Excellent (5) in the 5-value scale.

Figure 2: Average grade and mean percentile rank in the year-grade. Measure 1



positive and improving sentences, and a value of 0 to negative sentences. After doing this, I computed a simple average of the points obtained in each area in order to obtain a numeric grade ranging between 0 and 1. Multiplying by 10, this 0 to 1 grade was converted into a 0 to 10 grade, and it was translated afterwards into the 5-scale value with the same criteria outlined for Secondary School grades. The second type of measure (Measure 2 from now on), assigns a value of 1 to positive sentences and a value of 0 to improving and negative sentences. Average grades for each of the areas is then calculated in the same way.

For each student I computed her average grade in each academic year by averaging her grades for all the subjects taken in each of the 3 terms in the academic year. For those students that in the period under study were enrolled in some of the Kindergarten grades, two possible average grades were available depending if Measure 1 or 2 was used. In order to have a measure that is less sensitive to the type of measure used, I computed, for each student, the percentile rank in her grade and year. In what follows, results are going to be shown using the percentile rank and the average grade resulting after using the Measure 1 type of grades for Kindergarten. Robustness checks using the percentile rank in the class and the average grade using Measure 2 will be provided in the appendix.

I use the 5 period dataset to construct the treatment group. The treatment group consists of children whose father experienced an involuntary job loss (this includes those fathers closing their own business) at some point after the first academic year. In total, 54 out of the 178 children have been affected by father's job loss after academic year 2008.

Figure 2 shows the average average grade and percentile rank for treated and control students in the academic years 2008 and 2012. This will be a key figure in order to be able to interpret the effect of parental job loss on grades as a causal effect. Ideally, we would like to observe that prior to job loss there were no significant differences in the average educational measures for treated and control students. By taking a look at figure 2, one can see that in 2008,

Table 1: **Descriptive statistics. Children characteristics**

	Control	Treated	Total	Diff and t-test
Born Q1	0.242	0.185	0.225	0.0568
	(0.430)	(0.392)	(0.419)	(0.83)
Born Q2	0.298	0.241	0.281	0.0576
	(0.459)	(0.432)	(0.451)	(0.78)
Born Q3	0.274	0.407	0.315	-0.133*
	(0.448)	(0.496)	(0.466)	(-1.77)
Born Q4	0.185	0.167	0.180	0.0188
	(0.390)	(0.376)	(0.385)	(0.30)
Female	0.524	0.593	0.545	-0.0684
	(0.501)	(0.496)	(0.499)	(-0.84)
Ever repeated a grade	0.0403	0.0556	0.0449	-0.0152
	(0.198)	(0.231)	(0.208)	(-0.45)
Age	8.306	8	8.213	0.306
	(2.697)	(2.503)	(2.636)	(0.71)
Periods in school	4.976	4.944	4.966	0.0314
	(0.154)	(0.231)	(0.181)	(0.91)
N	124	54	178	

First line for each variable corresponds to its mean. Standard errors in parentheses. *, **, *** denote significance at the 10%, 5% and 1% levels. The 4th column shows the difference in means for treated and control individuals, and in parentheses, the value of the t-stat for the test of equality of means. A third row with the number of observations is shown in the case that a particular variable has missing values.

when all students in the sample had his father employed, there were no significant differences in none of the educational measures between treated and control students. In 2012, after some students have been exposed to parental job loss, relevant differences emerge. For the average grade measure, standard errors are too big to reject the null hypothesis of a t-test of equality of means (not shown) between treated and control students in 2012. For the percentile rank measure, though, I do reject the null of equality of means between treated and control students in 2012. In figure 3 in the appendix, I show the same graphs using measure type 2 to construct the percentile rank and the average grades, and the results are very similar.

Tables 1, 2 and 3 show descriptive statistics for the sample of 178 students analyzed. In each table, the first column reports the mean of some characteristics in the control group, the second column reports means for the treated group, and the third column for the whole sample. The last column reports, for each characteristic, the difference in the mean for control and treated individuals in the first row. The second row shows the value of a t-test that has as a null hypothesis the equality of means between control and treated students.

No significant differences emerge for the variables shown in Table 1, except for the third quarter of birth dummy. Compared to control students, there were more treated students born in the third quarter of the year. There are no significant differences in the means for variables containing information on the sex, age, if ever repeated a grade, and if the grades referred to periods in school (as opposed to grades from previous schools). Descriptive statistics of household characteristics in 2008, previous to job loss, are shown in Table 2. Families of treated students were living more in rented apartments (as opposed to owing, with or without mortgage, an apartment), and there were no treated students living in the first postcode area[11]. More significant differences emerge in Table 3, where several personal and 2008 labor market descriptive statistics for the fathers in the sample are shown. In this table, some of the variables have some missing information, so the number of observations available is shown in an additional third row[12]. The fathers of treated students had a lower level of income already in 2008, and a higher share of them was working in the industry and construction sectors, as opposed to working on the service sectors. Treated fathers had less years of tenure in the firm (defined for those owning her own business as number of years since they opened the business), and a lower share of permanent contracts. None of the fathers of treated students worked in the public sector and, on average, they were employed on, or owned, smaller firms. Contrary to what it could be expected, there are no significant differences in the level of education of the fathers of treated and control students. It is also interesting to note that there were no significant differences in their level of motivation at work in 2008.

The information in Tables 1 to 3 suggests that, without controlling for worker fixed effects, job loss during the Great Recession in Spain can not be considered as good as randomly assigned.

4 Estimation strategy

Let Y_{it} equal the educational outcome under study for child i at time t[13]. This education indicator could be either her average grade in academic year t or the percentile rank of the student in her grade-year combination based on her average grade. Let D_{it} denote a dummy variable that equals 1 from the year the father loses involuntarily his job[14]. By the sample restrictions outlined in the data section, this indicator equals 0 in the academic year 2008 for all students, since all fathers in the selected sample are employed at the beginning of the crisis. For control students, this dummy will take a value of 0 in every period. For treated students, it will be 1 from the year the father loses the job. That is, the treatment is an absorbing state. The main reason to define the job loss variable in such a way is that, under certain assumptions, father's job loss in my sample can be considered as exogenous to the worker whereas finding a

[11]This postcode area corresponds to the city center. Unfortunately, I do not have data on the level of income by postcodes, but according to census data, it is the area with the highest share of population born in Catalonia.

[12]In most of the cases, it was easy to detect that the information was missing because the father did not reply, by mistake, to one of the parts of the questionnaire. As a way to partially asses if these missing observations are related to father's job loss, I include a dummy in the table that is equal to 1 if income is missing. As it appears, there are no significant differences in the level of missing (father's) income between both treated and control students.

[13]This section follows the notation used by Angrist and Pischke (2008).

[14]Stevens and Schaller (2011) also define like this the measure of parental job loss. But, given that their outcome of study is grade repetition, the current year of parental job loss is separated from the dummies of job loss in prior years. In their case, job loss in the academic year, if exogenous, should not have an effect on whether the child is repeating that grade.

Table 2: **Descriptive statistics. Household characteristics in 2008**

	Control	Treated	Total	Diff and t-test
Number of children	1.976	2.111	2.017	-0.135
	(0.517)	(0.744)	(0.596)	(-1.21)
Household size	3.927	4.056	3.966	-0.128
	(0.528)	(0.787)	(0.619)	(-1.09)
Stable civil status	0.960	0.926	0.949	0.0338
	(0.198)	(0.264)	(0.220)	(0.84)
House: Owned	0.395	0.389	0.393	0.00627
	(0.491)	(0.492)	(0.490)	(0.08)
House: Paying mortgage	0.573	0.481	0.545	0.0911
	(0.497)	(0.504)	(0.499)	(1.12)
House: Rented	0.0161	0.0926	0.0393	-0.0765*
	(0.126)	(0.293)	(0.195)	(-1.85)
Moved in 2008-2012	0.137	0.115	0.131	0.0217
	(0.345)	(0.323)	(0.338)	(0.39)
Postcode 1	0.0484	0	0.0337	0.0484**
	(0.215)	(0)	(0.181)	(2.50)
Postcode 2	0.105	0.0741	0.0955	0.0308
	(0.308)	(0.264)	(0.295)	(0.64)
Postcode 3	0.637	0.648	0.640	-0.0111
	(0.483)	(0.482)	(0.481)	(-0.14)
Postcode 4	0.121	0.167	0.135	-0.0457
	(0.327)	(0.376)	(0.343)	(-0.77)
Postcode 5	0.0887	0.111	0.0955	-0.0224
	(0.285)	(0.317)	(0.295)	(-0.45)
N	124	54	178	

First line for each variable corresponds to its mean. Standard errors in parentheses. *, **, *** denote significance at the 10%, 5% and 1% levels. The 4th column shows the difference in means for treated and control individuals, and in parentheses, the value of the t-stat for the test of equality of means. A third row with the number of observations is shown in the case that a particular variable has missing values.

Table 3: **Descriptive statistics. Father characteristics in 2008**

	Control	Treated	Total	Diff and t-test
Education	0.419	0.315	0.388	0.105
beyond HS	(0.495)	(0.469)	(0.489)	(1.32)
Age	40.80	41.96	41.15	-1.165
	(4.788)	(4.526)	(4.728)	(-1.52)
High income	0.765	0.563	0.706	0.203***
	(0.426)	(0.501)	(0.457)	(2.63)
	115	48	163	
Income missing	0.0726	0.111	0.0843	-0.0385
	(0.260)	(0.317)	(0.279)	(-0.78)
Labour market characteristics				
Own business	0.242	0.315	0.264	-0.0729
	(0.430)	(0.469)	(0.442)	(-1.01)
Industry	0.250	0.413	0.296	-0.163**
	(0.435)	(0.498)	(0.458)	(-2.06)
	116	46	162	
Construction	0.155	0.370	0.216	-0.214***
	(0.364)	(0.488)	(0.413)	(-2.70)
	116	46	162	
Tenure since	1994.4	1998.6	1995.7	-4.213***
	(6.875)	(6.769)	(7.095)	(-3.78)
Permanent contract	0.989	0.714	0.915	0.275***
	(0.103)	(0.458)	(0.280)	(3.52)
	94	35	129	
Private sector	0.915	1	0.939	-0.0847***
	(0.280)	(0)	(0.239)	(-3.29)
	118	47	165	
Full time work	0.974	0.911	0.957	0.0632
	(0.159)	(0.288)	(0.204)	(1.39)
	117	45	162	
Big firm	0.448	0.152	0.364	0.296***
	(0.499)	(0.363)	(0.483)	(4.18)
	116	46	162	
High motivation	0.784	0.696	0.758	0.0881
	(0.414)	(0.465)	(0.430)	(1.17)
	111	46	157	

First line for each variable corresponds to its mean. Standard errors in parentheses. *, **, *** denote significance at the 10%, 5% and 1% levels. The 4th column shows the difference in means for treated and control individuals, and in parentheses, the value of the t-stat for the test of equality of means. A third row with the number of observations is shown in the case that a particular variable has missing values.

Table 4: **Characteristics of treated fathers in first and second period. Unrestricted sample**

	2009-2010	2011-2012	All FJL	Diff and t-test
Father educ	0.345	0.200	0.301	0.145
beyond HS	(0.479)	(0.408)	(0.462)	(1.32)
	58	25	83	
Father's age	41.17	41.88	41.39	-0.708
	(4.593)	(6.882)	(5.351)	(-0.47)
	58	25	83	
Father works in	0.759	0.680	0.735	0.0786
a firm in 2008	(0.432)	(0.476)	(0.444)	(0.74)
	58	25	83	
Industry (2008)	0.415	0.333	0.390	0.0818
	(0.497)	(0.482)	(0.491)	(0.67)
	53	24	77	
Construction (2008)	0.302	0.458	0.351	-0.156
	(0.463)	(0.509)	(0.480)	(-1.33)
	53	24	77	
Services (2008)	0.283	0.208	0.260	0.0747
	(0.455)	(0.415)	(0.441)	(0.69)
	53	24	77	

First line for each variable corresponds to its mean. Standard errors in parentheses. *, **, *** denote significance and the 10%, 5% and 1% levels. The 4th column shows the difference in means for treated and control, and in parentheses, the value of the t-stat for the test of equality of means. The third row shows the number of observations. There are 6 missing values in the dummy variables containing information on the sector of activity.

job afterwards can not.[15]

The observed educational outcome, Y_{it}, is either Y_{0it} or Y_{1it}, depending on the father's job loss status. The main assumption behind the estimation strategy in this paper is that conditioning on student fixed effects and observed covariates, the Great Recession in Spain generates employment shocks that are random in their timing. This assumption hides one potential risk for the consistency of my estimates, since I can not rule out the fact that unobserved time variant variables might be affecting at the same time the probability of job loss and the grades of the offspring. In order to minimize this concern, I show in Table 4 the main characteristics of the workers that lost their jobs, divided in two groups: those that lost their jobs in the first period of the crisis (2009-2010), and those that lost their jobs in the second period (2011-2012). Given that in my restricted sample there are only 11 workers losing the job in the second period and estimates can be very imprecise, I show these descriptive statistics both for the restricted sample (Table 17 in the appendix), and for a larger sample (that I will call unrestricted and I will use in the subsequent analysis to perform robustness checks) that only excludes students in post-compulsory education and those students whose father was already unemployed in 2008. In total, there are 83 students whose father lost the job after 2008 in this unrestricted sample. Of these, 58 fathers lost the job in the first period, whereas 25 of them lost their jobs in the second period.

Although there are some significant differences in the level of education and labour status of the father in 2008 in the restricted sample (see Table 17 in the appendix), the means of all

[15]The main assumption, i.e. that conditioning on worker fixed effects the Great Recession generates random employment shocks, can not be used to define a treatment variable that also includes information on finding a job afterwards. The combination of fixed effects and the Great Recession can only explain random entry into job loss. I can not account, for instance, for the level of job search effort intensity devoted by each worker in each period after job loss.

the variables in Table 4 (level of education, age at the moment of job loss, labour status and sector of activity in 2008) for workers losing their jobs in the first and second period are not significantly different from each other in the unrestricted sample. Thus, even if this evidence is not conclusive due to the few number of observations in each group, it does seem to suggest that the main characteristics of the workers losing their jobs in the first period of the crisis are not different from the characteristics of those workers that lost their job during the second period. It seems reasonable to assume, therefore, that omited time variant variables are not a cause of concern in terms of potential bias of the estimates. As a result, it is likely that father's job loss in this sample can be considered as good as randomly assigned after conditioning on student fixed effects and observed covariates:

$$E[Y_{0it}|A_i, X_{it}, X_i, t, D_{it}] = E[Y_{0it}|Ai, X_{it}, X_i, t] \tag{8}$$

where X_{it} is a vector of observed time varying covariates not affected by the job loss itself (like the stage of education the student is enrolled in); X_i is a vector of observed time invariant covariates (like sex, level of education of the father, permanent wealth, etc.), and A_i is a vector of unobserved but fixed confounders capturing the unobserved ability of the student. As Angrist and Pischke (2008) point out and I discussed above, the key to fixed effects estimation is therefore the assumption that the unobserved A_i appears without a time subscript in a linear model for $E[Y_{0it}|A_i, X_{it}, X_i, t]$:

$$E[Y_{0it}|A_i, X_{it}, X_i, t] = \alpha + \lambda_t + A_i'\gamma + X_i'\phi + X_{it}'\beta \tag{9}$$

Assuming that the causal effect of father's job loss is additive and constant, then:

$$E[Y_{1it}|A_i, X_{it}, X_i, t] = E[Y_{0it}|A_i, X_{it}, X_i, t] + \rho \tag{10}$$

which together with equation 9 implies:

$$\begin{aligned} &E[Y_{it}|A_i, X_{it}, X_i, t] = D_{it} * (E[Y_{0it}|A_i, X_{it}, X_i, t] + \rho) + (1 - D_{it}) * E[Y_{0it}|A_i, X_{it}, X_i, t] \\ &= \alpha + \lambda_t + \rho D_{it} + A_i'\gamma + X_i'\phi + X_{it}'\beta \end{aligned} \tag{11}$$

where ρ is the (yearly average) causal effect of father's job loss on children's school performance as long as the assumption of time invariant omitted variables holds. Using the panel nature of the data available, I can therefore estimate the following fixed effects model:

$$Y_{it} = \alpha_i + \lambda_t + \rho D_{it} + X_{it}'\beta + \epsilon_{it} \tag{12}$$

$$\alpha_i = \alpha + A_i'\gamma + X_i'\phi \tag{13}$$

where the individual fixed effect, α_i would capture any time invariant characteristic affecting the educational outcomes of the child, both at the child, household and father/mother level;

and λ_t is a vector of year dummies. Since I omit in the specification those factors that may change as a result of parental job loss (changes in income, civil status, etc.), ρ captures the (average) full effect of father's job loss on school performance for every year after job loss. That is, it captures the total effect of an exogenous negative change in the labour status (parental job loss) on the educational outcomes of their offspring, not holding other inputs constant. As Todd and Wolpin (2003) would put it, in this paper there is no attempt to incorporate in the model all the determinants of cognitive achievement. Instead, this paper makes use of a variable that arguably provides a source of exogenous variation analogous to that provided by randomisation. That is, I estimate a policy effect that corresponds to what is called in the evaluation literature as the local average treatment effect (LATE).

As seen in the graphs in the previous section, future father job losses do not seem to be associated with lower educational outcomes in 2008 for the treatment group. However, estimates of ρ would be biased if students affected by father's job loss had changed/left school by the academic year 2012[16]. This does not seem to be a cause for concern since the drop-out rate for the school in both kindergarten and primary school grades is quite stable and around 0.6% per year. In compulsory secondary school, the average annual drop-out rate is a bit larger and around 3.3%. However, it doesn't seem to be a reason for concern either, since it decreased (rather than increased) from academic year 2008 to academic year 2011 (last year for which I have data on school drop-out rates available). Also, the principals argued that the main reason for compulsory secondary school drop-out is related to the fact that some students turning 16 in the academic year are allowed to quit school by law once they turn 16, and some of them therefore abandon the school system. Also, the reader could think that estimates would be biased if students that otherwise would have enrolled in this particular school, did not do it as a result of father's job loss. However, given the sample restrictions applied, all the students in the restricted sample had to be enrolled in the school before the beginning of the Great Recession in order to be able to observe them both in 2008 and 2012. Finally, I am implicitly assuming here that school inputs are not altered by parental job loss. That is, that the school does not adapt the level of inputs administered to help those students suffering from parental job loss. Estimates of father's job loss would be (downward) biased if this assumption does not hold. All in all, given the characteristics of the sample outlined in Ruiz-Valenzuela (2014)[17], the results shown in the next section are probably a downward biased estimate of the effect of father's job loss on school performance for the Spanish population of students in compulsory education during the Great Recession in Spain.

[16]Since I only could distribute the survey to those parents of students that in the academic year 2012 were enrolled at school, it could be that previous to 2012, students affected by parental job loss had dropped out from this school and moved to a public one.

[17]Concerted school, slightly better students handing in the parental questionnaires, no immigrants, etc.

Table 5: **Average effect of FJL on the average grade**

	M.1	M.2	M.3	M.4	M.5	M.6
FJL	0.012	-0.113**	-0.118**	-0.142**	-0.086*	-0.093
	(0.111)	(0.057)	(0.057)	(0.066)	(0.050)	(0.057)
Mean	3.706	3.706	3.706	3.678	3.712	3.684
SD	0.839	0.839	0.839	0.855	0.888	0.898
N	890	890	890	830	1269	1191
Students (groups)		178	178	166	290	272
Subsample	Rest	Rest	Rest	Rest Exclude 2JL	Unrest	Unrest Exclude 2JL
Fixed effects	No	Yes	Yes	Yes	Yes	Yes
Extra controls	No	No	Yes	Yes	Yes	Yes

FJL (father's job loss): dummy equal to 1 from the year the father loses the job. Average grade for the whole sample (excluding students in post-compulsory education) has a mean of 3.69 and SD 0.89. *, **, *** denote significance at the 10%, 5% and 1% levels. Clustered robust standard errors at the student level in parentheses. All models include year dummies, and dummies for stage of education. Extra controls are indicators for whether the student is re-taking that particular grade, and whether the average grades belong to classes taken in the school where the survey was distributed. Definitions of subsamples explained in the text.

5 Results

5.1 Average effects of father's job loss on children's school performance

Table 5 shows the first set of results using as the dependent variable the average grade for each academic year. Standard errors are clustered at the student level. All models include year dummies, and dummies controlling for the stage of education the student is in year t. The results of an OLS regression are shown in column 1. Without controlling for fixed effects, the father's job loss variable (FJL from now onwards) does not have a significant effect on the average grade. However, in the fixed effects model shown in column 2 the coefficient of the FJL variable becomes negative and significant. After FJL, from a mean of 3.69 points (in a 1 to 5 scale), students suffer a decrease in the average grade of 0.113 points. In column 3 a dummy variable is added to control for repetition of grades (the variable equals 1 if the student is retaking that particular grade) and a dummy variable that captures whether the grades correspond to years in the school where the survey was administered. The point estimate barely changes after the inclusion of these additional explanatory variables.

In model 4, estimates for the fixed effect model are presented for a sample restricted to exclude those students whose fathers have experienced 2 job losses in the period. Stevens (1997) studies the effects of multiple job losses on earnings, and finds that much of the persistence in the earnings losses can be explained by additional job losses in the years following an initial displacement. Multiple job losses could be introducing, therefore, unobserved time varying heterogeneity that could bias the estimates. By excluding from the sample those students whose fathers lost the job more than once in the period under analysis, the estimate remains negative and significant, although slightly bigger in magnitude. From now on, I will show the results both for the initial restricted sample as well as for the one excluding more than a job loss in the period.

As a robustness check, the last two columns (models 5 and 6) use what I described in the data section as the unrestricted sample. This sample consists of all students in the dataset,

Table 6: **Average effect of FJL on percentile rank**

	M.1	M.2	M.3	M.4	M.5	M.6
FJL	-0.003	-0.044**	-0.044**	-0.055**	-0.035*	-0.040*
	(0.041)	(0.022)	(0.022)	(0.025)	(0.019)	(0.021)
Mean	0.526	0.526	0.526	0.519	0.508	0.503
SD	0.291	0.291	0.291	0.296	0.289	0.293
N	890	890	890	830	1269	1191
Students (groups)		178	178	166	290	272
Subsample	Rest	Rest	Rest	Rest	Unrest	Unrest
				Exclude 2JL		Exclude 2JL
Fixed effects	No	Yes	Yes	Yes	Yes	Yes
Extra controls	No	No	Yes	Yes	Yes	Yes

FJL (father's job loss): dummy equal to 1 from the year the father loses the job. Average percentile rank for the whole sample (excluding students in post-compulsory education) has a mean of 0.50 and SD 0.28. *, **, *** denote significance at the 10%, 5% and 1% levels. Clustered robust standard errors at the student level in parentheses. All models include year dummies, and dummies for stage of education. Extra controls are indicators for whether the student is re-taking that particular grade, and whether the average grades belong to classes taken in the school where the survey was distributed. Definitions of subsamples explained in the text.

except those that in the academic year 2012 were already in postcompulsory education, and those students whose father was already unemployed in 2008. In column 6 I add the additional restriction of excluding those students whose fathers experience more than a job loss in the period studied. Using the unrestricted sample, the magnitude of the point estimates is slightly smaller and standard errors increase, but in general the results are in line with those of the restricted sample and suggest that father's job loss has a negative impact on grades also in the unrestricted sample.

Table 6 presents the same structure but using the percentile rank of the student in each grade-year combination as a dependent variable. The same pattern described for the average grades emerges. The percentile rank in the class decreases around 4.4 percentage points in the restricted sample and 5.5 percentage points when students with fathers experiencing two job losses are excluded. Although slightly smaller in absolute terms, a negative and significant impact is also found in the unrestricted sample.

In terms of standard deviations, FJL entails an average decrease in children's average grades of about 13.2 to 16% of the (population) standard deviation in the restricted sample, and between 9 and 10% in the unrestricted one. In terms of the percentile rank, it implies a decrease of about 15.7 to 19.6% of the (population) standard deviation in the restricted sample, and around 12.5 to 14.3% in the unrestricted. Compared to Rege et al. (2011), that find an effect of father plant closure on average GPA of 16 year olds of about 6.3% of the (population) standard deviation, the results in my case show that the effects of father's job loss on the average grades of their offspring during a deep economic crisis are bigger in magnitude. However, the results in my sample are an average of the effects of FJL across different ages, since students included had ages ranging between 8 and 17 years old in the academic year 2012.[18]

[18] Table 18 in the appendix reproduces the results for models 3 and 4 using the two measures of school performance computed under the assumptions of measure 2 instead (see data section). The results obtained are almost identical. Thus, from now on I will only reproduce the results using the measures of school performance computed under the assumptions of measure 1.

Table 7: **Average effect of FJL on average grade and percentile rank. Random Effects**

	Average grade				Percentile rank			
	M.1	M.2	M.3	M.4	M.5	M.6	M.7	M.8
FJL	-0.102*	-0.106*	-0.135**	-0.136**	-0.039*	-0.041*	-0.052**	-0.052**
	(0.057)	(0.057)	(0.067)	(0.065)	(0.021)	(0.021)	(0.024)	(0.023)
Female		0.374***		0.384***		0.137***		0.136***
		(0.107)		(0.113)		(0.038)		(0.040)
Born Q1		0.551***		0.539***		0.213***		0.206***
		(0.166)		(0.173)		(0.058)		(0.061)
Born Q2		0.205		0.169		0.069		0.055
		(0.165)		(0.174)		(0.058)		(0.062)
Born Q3		0.340**		0.335**		0.125**		0.126**
		(0.155)		(0.161)		(0.054)		(0.056)
Father educ		0.349***		0.344***		0.138***		0.136***
beyond HS		(0.109)		(0.118)		(0.040)		(0.044)
Mean	3.706	3.706	3.678	3.678	0.526	0.526	0.519	0.519
SD	0.839	0.839	0.855	0.855	0.291	0.291	0.296	0.296
N	890	890	830	830	890	890	830	830
Students (groups)	178	178	166	166	178	178	166	166
Subsample	Rest	Rest	Rest	Rest	Rest	Rest	Rest	Rest
			Exclude 2JL	Exclude 2JL			Exclude 2JL	Exclude 2JL
Fixed effects	No	No	No	No	No	No	No	No

FJL (father's job loss): dummy equal to 1 from the year the father loses the job. Average grade for the whole sample (excluding students in post-compulsory education) has a mean of 3.69 and SD 0.89. Average percentile rank for the whole sample (excluding students in post-compulsory education) has a mean of 0.50 and SD 0.28. *, **, *** denote significance at the 10%, 5% and 1% levels. Clustered robust standard errors at the student level in parentheses. All models include year dummies, and dummies for stage of education, indicators for whether the student is re-taking that particular grade, and whether the average grades belong to classes taken in the school where the survey was distributed. Definitions of subsamples explained in the text.

Table 7 shows the results of the estimations of random effects models of the average grade (first 4 columns) and the percentile rank (last 4 columns), for the restricted sample, and excluding from the restricted sample those students with fathers that experienced 2 job losses in the period under analysis. This table is interesting for at least 2 reasons. First, by using the random effects estimator I can estimate the impact of time invariant variables and assess whether the results obtained are in line with those traditionally found in the economics of education literature. In general, the main regularities established in the empirical literature also hold for this sample (and also for the unrestricted one, see Table 19 in the appendix). Thus, females tend to perform better at school, those born in the first quarters of the year do better with respect to those born in the last quarter, and father's education (here defined as a dummy variable equal to 1 if the father has an education degree beyond high-school) has a positive and sizable impact both in the average grade and percentile rank of his offspring. The second reason is because I can compare the results of random versus fixed effects models. The fact that the point estimates between the 2 estimators do not differ by a significant amount (Hausman tests can not reject the null of non systematic differences between FE and RE coefficients) suggests that the shocks to employment could be exogenous to the worker, even without conditioning on his (time invariant) characteristics. Moreover, placebo tests for the effect of future father job losses on school performance prior to job loss provide additional support to the interpretation of the effects as being of a causal nature. Table 8 shows the results of the impact of future job losses on average grades in 2008 (the first academic year in the sample, where by construction all students have employed fathers). In all cases the estimates are highly imprecise and not

Table 8: **Placebo test: Impact of future job loss on the average grade and percentile rank of 2008**

	Average grade		Percentile rank	
	M.1	M.2	M.3	M.4
Future FJL	0.033	-0.062	-0.005	-0.031
	(0.114)	(0.135)	(0.045)	(0.052)
Father educ	0.291***	0.247**	0.114**	0.096**
beyond HS	(0.106)	(0.117)	(0.044)	(0.047)
Mean	3.955	3.921	0.518	0.511
SD	0.801	0.815	0.286	0.288
Students (groups)	178	166	178	166
Subsample	Rest	Rest Exclude 2JL	Rest	Rest Exclude 2JL

Future FJL: dummy equal to 1 if the father will experience job loss in the future (at some point in subsequent observed academic years). *, **, *** denote significance at the 10%, 5% and 1% levels. Robust standard errors in parentheses. All models include dummies for stage of education and whether the average grades belong to classes taken in the school where the survey was distributed. Definitions of subsamples explained in the text.

significantly different from zero.

An additional robustness check is presented in Table 20 in the appendix. In this table I only use the information corresponding to the academic years 2008, 2010 and 2012. As described in the data section, by restricting the sample to these periods I don't need to make any assumptions with regards to the date of job loss. Estimates from the fixed effect models show that the coefficients of the FJL variable are also negative and significant, and slightly bigger in magnitude (given that now ρ captures two year changes in grades), both for the percentile rank and the average grade measure.

Following the related literature, I now turn to analyze whether the impact of father's job loss is heterogeneous across different subgroups in the sample, and the possible mechanisms by which father's job loss has a negative effect on the school performance of their offspring.

5.2 Heterogeneous effects and possible mechanisms

5.2.1 Income

In this section I explore whether there are heterogeneous effects of FJL according to the level of income that fathers had previous to job loss. According to previous literature, displaced workers suffer short-run earning losses that persist in the long run (Jacobson et al., 1993). Thus, I also investigate whether income could be one of the mechanisms behind the negative effect of FJL on the school performance of their offspring. I classified fathers into two categories: those with low income in 2008 versus those with high income in 2008[19]. Table 9 presents the results for the restricted sample of 178 students in the first four columns (models 1 to 4). Columns 5 to 8 present the results when I exclude those students whose father has suffered more than a job loss in the period. In the first panel of the table, the variable under study is the percentile rank in the year and grade of the student. The second panel reproduces the same models but with the average grade as the dependent variable. Finally, the third panel

[19]Those in the low income category are those with a monthly net income in the lowest two categories in the survey (below 1499 euros). Those in the high income category are those with a monthly net income in the highest two categories in the survey (above 1500 euros).

Table 9: **Income. Differential effects and possible driving mechanism**

	All sample				Excluding fathers with 2 job losses			
	M.1	M.2	M.3	M.4	M.5	M.6	M.7	M.8
Panel 1: Percentile rank in the year-grade combination								
FJL	-0.043	0.009	-0.053**	-0.036	-0.064**	-0.001	-0.072**	-0.046*
	(0.026)	(0.045)	(0.027)	(0.024)	(0.028)	(0.050)	(0.028)	(0.028)
FJL * low income 2008	0.019				0.043			
	(0.047)				(0.056)			
Mean	0.533	0.531	0.534	0.533	0.527	0.521	0.529	0.527
SD	0.287	0.295	0.284	0.287	0.292	0.301	0.289	0.292
Panel 2: Average grade								
FJL	-0.086	0.016	-0.120*	-0.084	-0.115*	-0.017	-0.144**	-0.102
	(0.063)	(0.125)	(0.064)	(0.060)	(0.069)	(0.147)	(0.069)	(0.072)
FJL * low income 2008	0.005				0.033			
	(0.115)				(0.147)			
Mean	3.735	3.753	3.727	3.735	3.706	3.706	3.705	3.706
SD	0.832	0.841	0.829	0.832	0.850	0.873	0.842	0.850
N	820	245	575	820	760	215	545	760
Panel 3: Dummy equal to 1 if father has high income								
FJL	-0.318***	0.034	-0.562***		-0.339***	0.050	-0.611***	
	(0.099)	(0.073)	(0.124)		(0.100)	(0.093)	(0.141)	
Mean	0.643	0.029	0.915		0.663	0.033	0.923	
SD	0.479	0.168	0.280		0.473	0.179	0.267	
N	834	243	574		775	213	545	
Subsample	All -income observed	2008 Low income	2008 High income	All -income observed	All -income observed	2008 Low income	2008 High income	All -income observed

FE estimates. Measure 1 of both percentile rank and average grade used. FJL (father's job loss): dummy equal to 1 from the year the father loses the job.Average grade for the whole sample (excluding students in post-compulsory education) has a mean of 3.69 and SD 0.89. Average percentile rank for the whole sample (excluding students in post-compulsory education) has a mean of 0.50 and SD 0.28. *, **, *** denote significance at the 10%, 5% and 1% levels. Clustered robust standard errors at the student level (Panel 1 and 2) and at the household level (Panel 3) in parentheses. Panel 1 and 2 extra controls for all models are: year dummies, dummies for stage of education, a dummy for whether the student is re-taking that particular grade, and whether the grades belong to years in this school. Panel 3 extra controls are year dummies. Difference in N between panel 1 and 2, on the one hand, and 3, due to missing observations in father's income.

studies the effect of FJL on monthly income. Since the income variable has some missing values for some observations[20], columns 4 and 8 in this table reproduce the results of models 4 and 5 in tables 4 and 5, respectively, when I exclude the observations with missing parental income[21].

I focus first on the results shown in the first four columns of table 9. Model 1 in panel 1 shows that the difference in effect magnitude on the percentile rank between children of fathers with high versus low income in 2008 is not statistically significant. The same result is found when the dependent variable is the average grade. Thus, I do not find evidence of heterogeneous effects of FJL on school performance according to the level of income previous to job loss.

However, model 1 in panel 3 shows results that are in line with previous empirical evidence. Parental income suffers a statistically significant, sizable, and negative decrease after FJL. In order to assess the role of income changes as a possible mechanism driving the negative effect of FJL on school performance, I follow Rege et al. (2011) and divide the sample into two dif-

[20] I do not observe parental income in 2008 for a total of 15 students.

[21] Compared to the results in tables 4 and 5, the effect of FJL on both the percentile rank and grades becomes slightly smaller in magnitude and less precise when excluding the observations with parental income missing.

ferent subsamples according to parental income in 2008. The results are shown in models 2 and 3 of panel 3. The effect of FJL on income for the subsample of children whose fathers were in the high income group in 2008 is negative, statistically significant and also statistically different from the effect on the complementary subsample. However, even though the estimates in panel 1 and 2 suggest sizable differences between the school performance in both subsamples, the estimates for the low income category are very imprecise, and its confidence interval overlaps with the one for the estimate in the high 2008 income subsample. Thus, like Stevens and Schaller (2011), I find no clear evidence supporting the hypothesis that income could be a mechanism behind the effect of FJL on school performance. Excluding those children whose fathers suffered two job losses in the period, the results are very similar to those already described.

5.2.2 Motivation at work

A strand of literature in the Social Psychology field suggests that workers affected by massive layoffs have prevalent feelings of job insecurity and job loss leaves them anxious, angry and demoralized (Barling et al., 1999b). Therefore, it could be that their level of motivation in subsequent jobs resulted affected after job loss. At the same time, (Barling et al., 1999b) state that from as young as 5 years of age, children understand such concepts as pay, labor disputes, unemployment, and, in general, the working conditions of their parents. Are there differential effects of FJL on school performance, between those children whose fathers were highly motivated at work previous to lose their jobs and those children whose fathers were not as motivated? Does motivation at work change after job loss, and if so, could it be a driving mechanism for the effect of FJL on school performance?

Results are presented in table 10 under the same structure as in table 9, with the difference being that in panel 3 the effects of FJL on motivation at work are studied instead. Model 1 in both panel 1 and 2 suggest that there are no significant differences on school performance between children whose parents were highly versus low motivated at their jobs in 2008. However, albeit imprecise, the estimates seem to suggest that those children whose fathers had already a low motivation at work suffered a lower negative impact on school performance. Separating the sample into two different subsamples, the effect of FJL on motivation at work[22] for fathers is significantly different and goes in opposite directions. Fathers who were highly motivated in their jobs in 2008, suffer a significant reduction in their level of motivation in their new jobs, once job loss occurs. On the contrary, fathers who were less motivated at work in 2008 increase significantly their level of motivation at work after job loss. These differences might be behind the difference in magnitude found on school performance between the two subsamples, although this difference is not statistically significant.

Results when excluding those children whose fathers suffer two job losses in the period seem

[22] Available only for those that found a new job after job loss

Table 10: **Motivation at work. Differential effects and possible driving mechanism**

	All sample				Excluding fathers with 2 job losses			
	M.1	M.2	M.3	M.4	M.5	M.6	M.7	M.8
Panel 1: Percentile rank in the year-grade combination								
FJL	-0.050*	-0.020	-0.051*	-0.039	-0.069**	-0.014	-0.069**	-0.046
	(0.029)	(0.061)	(0.029)	(0.026)	(0.032)	(0.064)	(0.032)	(0.029)
FJL * low	0.039				0.069			
motiv 2008	(0.052)				(0.059)			
Mean	0.530	0.515	0.535	0.530	0.525	0.503	0.532	0.525
SD	0.292	0.286	0.294	0.292	0.297	0.288	0.299	0.297
Panel 2: Average grade								
FJL	-0.131*	0.053	-0.156**	-0.091	-0.172**	0.066	-0.201**	-0.107
	(0.071)	(0.152)	(0.071)	(0.065)	(0.082)	(0.161)	(0.081)	(0.074)
FJL * low	0.137				0.195			
motiv 2008	(0.129)				(0.148)			
Mean	3.709	3.646	3.729	3.709	3.683	3.612	3.706	3.683
SD	0.850	0.870	0.843	0.850	0.865	0.878	0.860	0.865
N	785	190	595	785	735	180	555	735
Panel 3: Dummy equal to 1 if father is highly motivated								
FJL	-0.034	0.578**	-0.383***		-0.040	0.661***	-0.507***	
	(0.172)	(0.217)	(0.139)		(0.159)	(0.224)	(0.158)	
Mean	0.771	0.152	0.964		0.770	0.159	0.962	
SD	0.420	0.360	0.186		0.421	0.367	0.191	
N	748	178	558		710	170	528	
Subsample	All -motiv observed	2008 Low motiv	2008 High motiv	All -motiv observed	All -motiv observed	2008 Low motiv	2008 High motiv	All -motiv observed

FE estimates. Measure 1 of both percentile rank and average grade used. FJL (father's job loss): dummy equal to 1 from the year the father loses the job. Average grade for the whole sample (excluding students in post-compulsory education) has a mean of 3.69 and SD 0.89. Average percentile rank for the whole sample (excluding students in post-compulsory education) has a mean of 0.50 and SD 0.28. *, **, *** denote significance at the 10%, 5% and 1% levels. Clustered robust standard errors at the student level (Panel 1 and 2) and at the household level (Panel 3) in parentheses. Panel 1 and 2 extra controls for all models are: year dummies, dummies for stage of education, a dummy for whether the student is re-taking that particular grade, and whether the grades belong to years in this school. Panel 3 extra controls are year dummies. Difference in N between panel 1 and 2, on the one hand, and 3, due to missing observations in father's motivation at work. This can be real missing values or missing values due to periods in unemployment (in those periods, motivation at work is not defined).

to be more supportive of the social psychologists hypothesis. Even though the interaction is not significant in either panel 1 or 2, the estimates are positive and more precise than the ones shown in the left panel of the table.

5.2.3 Father's education

I follow the related empirical literature and study whether the effect of FJL concentrates on those children whose fathers have a lower educational level. As Stevens and Schaller (2011), I group fathers into two groups. Those with a high level of education are those with an educational level beyond high-school, and those with a low level of education are those that have a high-school diploma or less. Table 11 has the same structure as table 9 except that columns 4 and 8 are not shown, since there are no missing values for the education of the father. The results in the left part of the table suggest that the negative effects of FJL are concentrated on those children whose father has a low level of education. The interaction of FJL with a dummy equal to 1 if the father has a high level of education is positive for the two measures of school performance, although only significant at the 10% level for the average grade measure.

Table 11: **Other heterogeneous effects: Father's education**

	All sample			Excluding fathers with 2 job losses		
	M.1	M.2	M.3	M.4	M.5	M.6
Panel 1: Percentile rank in the year-grade combination						
FJL	-0.061**	-0.061**	-0.014	-0.079***	-0.079***	0.019
	(0.025)	(0.027)	(0.042)	(0.026)	(0.027)	(0.060)
FJL * Father	0.048			0.102*		
high educ	(0.041)			(0.057)		
Mean	0.527	0.478	0.606	0.521	0.475	0.597
SD	0.291	0.281	0.291	0.296	0.283	0.303
Panel 2: Average grade						
FJL	-0.171**	-0.169**	-0.008	-0.213***	-0.210***	0.092
	(0.071)	(0.074)	(0.081)	(0.075)	(0.077)	(0.110)
FJL * Father	0.166*			0.314***		
high educ	(0.093)			(0.118)		
Mean	3.712	3.579	3.924	3.684	3.560	3.894
SD	0.840	0.851	0.778	0.857	0.860	0.809
N	890	545	345	830	520	310
Panel 3: Dummy equal to 1 if father has high income						
FJL	-0.318***	-0.361***	-0.229	-0.339***	-0.339**	-0.346
	(0.099)	(0.118)	(0.174)	(0.124)	(0.132)	(0.308)
Mean	0.643	0.571	0.755	0.663	0.591	0.785
SD	0.479	0.495	0.431	0.473	0.492	0.412
N	834	511	323	775	487	288
Subsample	All observed	Father low education	Father high education	All observed	Father low education	Father high education

FE estimates. Measure 1 of both percentile rank and average grade used. FJL (father's job loss): dummy equal to 1 from the year the father loses the job. Average grade for the whole sample (excluding students in post-compulsory education) has a mean of 3.69 and SD 0.89. Average percentile rank for the whole sample (excluding students in post-compulsory education) has a mean of 0.50 and SD 0.28. *, **, *** denote significance at the 10%, 5% and 1% levels. Clustered robust standard errors at the student level (Panel 1 and 2) and at the household level (Panel 3) in parentheses. Panel 1 and 2 extra controls for all models are: year dummies, dummies for stage of education, a dummy for whether the student is re-taking that particular grade, and whether the grades belong to years in this school. Panel 3 extra controls are year dummies. Difference in N between panel 1 and 2, on the one hand, and 3, due to missing observations in father's income.

On the right section of the table, though, the interaction is positive, significant, and bigger in magnitude than the estimates of the FJL variable for those children whose father has a low level of education. Thus, these results would indicate that on the one side, the effect of job loss is concentrated on disadvantaged families, as measured by the level of education of the father. On the other, that there is no effect, or a slightly positive effect on the school performance measures, if FJL occurs on families where the father has a high level of education. The direction of the results is in line with the ones found by Rege et al. (2011) and Stevens and Schaller (2011), although in their case, the confidence intervals around the estimates were too large to draw any strong conclusions.

These differences across the two subgroups do not seem to be driven by income effects. Panel 3 shows that there are large and negative decreases in income in the two subsamples, and even though the estimate for the subsample of children whose father has high education is not significant, the confidence intervals for estimates in the two subsamples overlap.

5.2.4 Closing own business versus losing the job while employed in a firm

Given the nature of my data, the indicator of father's job loss includes fathers displaced while working for a firm and fathers that owned his own business in 2008, but closed it down after the

Table 12: **Other heterogeneous effects: Closing own business versus losing the job in a firm**

	All sample			Excluding fathers with 2 job losses		
	M.1	M.2	M.3	M.4	M.5	M.6
Panel 1: Percentile rank in the year-grade combination						
FJL	-0.077**	-0.031	-0.076**	-0.069**	-0.049	-0.063*
	(0.031)	(0.028)	(0.037)	(0.034)	(0.033)	(0.036)
FJL * Worker	0.044			0.019		
in a firm in 2008	(0.039)			(0.046)		
Mean	0.527	0.549	0.466	0.521	0.544	0.458
SD	0.291	0.286	0.299	0.296	0.291	0.302
Panel 2: Average grade						
FJL	-0.214**	-0.066	-0.217**	-0.210*	-0.098	-0.200*
	(0.093)	(0.067)	(0.103)	(0.108)	(0.081)	(0.112)
FJL * Worker	0.137			0.100		
in a firm in 2008	(0.110)			(0.132)		
Mean	3.712	3.784	3.509	3.684	3.760	3.479
SD	0.840	0.826	0.849	0.857	0.847	0.851
N	890	655	235	830	605	225
Panel 3: Dummy equal to 1 if father has high income						
FJL	-0.318***	-0.309***	-0.316	-0.339***	-0.340**	-0.333
	(0.099)	(0.115)	(0.186)	(0.124)	(0.148)	(0.218)
Mean	0.643	0.640	0.652	0.663	0.670	0.645
SD	0.479	0.481	0.477	0.473	0.471	0.480
N	834	627	207	775	578	197
Subsample	All observed	2008 Father worker firm	2008 Father own business	All observed	2008 Father worker firm	2008 Father own business

FE estimates. Measure 1 of both percentile rank and average grade used. FJL (father's job loss): dummy equal to 1 from the year the father loses the job. Average grade for the whole sample (excluding students in post-compulsory education) has a mean of 3.69 and SD 0.89. Average percentile rank for the whole sample (excluding students in post-compulsory education) has a mean of 0.50 and SD 0.28. *, **, *** denote significance at the 10%, 5% and 1% levels. Clustered robust standard errors at the student level (Panel 1 and 2) and at the household level (Panel 3) in parentheses. Panel 1 and 2 extra controls for all models are: year dummies, dummies for stage of education, a dummy for whether the student is re-taking that particular grade, and whether the grades belong to years in this school. Panel 3 extra controls are year dummies. Difference in N between panel 1 and 2, on the one hand, and 3, due to missing observations in father's income.

crisis hit the Spanish economy. Do the effects of FJL on school performance differ according to the type of ownership relation that the father had with the firm previous to job loss? If job loss carries negatives consequences for the displaced worker, even more negative costs could be expected for those fathers who lost their jobs because their own business failed. Ucbasaran et al. (2013) review the literature on the consequences of business failure for entrepreneurs, and classify the costs of business failure into financial, social and psychological. In my sample though, even if possibly present, those effects could be expected to be lower than under normal circumstances, because failure could be easily associated with the economic crisis, and not with personal failure.

With the same structure as table 11, table 12 presents the results for this section. The interaction term summarizing the effects of FJL on school performance for those children whose father worked for a firm is positive, but insignificant in all cases. Splitting the sample, the loss in income is very similar in magnitude for both subsamples, although the estimate is not significant for the subsample of those children whose fathers owned a firm in 2008. In general, even though insignificant, the estimates do suggest a larger effect for those children whose fathers closed their own business after 2008, that is not related with their loss in income.

5.2.5 Age of the student

The early childhood development literature emphasizes the importance of parental characteristics and early home environment in producing cognitive skills. Following this literature, Cunha et al. (2006) propose a model of skill accumulation in which childhood has more than one stage and by which early investments in skills are both self-productive (skills produced at one stage augment skills attained at later stages), and complementary (skills produced at one stage raise the productivity of investment at subsequent stages). Thus, everything else equal, the negative shock to parental inputs that parental job loss produces, should have bigger effects on school performance the younger the children are when this negative occurs.

However, parental job loss could also distort the incentives to study of children suffering from parental job loss. A priori, one would expect that these distortions in incentives are bigger the older the children are when parental job loss occurs, given that older children are more aware of the value of education. As seen before, though, the direction of the effect of FJL on student's incentives is not clear. On the one hand, it could be that children of those fathers suffering job loss have an additional incentive to perform better at school to avoid experiencing job loss themselves in the future. In this case, parental job loss would have a more negative effect for younger children. But on the other hand, parental job loss could demotivate those children affected, and in this case, it would not be clear whether younger or older children are more affected. All in all, the expected sign of the effect of parental job loss across children of different ages is not clear. I now turn to comment on the results to shed some light on the existence of differential effects across different ages.

Table 13 presents the results for all the sample in models 1 to 3. In each of these models, different definitions capture the differential effects of FJL across different ages. In model 1, the FJL variable is interacted with a dummy equal to 1 for those students that in the last observed academic year, 2012, where in secondary school[23]. Although the interaction is not significant, its positive sign suggests that the effect of parental job loss on the percentile rank is lower for those children that in 2012 were already in secondary school. That is, it suggests a lower negative effect of FJL for older students. In the second model, the FJL variable is interacted with the dummy variables for the stage of education the children are enrolled in a particular year. As the baseline category, the FJL estimate measures the effect of FJL in primary grades. Again, even though the interaction for both FJL - enrolled in kindergarten and FJL - enrolled in secondary, are statistically insignificant, their sizes suggest that the negative effect of FJL is more detrimental in primary grades. Finally, model 3 interacts the FJL variable with dummies that capture the moment in which FJL happened[24]. In this case, the baseline category measures the effect of FJL if job loss happened while the student was in Primary school. In this case

[23] That is, if the student is in Secondary School in 2012 the dummy variable takes on a value of 1 for all the 5 periods.

[24] For instance, if job loss happened while in Secondary School, then FJL happened in Secondary is equal to 1 for all the 5 periods observed.

Table 13: **Other heterogenous effects: Age of the student**

	All sample			Excluding fathers with 2 job losses		
	M.1	M.2	M.3	M.4	M.5	M.6
FJL	-0.063**	-0.059***	-0.047**	-0.081**	-0.074***	-0.053**
	(0.028)	(0.021)	(0.021)	(0.032)	(0.023)	(0.025)
FJL * Student in	0.040			0.051		
Secondary in 2012	(0.041)			(0.046)		
FJL * Kinder		0.112			0.122	
		(0.088)			(0.116)	
FJL * Secondary		0.021			0.031	
		(0.038)			(0.042)	
FJL * FJL happened			-0.001			-0.045
in kinder			(0.082)			(0.092)
FJL * FJL happened			0.005			0.010
in secondary			(0.057)			(0.059)
Mean	0.527	0.527	0.527	0.521	0.521	0.521
SD	0.291	0.291	0.291	0.296	0.296	0.296
N	890	890	890	830	830	830

FE estimates. Measure 1 for percentile rank used. FJL (father's job loss): dummy equal to 1 from the year the father loses the job. Average grade for the whole sample (excluding students in post-compulsory education) has a mean of 3.69 and SD 0.89. Average percentile rank for the whole sample (excluding students in post-compulsory education) has a mean of 0.50 and SD 0.28. *, **, *** denote significance at the 10%, 5% and 1% levels. Clustered robust standard errors at the student level in parentheses. Extra controls for all models are: year dummies, dummies for stage of education, a dummy for whether the student is re-taking that particular grade, and whether the grades belong to years in this school.

though, the interactions are highly insignificant, and would indicate that the timing of parental job loss does not matter. The results excluding those children whose fathers experience more than a job loss in the period are shown in the right part of the table, and are very similar to the ones already commented. Also, results using the average grade as the dependent variable are not shown, but the same picture emerges. Unfortunately, the evidence in this section does not offer a clear picture, although it seems to suggest that a more detrimental effect of FJL could be expected, in general, the younger the children are.

5.2.6 Sex of the student

In their test for differential effects of FJL on school performance across boys and girls, Rege et al. (2011) find no significant differences, although the difference in the magnitude suggested a larger negative effect for boys. Even though the interaction is not significant in any of the four cases but one (Table 14, panel 2, model 4), the difference in magnitude in my case suggests rather the contrary. The negative effect of FJL seems to be larger for boys than for girls. The evidence in panel 3 indicates that this differential effect can not be attributed to differential income changes after job loss for the subsample of boys, since both estimates are negative, statistically significant, and the confidence intervals for the FJL across both subsamples overlap.

5.2.7 Other possible mechanisms: occupation status, relocation, civil status changes and mother's changes in the labor market

Following the recent empirical literature on the impact of FJL on school performance, I explore other likely mechanisms by which FJL could be affecting the school performance of their off-

Table 14: **Other heterogeneous effects: Sex of the student**

	All sample			Excluding fathers with 2 job losses		
	M.1	M.2	M.3	M.4	M.5	M.6
Panel 1: Percentile rank in the year-grade combination						
FJL	-0.057*	-0.089**	-0.018	-0.087**	-0.114***	-0.014
	(0.034)	(0.036)	(0.027)	(0.034)	(0.036)	(0.033)
FJL * female	0.018			0.053		
	(0.041)			(0.046)		
Mean	0.527	0.458	0.584	0.521	0.456	0.576
SD	0.291	0.292	0.279	0.296	0.296	0.285
Panel 2: Average grade						
FJL	-0.186**	-0.251***	-0.040	-0.267***	-0.325***	-0.019
	(0.091)	(0.091)	(0.070)	(0.096)	(0.097)	(0.084)
FJL* female	0.113			0.217*		
	(0.109)			(0.124)		
Mean	3.712	3.522	3.869	3.684	3.496	3.845
SD	0.840	0.906	0.747	0.857	0.918	0.765
N	890	405	485	830	385	445
Panel 3: Dummy equal to 1 if father has high income						
FJL	-0.318***	-0.422***	-0.234*	-0.339***	-0.442***	-0.254
	(0.099)	(0.137)	(0.125)	(0.124)	(0.163)	(0.164)
Mean	0.643	0.660	0.628	0.663	0.666	0.661
SD	0.479	0.474	0.484	0.473	0.472	0.474
N	834	385	449	775	365	410
Subsample	All observed	Boys	Girls	All observed	Boys	Girls

FE estimates. Measure 1 of both percentile rank and average grade used. FJL (father's job loss): dummy equal to 1 from the year the father loses the job. Average grade for the whole sample (excluding students in post-compulsory education) has a mean of 3.69 and SD 0.89. Average percentile rank for the whole sample (excluding students in post-compulsory education) has a mean of 0.50 and SD 0.28. *, **, *** denote significance at the 10%, 5% and 1% levels. Clustered robust standard errors at the student level (Panel 1 and 2) and at the household level (Panel 3) in parentheses. Panel 1 and 2 extra controls for all models are: year dummies, dummies for stage of education, a dummy for whether the student is re-taking that particular grade, and whether the grades belong to years in this school. Panel 3 extra controls are year dummies. Difference in N between panel 1 and 2, on the one hand, and 3, due to missing observations in father's income.

Table 15: **Other possible mechanisms: effects of FJL on other variables**

	All sample				Excluding fathers with 2 job losses			
	M.1	M.2	M.3	M.4	M.5	M.6	M.7	M.8
Dep variable:	Father working	Moved in the year	Stable civil status	Mother working	Father working	Moved in the year	Stable civil status	Mother working
FJL	-0.249***	-0.040	-0.009	-0.111*	-0.284***	-0.049	-0.009	-0.143*
	(0.066)	(0.033)	(0.006)	(0.061)	(0.064)	(0.042)	(0.006)	(0.074)
Mean	0.941	0.019	0.956	0.784	0.945	0.021	0.953	0.775
SD	0.236	0.137	0.204	0.412	0.228	0.142	0.211	0.418
N	895	885	895	894	835	825	835	834

FE estimates. FJL (father's job loss): dummy equal to 1 from the year the father loses the job. *, **, *** denote significance at the 10%, 5% and 1% levels. Clustered robust standard errors at the household level in parentheses. All models include year dummies. Dependent variables are, respectively, dummy variables equal to 1 if the father is working, the family has changed residence in the year, the civil status of the parents is classified as stable (married or living together), and the mother is working.

spring[25]. First, table 15 shows the effect of FJL on several potential mechanisms. Table 16 shows then the results after re-estimating the original model under different sample restrictions. As Rege et al. (2011) point out, though, the results in table 16 should be interpreted cautiously because the sample restrictions are likely endogenous to job loss. As in the precedent sections, results in both tables are presented for the whole sample (models 1 to 4), and excluding those children whose fathers experience more than a job loss in the period (models 5 to 8).

The dependent variable in model 1 is a dummy variable equal to 1 if the father is working in that particular year. There is a consensus among the extensive literature on job displacement on the negative short-run impact of job loss on the re-employment probabilities of the displaced worker (see table 3 in Kletzer (1998) or the more recent work by Rege et al. (2009) on the impact of job displacement on the disability entry rate in Norway). Given that job loss in my sample is produced in a context of a deep economic recession, the effects of job loss on subsequent employment status are expected to be even more pronounced than those found in the literature. Indeed, the probability that the father is working after job loss decreases by almost 25 percentage points. In model 1 (and 5) in table 16, I exclude from the analysis those children whose fathers are not back to work in 2012. This sample restriction excludes basically fathers that have suffered from job loss, so a priori, a modest attenuation of the effects on school performance are expected. Applying this restriction barely changes the estimates of FJL on the percentile rank, and decreases modestly the estimates of FJL on the average grade (and makes them more imprecise). But all in all, as in Rege et al. (2011), the employment implications of job loss do not appear to be important mechanisms in explaining the negative effect of FJL on school performance.

The recent literature on the effects of parental job loss on the educational outcomes of their offspring often analyzes whether those parents suffering job loss have a higher likelihood of residential mobility or marriage dissolution, since both events might be associated with poorer educational outcomes. I find no significant effects of FJL on a dummy variable that equals 1 if the family has changed its residence during that particular year (table 15, model 2 and

[25]I follow closely in this section the empirical strategy used by Rege et al. (2011).

6). Excluding from the main model those observations of children that suffered residential relocation in the period under observation (table 16, models 2 and 6), the estimates of FJL on school performance decrease modestly and become slightly more imprecise, but the main conclusions hold. Eliason (2012) and Charles and Stephens (2004) document an excess risk of divorce among couples in which the husband was displaced in Sweden, and the spousal in the US, respectively. I find no significant effect on the civil status of the parents after FJL in my sample. Accordingly, after restricting the sample to those children whose parents do not experience any civil status change during the period of observation, the estimates of FJL on school performance barely change. However, as Piketty (2003) results suggest, it is parental conflicts (rather than separation/divorce per se) that are bad for children and, in particular, for their school performance. Unfortunately, there is no variable in my sample to measure the level of conflict between the parents in order to assess its role as a potential mechanism behind the effect of FJL on school performance.

Lastly, I analyze whether there is an effect on the employment status of the mother after FJL. My results contrast with those obtained by Rege et al. (2011). Instead of increasing their participation in the labor market, mothers experience a significant decrease in the probability of being employed of 11 percentage points after the father loses the job. In fact, a measure of mother job loss constructed in the same fashion as the FJL measure, displays a correlation in 2012 of 0.2 for the sample of 178 students considered. However, restricting the sample to those children whose mothers did not suffer any labor situation change, the estimates of FJL on school performance decrease only modestly. Additionally, tables 21 in the appendix shows that the effect of mother job loss on school performance, although negative, is of a small magnitude and always insignificant. Moreover, when both father and mother job loss are introduced in the model, the father job loss coefficient retains its sign and magnitude, whereas mother job loss is not statistically different from zero in any of the subsamples. Thus, it does not seem that labor status changes suffered by the mother could be one of the main drivers of the effect of FJL on school performance.

Table 16: **Other possible mechanisms: Effects of FJL on percentile rank and average grades. Sample restrictions**

	All sample				Excluding fathers with 2 job losses			
	M.1	M.2	M.3	M.4	M.5	M.6	M.7	M.8
Panel 1: Percentile rank in the year-grade combination								
FJL	-0.044*	-0.038	-0.045**	-0.038	-0.055*	-0.046	-0.056**	-0.046
	(0.026)	(0.024)	(0.022)	(0.035)	(0.029)	(0.028)	(0.025)	(0.036)
Mean	0.541	0.543	0.525	0.551	0.539	0.536	0.518	0.548
SD	0.290	0.284	0.292	0.290	0.292	0.290	0.297	0.293
Panel 2: Average grade								
FJL	-0.088	-0.095	-0.120**	-0.098	-0.094	-0.113	-0.145**	-0.129
	(0.063)	(0.060)	(0.057)	(0.089)	(0.073)	(0.072)	(0.066)	(0.093)
Mean	3.726	3.758	3.706	3.760	3.716	3.728	3.678	3.744
SD	0.832	0.811	0.843	0.815	0.842	0.830	0.859	0.823
N	790	770	885	600	760	710	825	580
Sample restriction	Father working in 2012	Not moving in the period	Stable civil status	Mother: no labour status change	Father working in 2012	Not moving in the period	Stable civil status	Mother: no labour status change

FE estimates. Measure 1 of both percentile rank and average grade used. FJL (father's job loss): dummy equal to 1 from the year the father loses the job. Grade percentile rank for the entire population of 408 students available has mean 0.5 and SD 0.2871. Average grade for the entire population of 408 students available has mean 3.64 and SD 0.90. *, **, *** denote significance at the 10%, 5% and 1% levels. Clustered robust standard errors at the student level in parentheses. Extra controls for all models are: year dummies, dummies for stage of education, a dummy for whether the student is re-taking that particular grade, and whether the grades belong to years in this school.

6 Conclusion

This paper studies whether the detrimental effects of job loss extend beyond the affected worker. In particular, this article assesses the impact of father's job loss on the school performance of their offspring during the current Great Recession in Spain. In a simple one period static model in which children decide the level of effort they exert at school each academic year, and effort positively influences school performance, parental job loss is assumed to affect both the marginal returns and marginal costs of effort, by making children more or less productive while studying, and altering their incentives to study. The data collected and the estimation strategy followed in this paper have allow me to estimate the total effect of an exogenous change in parental job loss on the educational performance of their offspring. That is, not holding other inputs constant.

As Rege et al. (2011) point out, estimating a causal relationship between parental job loss and child outcomes faces two main challenges: concerns of omitted variable data and the scarcity of appropriate data. This paper has addressed both of them by exploiting the recent developments in the Spanish labor market and by using a panel dataset specifically designed to address this question. Thus, the empirical strategy followed in this article has relied on the fact that, conditioning on student fixed effects and observed covariates, the Great Recession in Spain generates exogeneous variation in job loss analogous to that provided by randomization. That is, the policy effect that I have estimated in this paper corresponds to what is called in the evaluation literature as the local average treatment effect (LATE).

The results in this paper imply that father's job loss entails an average decrease in children's average grades of about 13.2 to 16% of a population standard deviation, and a reduction of about 15.7 to 19.6% of a (population) standard deviation in the percentile rank measure. Compared to Rege et al. (2011), that find an effect of father plant closure on average GPA of 16 year olds of about 6.3% of the population standard deviation, the results in my case show that the effects of father's job loss on the average grade of their offspring during a deep economic crisis (for children aged 8 to 17) are bigger in magnitude. Moreover, given the panel nature of my data, I can show that school performance prior to father's job loss is not affected by future job losses, suggesting a causal link between father's job loss and children's educational outcomes.Rege et al. (2011) compare their estimates with the results summarized by Hanushek (2006) about the STAR experiment: large class size reductions of around 8 students are necessary in order to increase students' achievement by 20% of the standard deviation. Thus, the effects of father's job loss on the school performance of their offspring during the economic recession in Spain are not negligible. Importantly, these results are pointing out a mechanism through which further inequalities in the Spanish society might develop during and after a deep economic crisis.

In this respect, the effect of father's job loss appears to be largely concentrated among children of already disadvantaged families in terms of the level of education of the father, but not in terms of the level of income of the father at the beginning of the crisis. Also, even though imprecise, the results seem to be larger for those children whose father closed his own business after 2008, and more concentrated on boys rather than on girls. Even if in the whole sample father's job loss is associated with a significant decrease in income, these differential effects do not seem to be driven by changes in income. Thus, I find no clear evidence supporting the hypothesis that income could be a mechanism behind the effect of father's job loss on school performance.

Like Rege et al. (2011) and Stevens and Schaller (2011), I also find that the occupational status of the father, residential relocation or changes in civil status are not the main drivers of the effect of father's job loss on school performance of their offspring. Interestingly, I find that mothers experience a significant decrease in the probability of being employed after the father loses the job. However, restricting the sample to those children whose mothers did not suffer any labor situation change, the estimates of father's job loss on school performance decrease only modestly. Additionally, the effect of mother's job loss on school performance, although negative, is of a small magnitude and always insignificant. Thus, mother labor status changes do not seem to be behind the effect of father's job loss either.

One of the mechanisms that had not been studied so far is the changes in the motivation at the workplace after job loss (for those fathers who were able to find a job after job loss). I find that fathers who were highly motivated in their jobs in 2008, suffer a significant reduction in their level of motivation in their new jobs, once job loss occurs. On the contrary, fathers who were less motivated at work in 2008 increase significantly their level of motivation at work after job loss. And even though the estimates are imprecise, the effect of father's job loss seems to be larger for those children whose father was highly motivated previous to job loss. These results would be in line with the theories of the Social Psychologists, that argue that after job loss, workers have prevalent feelings of job insecurity, and job loss leaves them anxious, angry and demoralized (Barling et al., 1999b), and these negative feelings and mood could, in turn, affect the school performance of their offspring. Unfortunately, the number of mothers that after job loss are back to work are very few in this sample, and the data does not offer a clear picture with regards to the effects of mother's job loss and their motivation at work after job loss, although a negative correlation is found. Moreover, given the negative effects on mood that parental job loss carries for the worker, it is likely that parental conflict increases after job loss. As Piketty (2003) results suggest, it is parental conflicts (rather than separation/divorce per se) that are bad for children and, in particular, for their school performance. Unfortunately, there is no variable in my sample to measure the level of conflict between the parents, but future research should assess this channel.

One of the advantages of working with this particular sample is that almost all the students are enrolled at the same school during the period of observation. This means that, under the assumption that the school does not react to father's job loss, there is no differential change in the level of school inputs between treated and control students during the whole period. The driving mechanisms behind the negative effect of father's job loss have to be found, therefore, at the family level. In light of the simple theoretical model described above, and even if more data is needed in order to disentangle the mechanisms behind the negative effect of father's job loss, the results here and in the related literature seem to suggest that, in general, there could be a decrease in the return to effort after parental job loss that is not compensated by a decrease in the marginal costs of effort.

Given the current massive employment destruction that has been taking place in several advanced economies, the present study wants to contribute to underline the importance of understanding the mechanisms behind the negative and sizable effect of father's job loss on children's school performance. Besides the importance of the question in terms of granting equality of opportunity to individuals in society, the answer also has important implications for the economy as a whole, if we are aware of the paramount importance of human capital for economic growth.

7 Appendix

Figure 3: Average percentile rank and average grade. Measure 2

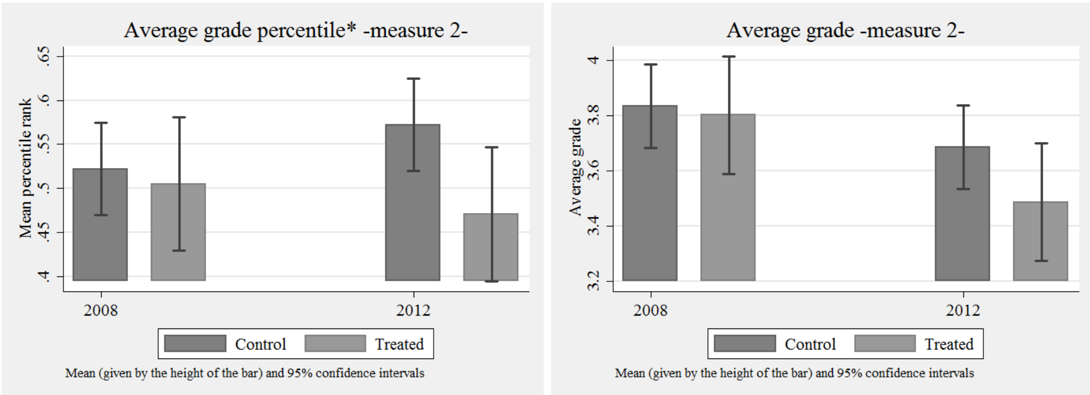


Table 17: **Characteristics of treated fathers in first and second period. Restricted sample**

	2009-2010	2011-2012	All FJL	Diff and t-test
Father educ beyond HS	0.372	0.0909	0.315	0.281*
	(0.489)	(0.302)	(0.469)	(1.81)
	43	11	54	
Father's age	41.44	44	41.96	-2.558
	(4.002)	(5.967)	(4.526)	(-1.35)
	43	11	54	
Father works in a firm in 2008	0.744	0.455	0.685	0.290*
	(0.441)	(0.522)	(0.469)	(1.87)
	43	11	54	
Industry (2008)	0.436	0.364	0.420	0.0723
	(0.502)	(0.505)	(0.499)	(0.42)
	39	11	50	
Construction (2008)	0.282	0.545	0.340	-0.263
	(0.456)	(0.522)	(0.479)	(-1.64)
	39	11	50	
Services (2008)	0.282	0.0909	0.240	0.191
	(0.456)	(0.302)	(0.431)	(1.31)
	39	11	50	

Table 18: **Robustness check: average effect of FJL on average grade and percentile rank (type 2 measure)**

	Average grade		Percentile rank	
	M.1	M.2	M.3	M.4
FJL	-0.104	-0.135*	-0.041*	-0.055**
	(0.064)	(0.072)	(0.024)	(0.027)
Mean	3.647	3.620	0.526	0.519
SD	0.835	0.850	0.292	0.297
N	890	830	890	830
Students (groups)	178	166	178	166
Subsample	Rest	Rest	Rest	Rest
		Exclude 2JL		Exclude 2JL
Fixed effects	Yes	Yes	Yes	Yes

FJL (father's job loss): dummy equal to 1 from the year the father loses the job. Average grade for the whole sample (excluding students in post-compulsory education) has a mean of 3.58 and SD 0.86. Average percentile rank for the whole sample (excluding students in post-compulsory education) has a mean of 0.50 and SD 0.28. *, **, *** denote significance at the 10%, 5% and 1% levels. Clustered robust standard errors at the student level in parentheses. All models include year dummies, and dummies for stage of education, indicators for whether the student is re-taking that particular grade, and whether the average grades belong to classes taken in the school where the survey was distributed. Definitions of subsamples explained in the text.

Table 19: **Average effect of FJL on average grade and percentile rank. Random Effects (unrestricted sample)**

	Average grade				Percentile rank			
	M.1	M.2	M.3	M.4	M.5	M.6	M.7	M.8
FJL	-0.082	-0.087*	-0.109*	-0.111*	-0.032*	-0.034*	-0.043**	-0.044**
	(0.050)	(0.049)	(0.058)	(0.057)	(0.018)	(0.018)	(0.020)	(0.020)
female		0.333***		0.339***		0.125***		0.126***
		(0.080)		(0.085)		(0.029)		(0.030)
Born Q1		0.446***		0.418***		0.185***		0.175***
		(0.127)		(0.133)		(0.045)		(0.047)
Born Q2		0.228**		0.207*		0.091**		0.086**
		(0.115)		(0.120)		(0.040)		(0.042)
Born Q3		0.269**		0.258**		0.110***		0.107***
		(0.115)		(0.118)		(0.040)		(0.041)
Father educ		0.335***		0.330***		0.132***		0.128***
beyond HS		(0.082)		(0.088)		(0.030)		(0.032)
Mean	3.712	3.712	3.684	3.684	0.508	0.508	0.503	0.503
SD	0.888	0.888	0.898	0.898	0.289	0.289	0.293	0.293
N	1269	1269	1191	1191	1269	1269	1191	1191
Students (groups)	290	290	272	272	290	290	272	272
Subsample	Unrest	Unrest	Unrest	Unrest	Unrest	Unrest	Unrest	Unrest
			Exclude 2JL	Exclude 2JL			Exclude 2JL	Exclude 2JL
Fixed effects	No	No	No	No	No	No	No	No

FJL (father's job loss): dummy equal to 1 from the year the father loses the job. Average grade for the whole sample (excluding students in post-compulsory education) has a mean of 3.69 and SD 0.89. Average percentile rank for the whole sample (excluding students in post-compulsory education) has a mean of 0.50 and SD 0.28. *, **, *** denote significance at the 10%, 5% and 1% levels. Clustered robust standard errors at the student level in parentheses. All models include year dummies, and dummies for stage of education, indicators for whether the student is re-taking that particular grade, and whether the average grades belong to classes taken in the school where the survey was distributed. Definitions of subsamples explained in the text.

Table 20: **Robustness check: average effect of FJL on average grade and percentile rank (3 periods: 2008, 2010, 2012)**

	Average grade		Percentile rank	
	M.1	M.2	M.3	M.4
FJL	-0.171***	-0.185**	-0.057**	-0.064**
	(0.062)	(0.073)	(0.026)	(0.028)
Mean	3.736	3.707	0.527	0.521
SD	0.853	0.869	0.294	0.299
N	534	498	534	498
Students (groups)	178	166	178	166
Subsample	Rest	Rest	Rest	Rest
		Exclude 2JL		Exclude 2JL
Fixed effects	Yes	Yes	Yes	Yes

FJL (father's job loss): dummy equal to 1 from the year the father loses the job. Average grade for the whole sample (excluding students in post-compulsory education) has a mean of 3.69 and SD 0.89. Average percentile rank for the whole sample (excluding students in post-compulsory education) has a mean of 0.50 and SD 0.28. *, **, *** denote significance at the 10%, 5% and 1% levels. Clustered robust standard errors at the student level in parentheses. All models include year dummies, and dummies for stage of education, indicators for whether the student is re-taking that particular grade, and whether the average grades belong to classes taken in the school where the survey was distributed. Definitions of subsamples explained in the text.

Table 21: **Average effect of MJL on average grade and percentile rank**

	Average grade		Percentile rank	
	M.1	M.2	M.3	M.4
MJL	-0.040	-0.057	-0.017	-0.029
	(0.085)	(0.092)	(0.030)	(0.032)
Mean	3.702	3.723	0.528	0.535
SD	0.841	0.826	0.291	0.289
N	835	820	835	820
Students (groups)	167	164	167	164
Subsample	Rest	Rest	Rest	Rest
		Exclude 2JL		Exclude 2JL
Fixed effects	Yes	Yes	Yes	Yes

MJL (mother's job loss): dummy equal to 1 from the year the mother loses the job. Average grade for the whole sample (excluding students in post-compulsory education) has a mean of 3.69 and SD 0.89. Average percentile rank for the whole sample (excluding students in post-compulsory education) has a mean of 0.50 and SD 0.28. *, **, *** denote significance at the 10%, 5% and 1% levels. Clustered robust standard errors at the student level in parentheses. All models include year dummies, and dummies for stage of education, indicators for whether the student is re-taking that particular grade, and whether the average grades belong to classes taken in the school where the survey was distributed. Definitions of subsamples explained in the text.

Table 22: **Average effect of FJL and MJL on average grade and percentile rank**

	Average grade		Percentile rank	
	M.1	M.2	M.3	M.4
FJL	-0.117**	-0.142**	-0.043*	-0.053**
	(0.057)	(0.066)	(0.022)	(0.025)
MJL	-0.012	-0.006	-0.010	-0.017
	(0.085)	(0.094)	(0.030)	(0.033)
Mean	3.706	3.678	0.526	0.519
SD	0.839	0.855	0.291	0.296
N	890	830	890	830
Students (groups)	178	166	178	166
Subsample	Rest	Rest	Rest	Rest
		Exclude 2JL		Exclude 2JL
Fixed effects	Yes	Yes	Yes	Yes

FJL/MJL (father's/mother's job loss): dummy equal to 1 from the year the father/mother loses the job. Average grade for the whole sample (excluding students in post-compulsory education) has a mean of 3.69 and SD 0.89. Average percentile rank for the whole sample (excluding students in post-compulsory education) has a mean of 0.50 and SD 0.28. *, **, *** denote significance at the 10%, 5% and 1% levels. Clustered robust standard errors at the student level in parentheses. All models include year dummies, and dummies for stage of education, indicators for whether the student is re-taking that particular grade, and whether the average grades belong to classes taken in the school where the survey was distributed. Definitions of subsamples explained in the text.

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