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

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Abstract
This paper studies the effect of parental job loss on children's school performance during the Great Recession in Spain, using an original panel dataset for students observed since the beginning of the crisis in a school in the province of Barcelona. By using fixed effects, this paper is more likely to deal with the problem of selection into troubled firms which is prevalent in the literature. Fixed effect estimates show that students experience a negative and significant decrease on average grades of about 13% of a standard deviation after father's job loss. The impact of paternal job loss is not homogeneous across students, but it is largely concentrated among children whose fathers suffer long unemployment spells after job loss and students in already disadvantaged families in terms of the father's education level. These results suggest that paternal job loss is a mechanism through which further inequalities might develop during and after a deep economic crisis.

Keywords: Parental job loss, school performance, Great Recession
JEL codes: I20; I24; J63; J65

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1 Introduction

Millions of jobs have been destroyed since the onset of the Great Recession in 2008. Out of the economies that have been severely hit in terms of employment, Spain is one of the front runners. According to the Labour Force Survey data, almost 4 million jobs were destroyed between 2007 and 2012. The available evidence indicates that job loss has negative effects for the affected worker. Among these negative consequences we find short-run earning losses that persist in the long-run, lower re-employment probabilities, prevalent feelings of job insecurity, worse physical and mental health, an increased risk of divorce and, upon re-employment, a moderate increase in workplace injuries.[1] These negative consequences have a direct effect on some of the inputs that are generally seen as affecting the production function for cognitive achievement. Accordingly, several studies (reviewed in Section 2) have assessed whether parental job loss has a negative impact on children's educational outcomes. This paper studies the impact of father's job loss on children's school performance during the Great Recession in Spain.[2] Given the dimensions of the Great Recession in terms of job loss, the effect of parental job loss is potentially big. The results presented in this paper shed light on how a deep economic recession disproportionately affecting some sectors in the economy impacts the educational outcomes of students whose fathers are severely hit by the downturn.

As Rege et al. (2011) note, estimating a causal relationship between parental job loss and children's outcomes faces two main challenges: finding a source of exogenous variation for parental job loss; and the scarcity of appropriate data. This paper addresses both of them by exploiting the developments in the Spanish labour market during the Great Recession and by employing a panel dataset specifically designed to address this question. As will be made clear in Section 2, the main papers in the literature have used plant closures to identify the causal impact of father's job loss on their offspring's school outcomes, but cannot control for student fixed effects (unlike this paper). The research conducted for this paper involved collecting data on the school performance and parental labour market status of over 400 children aged 3 to 18 for the academic years 2007-2008 to 2011-2012 in a school in the province of Barcelona. Figure 1 shows the unemployment rates in the EU-27, Euro area, Spain and the province of Barcelona. Both the Spanish unemployment rate and the unemployment rate in the province of Barcelona reached its minimum in 2007 and started increasing dramatically thereafter.[3] Under the assumption that the vast majority of employment destruction observed in this period is due to the Great Recession (i.e. workers would not have lost their jobs otherwise), job losses during this period could arguably be considered as exogenous to the worker. Or as Gregg et al. (2012) put

[1]See, among others, Jacobson et al. (1993), Kletzer (1998), Couch and Placzek (2010), Von Wachter et al. (2009), Huttunen et al. (2011), Barling et al. (1999b), Eliason and Storrie (2009a), Eliason and Storrie (2009b), Eliason (2012), Charles and Stephens (2004), Leombruni et al. (2013).

[2]Paternal job loss, rather than maternal job loss, is the main focus of this paper. This is because in Spain, the father tends to be the main breadwinner and because psychological effects of both job loss and unemployment tend to be higher for men than for women (Kuhn et al., 2009). Nonetheless, average results of maternal job loss on children's school performance will also be shown.

[3]Unemployment rates in Spain and the province of Barcelona were 25% and 22.6%, respectively, in 2012. The pattern for prime aged men is very similar to the one shown in Figure 1.

it, the recession could provide an exogenous shock to employment analogous to exploring job displacement for known plant closures. However, recent evidence has shown that there is non-random selection of workers into closing or struggling firms (Card et al., 2013). Accordingly, it could be that those losing their jobs during the Great Recession in Spain have some unobserved characteristics that affect both their labour market status and the school performance of their children. In order to address this last challenge, the panel nature of the data collected allows us to control for time-invariant unobserved characteristics of the student by using student fixed effects.

Fixed effect estimates of the effect of father's job loss on the average grade are negative and statistically significant. Paternal job loss entails an average decrease in children's grades of around 13% of a standard deviation. Importantly, placebo tests show that the average grade prior to father's job loss is not affected by future job losses experienced by the father. Additionally, the negative effect of father's job loss does not seem to be driven by those students whose fathers had lower tenure at the firm prior to job loss, but rather, by those fathers that had a more stable situation prior to losing the job. Also, the average grade does not exhibit a negative trend prior to treatment and the results are robust to the inclusion of group specific trends. Interestingly, the average impact of mother's job loss on school performance is close to zero and non-significant, and the effect of father's job loss retains its sign and magnitude after controlling for mother's job loss. These results are in line with those found by Rege et al. (2011) that argue that a disparate effect of job loss across fathers and mothers is consistent with recent empirical studies documenting that the mental distress experienced by displaced workers is generally more severe for men than for women (see, for instance, Kuhn et al. (2009)).

The results suggest that the negative impact of father's job loss on school performance is mainly driven by those fathers that suffer longer unemployment spells. Related to this, the effect of father's job loss appears to be largely concentrated among children of already disadvantaged families in terms of paternal education. One of the potential mechanisms that could be driving the results is the observed decline in income after the father's job loss. However, the heterogeneous results found for different subgroups do not seem to be fully explained by different income losses. Moreover, it is important to note that these results are obtained for students that are enrolled in the same school during period of observation. The observed reduction in income cannot be linked, therefore, to changes in the school attended after job loss. An alternative channel by which reductions in income could partly explain the results in this paper is if fathers as a consequence spend less time helping with homework or other school activities. Additionally, income reductions after father's job loss could entail higher stress or financial anxiety and uncertainty for affected individuals and households, as some papers in the social psychology field and health economics have suggested (see, for instance, Lim and Sng (2006) and Kuhn et al. (2009)). Unfortunately, the data does not allow us to test these alternative channels. They merit consideration for future research.

This paper's contribution to the literature is threefold. First, the focus on job loss due to the Great Recession in Spain combined with the use of fixed effects makes our measure of job loss more likely to fulfill the exogeneity assumption than most other papers in the literature, as will be shown in Section 2. Second, a variety of heterogeneous effects and mechanisms not explored before are identified, such as unemployment duration after job loss and tenure at the firm prior to losing the job. Third, analysing Spain during the Great Recession is interesting given that the results suggest that paternal job loss is a mechanism through which further inequalities might develop during and after a deep economic crisis. Similar results could therefore potentially be expected in other economies that have been highly affected by the Great Recession in terms of employment losses, like Greece or Portugal.[4]

The structure of the paper is as follows. Section 2 reviews the literature most closely related to this paper. Section 3 describes the original dataset used in the paper and Section 4 presents the estimation strategy. Section 5 shows the main results and robustness checks and Section 6 concludes.

2 Previous literature

Family background characteristics have typically been seen as important inputs determining child development.[5] One of the main features of family background is the labour market status of parents, and in particular, experiences of transitions in and out of employment. As a result, an emerging literature has tried to identify whether parental job loss has an effect on the education attainment and school performance of children. Appendix A describes a simple theoretical model to provide intuition on how parental job loss may affect the school performance of their offspring, both through its impact on the education production function and the marginal costs of studying.

As Rege et al. (2011) point out, estimating a causal relationship between parental job loss and children's outcomes faces two main challenges: finding a source of exogenous variation for parental job loss and the scarcity of appropriate data. Table 1 summarises most of the existing papers in the economic literature, together with some examples from the literature in developmental psychology and sociology. The articles are divided by their use of the data available; and the estimation strategy and main results are briefly summarised.

The results of the articles in the first panel of Table 1 are obtained by using the data in a cross-sectional fashion (i.e. even if the 3 studies reported use panel data, the use they make of

[4]These countries also have similar unemployment insurance gross replacement rates (although net replacement rates are higher in Portugal and Greece than in Spain). In terms of unemployment duration, the Spanish benefits last longer than those in the other two countries. For more data on this and comparisons with the rest of EU member states, see Esser et al. (2013).

[5]See Björklund and Salvanes (2011) for a summary and evaluation of recent empirical research on education and family background.

the data for these particular papers is cross-sectional; that is, the outcome variable is observed only once for a given individual). Kalil and Wightman (2011) and Pan and Ost (2014) use the Panel Study of Income Dynamics to study the impact of parental layoff on any postsecondary education by age 21 and higher education enrollment, respectively, in the US. The treatment in Kalil and Wightman (2011) is whether the head of the household has ever reported an involuntary job loss by the time the child is 21. In their OLS results, they control for several characteristics that could be affecting both the treatment and the outcome, like the level of education of the head of the household. The main problem that this type of paper faces in order to get at causal effects is that those suffering involuntary job losses are systematically different from those that remain continually employed.[6] Pan and Ost (2014) try to overcome this problem by using variation in the timing of parental layoff. In their study, all families experience a layoff at some point. The treatment group is formed by those individuals that experience parental layoff at ages 15-17, whereas subjects in the control group experience parental layoff at ages 21-23 (i.e. after the outcome variable, higher education enrollment, is observed). Gregg et al. (2012) use the British Cohort Study to construct their group of displaced fathers. They combine information on whether fathers worked in industries hit hard by the 1980's crisis with whether they were either out of work or employed in a different industry by 1986. They argue that the extent to which the industry is hit (and hence the likelihood that the father is displaced) is deemed exogenous to the father's unobserved characteristics and to the child's educational development. However, there is still the possibility that workers with different unobserved characteristics sort themselves into different industries.

The second panel of Table 1 summarises studies that use repeated cross sections, i.e., the outcome variable is still observed once for a given individual, but the authors pool together different cross-sections in their analysis. In this group, both Coelli (2011) and Hilger (2014) study college enrollment. Coelli (2011) constructs the treatment group as those students whose parents (the main income earner) suffered job loss due to permanent layoff or firm closure. It is common in this literature to assume that this type of parental job loss (as opposed to being fired, for instance) is likely to be exogenous to the worker. The same strategy is used by Rege et al. (2011) to study the impact of father's job loss on an average measure of their children's school performance at age 16. Hilger (2014)'s findings, however, contradict those in Coelli (2011) and Pan and Ost (2014). Hilger (2014) finds very small effects of paternal job loss on college enrollment and shows that firm closures generate much larger effects on child outcomes, but that these larger effects stem entirely from selection on unobservables into employment at closing firms.[7]

In the last panel of Table 1, the studies - including the present one - use panel data and can therefore observe the outcome variable in more than one period for a given individual. If the

[6] Kalil and Wightman (2011) recognise the potential for unobserved factors influencing selection in their study.

[7] See Card et al. (2013) for a recent contribution showing evidence on the rising assortativeness in the assignment of workers to establishments.

characteristics that drive assortativeness into different firms are constant over time (i.e. level of education, how productive an individual is, permanent character traits, etc.), then the use of panel data has an advantage when trying to identify the causal effect of parental job loss. Both Kalil and Ziol-Guest (2008) and Stevens and Schaller (2011) use the Survey of Income and Program Participation in their studies. Kalil and Ziol-Guest (2008) define the treatment as involuntary job losses 24 months prior to outcome measurement, whereas Stevens and Schaller (2011) use involuntary job losses of the household head that happened after the first wave of the panel. The outcome variable in both articles is grade retention (a variable that even if important to measure attainment is a low frequency one), although only Stevens and Schaller (2011) take advantage of the panel dimension in the data to obtain fixed effect estimates.

This paper combines different positive aspects of the papers just reviewed to try to get a closer approximation of causal effects. In this sense, the treatment is defined using a type of natural experiment, i.e. job losses during the Great Recession in Spain, combined with an original panel data set that allows us to control for fixed effects in order to address potential selection issues. The prior study that produced fixed effect estimates (Stevens and Schaller, 2011) used a low frequency measure (grade retention), and did not have the additional push into job loss given by the Great Recession. Also, the scenario used to measure the impact of both father's and mother's job loss on the school performance of their offspring is substantially different. Job loss in this paper happens in a context of a deep recession when finding a job afterwards is expected to be harder than in normal circumstances. The effects, therefore, are expected to be more detrimental than those reported in the literature and, in particular, than those found by Rege et al. (2011). These authors use a very similar outcome variable, although students in their sample are observed only at age 16.

People suffering from job loss are likely to suffer longer unemployment spells afterwards. Therefore, this paper is also related to a strand of literature that analyses the impact of parental unemployment on their offspring's school outcomes (see Ermisch et al. (2004), Kertesi and Kezdi (2007) or Pinger (2013); or Parsons et al. (2013) for an example in the sociological literature). More generally, given the expected negative impact on family income after parental job loss, this paper is also related to the literature analysing the effect of income on child development. Examples of this are Blau (1999), Shea (2000) and Dahl and Lochner (2012).

3 Data

The empirical analysis uses an original dataset collected to address the research questions that motivate this article. Excluding students in post-compulsory education, the dataset contains information on the parental labour market situation and school performance of 358 students between the ages of 3 and 16 in a school in the province of Barcelona. Appendix B presents a more detailed description of the questionnaire design, data collection, survey and item non-response and representativeness of the data. In particular, for each student we observe the grades given by their teachers in all the subjects taken from the academic year 2007-2008 to the academic year 2011-2012.[8]

On the parental side, a survey was designed to collect personal characteristics (age, level of education, civil status, etc.) and labour market information (labour market status, characteristics of the job, reasons for job loss or for switching jobs, etc.). Both parents were asked to answer the survey as long as they were living in the same household as the children. The information on parental labour market status (and job characteristics if employed), was collected retrospectively. That is, in February 2012, when the survey was distributed, parents were asked about their labour market situation and job characteristics in January 2012, January 2010 and January 2008. If their employment situation changed at some point after January 2008, parents were asked to provide information on the month and year when this change occurred. With information about these three points in time and the dates regarding employment status changes, we have reconstructed their labour market situation for the five periods in which we also observe the grades of their offspring. Due to missing data for some individuals, we had to make some reasonable assumptions regarding the dates of job loss. Even if we are able to use the five years of information by making these assumptions, they could be introducing some measurement error in the dates regarding changes in employment. Thus, even if the main results use the five period dataset, we will perform robustness checks using only the three years (2008, 2010 and 2012), for which information regarding the labour market status is certain and where there is thus no need to make any assumptions.

The main treatment group consists of children whose fathers experienced an involuntary job loss at some point after the first academic year (2008). For sample size reasons, this includes fathers closing their own business and unemployed fathers who state that these changes were voluntarily. Results will also be shown when classifying this latter group of fathers in the control group instead. As pointed out in Section 1, paternal job loss, rather than maternal job loss, is the main focus of this paper. However, the role of maternal job loss will also be addressed.

The school granted us access, from academic year 2008 to academic year 2012, to the grades obtained by those students whose parents answered the questionnaire. The format of the grades for each stage of education is described in Section B3 in Appendix B. After some transformations to homogenise grades between stages of education, all the students in the sample have grades ranging from 1 to 5 (where 1 means that the student has failed the subject and 5 is the best possible grade). Based on this information, we constructed a summary measure of each student's performance during the academic year. In particular, the main measure used throughout the analysis is the average grade obtained each academic year by each student. This measure is obtained by averaging the student's grades in all subjects taken during the three

[8] Section B3 in the Appendix describes in detail the data on school outcomes. The academic year in Spain starts in September and finishes at the end of June. When later in the text we refer to the academic year 2008 (and so on), this refers to the academic year running from September 2007 to June 2008.

terms in a given academic year.[9]

Given the focus on father's job loss, we are restricted to working with the sample of students that live in a two-parent household. This leaves us with a sample of 332 available students. In all cases in which the student does not live with both parents, we observe the student living only with the mother. Therefore, in these cases there is no information on the labour characteristics of the father. Unfortunately, if parental job loss leads to separation or divorce and the father moves out during the period under analysis, we will not be able to observe these fathers. Thus, our results are limited to the sample of students whose parents have stayed together during the period under analysis.[10] In the results section we will conduct robustness checks using mother's job loss when the father is absent. Additionally, in order to be able to compare the school performance of students before the start of the Great Recession and at the end of the period analysed we need to work with the sample of students that were enrolled in the school since the academic year 2008. This reduces the available sample to 193 students, but results will also be shown for the full sample of 332 students observed in 2012.[11]

Two exclusion criteria are applied to create the final sample. First, given that the sample does not seem to be representative of students with an immigrant background (see Appendix B), students whose fathers do not hold Spanish citizenship are excluded (10 students). The second exclusion criteria is important for the identification strategy and internal validity and has to do with the employment status of fathers in the first period of observation. Following Stevens and Schaller (2011) we restrict the sample to those students whose fathers were employed in January 2008. That is, all the students in the working sample have their fathers employed in the first period. After applying this restriction the analytic sample consists of 178 students in compulsory education whose grades were observed for all five academic years from 2008 to 2012 and whose fathers were employed at the beginning of the crisis (in academic year 2008). Furthermore, they are all Spanish citizens who were present in the family home throughout the period. Robustness checks will be conducted by showing the results for the full sample of 332 students.

[9]Even if not shown, results using the average grade obtained in the main subjects of Mathematics and Language are similar.

[10]Only 3 mothers stated that they were single in 2008; and there are only 8 cases in which the mother reports a separation or divorce after the 2008 academic year.

[11]There is a majority of students that we cannot observe in 2008 because they were too young to be in school in the academic year 2007-2008. These are children that in the academic year 2012 were enrolled in the first grade of primary school or below. See Appendix B for a description of the Spanish education system. Kindergarten in this paper is based on the British/Australian definition (rather than the definition used in North America) and refers to the stage of education where children below the age of compulsory education play and learn; i.e. a nursery school. The remaining students that are not observed in academic year 2008 are those that entered the school during secondary school. That is, they graduated from primary school elsewhere, and enrolled in the school where the data was collected once they moved to secondary school.

3.1 Descriptive statistics

Figure 2 shows the average grades for treated and control students in the academic years 2008 and 2012.[12] It can be seen that in the 2008 academic year, when all fathers in the sample were employed, there were no significant differences in the average grade between treated and control students. If anything, treated students were doing slightly better in 2008, prior to treatment. Looking at the results for 2012, one can see that both treated and control students suffer a decrease in school performance as they progress in the education system (this will be captured by year and stage of education dummies in the regression analysis). However, the group of students that have been affected by paternal job loss suffers a bigger decrease. Without additional controls the difference in means is not statistically significant at conventional levels, but will become so when standard errors are reduced by further controlling for year, stage of education dummies and student fixed effects in the regression analysis.

Tables 2 and 3 show descriptive statistics for the working sample of 178 students, measured in 2008 (unless otherwise stated). In each table, the first three columns report means and standard deviations for different variables for the control, treated and overall analytic sample, respectively. The last column reports 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 a null hypothesis of equality of means between control and treated students. Table 2 shows descriptive statistics for several child and household characteristics. Except for the quarter of birth dummies, there are no statistically significant differences between treated and control students in terms of gender, age, whether they are the first-born or had ever repeated a grade before the 2008 academic year. Descriptive statistics of household characteristics in 2008, previous to job loss, are shown in the second part of the table. There are no significant differences between treated and control students in the average number of children living in the home, household size (measured in 2012), the language spoken at home, whether the mother was living with the partner or was married (i.e. stable civil status), whether the mother had a job, or whether the family lived in a neighborhood close to the school area.[13] As pointed out in Section 1, it is unlikely that fathers losing their jobs during the Great Recession in Spain are randomly selected across the whole population of working fathers in Spain. This is reflected in Table 3, where several personal and 2008 labour market characteristics of fathers in the analytic sample are shown.[14] The fathers of treated students already had a lower level of income in 2008, and a higher fraction was working

[12]The figure uses the raw average grade, although the analysis will use average grades that are standardised using the mean and standard deviation of the whole sample. Standardisation is not performed at the year level, or at the year and cohort level, because the number of observations available for each group would be rather small. Instead, the analysis below uses the average grade standardised based on the mean and standard deviation of all students in the sample, and will always control for year and stage of education dummies.

[13]The data for the home-ownership and household size dummies refer to 2012, and therefore, it could potentially be affected by treatment. Unfortunately, data for 2008 is not available. The data for 2012 is nonetheless reproduced at the end of Table 2 because it will be discussed in Section 5.

[14]Some of the variables in this table have some missing information, so the number of observations available is shown in an additional (third) row. As a way to partially asses if these missing observations are related to father's job loss, we 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 income between treated and control students.

in the industry and construction sectors.[15] Treated fathers had fewer years of tenure at the firm (defined for those owning their own business as the 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 by (or owned) smaller firms. Contrary to what might 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. All in all, the information in this table seems to suggest that, without controlling for student (worker) fixed effects, job loss during the Great Recession in Spain cannot be considered to be as good as randomly assigned.

4 Estimation strategy

This section describes the identification strategy used in this paper to identify the impact of father's job loss on school performance (measured by the average grade) during the Great Recession in Spain. Appendix A describes a simple theoretical model providing intuition on how parental job loss could affect the school performance of their offspring.

Let Y_{it} equal the standardised average grade for child i at time t described in Section 3. Let D_{it} denote a dummy variable that equals 1 from the year the father involuntarily loses his job.[16] On account of the sample restrictions outlined in Section 3, this indicator equals 0 in the 2008 academic year for all students, since all fathers in the analytic sample are employed at the beginning of the Great Recession. 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, conditioning on student fixed effects, father's job loss in our sample is more likely to be unrelated to unobserved worker's characteristics than finding a job afterwards. The main assumption in the paper is that conditioning on worker fixed effects the Great Recession generates employment shocks that are random in their timing. We discuss the plausibility of this assumption below and test it insofar as we can. However, this assumption cannot be invoked when analysing the effect of getting back to employment after job loss. The combination of fixed effects and the Great Recession can only explain random entry into job loss. After job loss we cannot account for, among other things, the level of job search effort devoted by each worker in each period after job loss. However, we will explore in Section 5.3 whether our results change when using alternative treatment definitions (i.e. allowing the treatment variable to switch back to 0 once the worker finds a new job).

[15] High income is a variable derived from the following survey question: NET monthly income in euros (includes salary, unemployment benefits, pension, or other subsidies). Possible answers are (1) less than 999 euros, (2) Between 1000 and 1499 euros, (3) Between 1500 and 1999 euros and (4) More than 2000 euros. The father is classified as having a high income in 2008 if he marked options (3) or (4).

[16] Stevens and Schaller (2011) also adopt this definition, but given that their outcome of study is grade repetition, the 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.

The observed average grade, Y_{it}, is either Y_{0it} or Y_{1it}, depending on the father's job loss status.[17] If the main assumption stated above holds, then omitted time variant variables or pre-trends should not be a cause for concern (we will address this later in the section). As a result, father's job loss in this sample could be considered as good as randomly assigned after conditioning on student fixed effects and observed covariates:

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

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

$$E[Y_{0it}|A_i, X_{it}, X_i, t] = \alpha + \lambda_t + A_i'\gamma + X_i'\phi + X_{it}'\beta \tag{2}$$

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

$$E[Y_{1it}|A_i, X_{it}, X_i, t] = E[Y_{0it}|A_i, X_{it}, X_i, t] + \rho \tag{3}$$

which together with Equation 2 implies:

$$\begin{aligned} &E[Y_{it}|A_i, X_{it}, X_i, t] = D_{it} * (E[Y_{0it}|A_i, X_{it}, X_i, t] + \rho) + (1 - D_{it}) * E[Y_{0it}|A_i, X_{it}, X_i, t] \\ &= \alpha + \lambda_t + \rho D_{it} + A_i'\gamma + X_i'\phi + X_{it}'\beta \end{aligned} \tag{4}$$

where ρ captures the average causal effect of job loss on children's average grade as long as we can assume the absence of relevant time variant omitted variables. Using the panel nature of the data available, we can therefore estimate the following fixed effects model:

$$Y_{it} = \alpha_i + \lambda_t + \rho D_{it} + X_{it}'\beta + \epsilon_{it} \tag{5}$$

$$\alpha_i = \alpha + A_i'\gamma + X_i'\phi \tag{6}$$

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 represents a vector of year dummies. ρ captures the full effect of father's job loss on the average grades obtained by their offspring. This may incorporate changes in income, civil status, etc. Their role as potential mechanisms driving the results will be discussed in Section 5.

As a result of the estimation strategy used, ρ captures the total effect of an arguably exogenous negative change in the labour market status of fathers (i.e. job loss) on the educational outcomes of their offspring, without holding other inputs constant. In this paper there is no

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

attempt to incorporate all the determinants of cognitive achievement in the model, as Todd and Wolpin (2003) would put it. Instead, this paper makes use of an event (the Great Recession) that arguably provides a source of exogenous variation for father's job loss once student/worker's fixed effects are accounted for. Additionally, as Imbens and Angrist (1994) point out, in models with panel data and fixed effects, the data are only informative about the impact of binary regressors on individuals for whom the value of the regressor changes over the period of observation. According to these authors, the local average treatment effect (LATE) is analogous to a regression coefficient estimated in linear models with individual fixed effects using panel data. In this sense, the estimates in this paper, rather than identifying average population effects, could be seen as measuring a local average treatment effect, namely, the effect of father's job loss for those students whose fathers lost their jobs due to the Great Recession. As seen in the descriptive statistics tables in Section 3, fathers who lost their jobs were all employed in the private sector and proportionately more in the industry and construction sectors. Like other studies identifying local average treatment effects, this study could be subject to the question about whether the effect of parental job loss for those students whose fathers lost the job during the Great Recession in Spain is an effect of primary interest.[18] Given the dimensions of the Great Recession in terms of job loss, the answer to this question seems relevant. The results in this paper will shed some light on how a deep economic recession disproportionately affecting some sectors in the economy impacts the educational outcomes of students whose fathers are severely hit by the downturn.

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 our estimates, since we cannot rule out the possibility that unobserved time variant variables might simultaneously be affecting the probability of father's job loss and the grades of their offspring. In this sense, a major concern for the estimation strategy is given by the fact that fathers who lost their jobs during the period under analysis could have been on a negative trajectory in the labour market prior to 2008. And this in turn, could have had an impact on average grades even before the beginning of the Great Recession.[19] Unfortunately, pre-2008 data on school performance is not available. However, data for the three terms in the academic year 2007-2008 is available for students in compulsory education. Figure 3 shows that in the academic year 2008, prior to treatment for any of the students in the analytic sample, there is no evidence of a differential trend in the average grade. The difference in means between control and treated students is not statistically significant in any of the three terms of the 2008 academic year. Another way to address this issue is to check whether the impact of father's job loss is mainly driven by students whose fathers had a lower labour market attachment prior to losing their jobs. As we will show in Section 5, this does not seem to be the case in our

[18]See, for instance, the contribution by Heckman and Urzua (2010) and the critique contained therein as to the questions that LATE can answer.

[19]However, it is important to note that the individual fixed effect controls for static pre-2008 labour market experience (i.e. number of years in unemployment prior to the Great Recession).

sample. Additionally, the main characteristics of workers who lost their jobs in the first period of the crisis (2009-2010) and those that lost their jobs in the second period (2011-2012) are not significantly different from each other. That is, it seems that the Great Recession was not affecting different type of workers throughout the period (see Table 4).

Even if treated students do not seem to be on a different trend prior to father's job loss, a further potential concern with the specification in Equation 5 is that estimates might be driven by negative trends in school performance for particular groups of students. For instance, one might think that students from low socioeconomic backgrounds would have experienced a different evolution of grades even in the absence of father's job loss. To make sure that the estimates do not simply reflect differential group trends, the model is augmented by interacting the year dummies with certain group specific characteristics. This is represented by δ_{tj} in Equation 7:

$$Y_{ijt} = \alpha_i + \lambda_t + \delta_{tj} + \rho D_{it} + X'_{it}\beta + \epsilon_{ijt} \tag{7}$$

where j stands for different group characteristics measured in 2008, like father's education, father's income category, father's industry or student's gender. In the empirical analysis, the group specific trends are introduced one by one, and then a final model presents the results when several group specific trends are introduced at the same time.

Estimates of ρ could also be biased for reasons related to attrition. For instance, our estimates would be biased if students affected by father's job loss had changed or left school by the 2012 academic year. Given that we could only distribute the survey to those students enrolled in the school where the data was collected during the 2012 academic year, it could be that prior to 2012 students affected by parental job loss had dropped out from this school and enrolled in a state (public) one. 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 during the period of observation and only around 0.6% per year. In compulsory secondary school, the average annual drop-out rate is a bit larger at around 3.3%. However, rather than increasing, it decreases from academic year 2008 to academic year 2011 (i.e. the last year for which we have data on school drop-out rates available). Moreover, the school cannot dismiss students if parents stop paying the school fees.[20] Additionally, the reader might reason that estimates would be biased if students who otherwise would have enrolled in this particular school did not do so as a result of their father's job loss. However, given the sample restrictions applied, the students in the analytic 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.

Moreover, we are implicitly assuming here that school inputs are not altered by parental

[20]Soft information coming from the principals in April 2012 confirms that job loss related attrition does not seem to be a problem in this sample. Since the onset of the Great Recession, children from 2 families had left the school because the family had decided to go back to their original countries and children from 1 family had left the school because the family moved to another municipality.

job loss. This assumption would fail to hold if teacher evaluations differ after father's job loss. Empirical evidence has shown that evaluations using teacher and externally administered tests differ (see, for instance, Burgess and Greaves (2013) and Gibbons and Chevalier (2008)). Two of the main reasons that have been put forward to explain this divergence are teacher bias (or statistical discrimination/stereotypes) and information (teacher assessments are based on longer observation whereas tests evaluate the performance on a specific day). The important question for the consistency of ρ is whether teacher biases could potentially affect our estimates. On the one hand, if teacher bias is fixed (for instance, teachers have a bias towards students from certain socioeconomic groups), this would be captured by α_i. In this case, ρ would not be affected. On the contrary, estimates of ρ would be biased if teacher's perceptions of academic performance change when the father loses his job. Existing evidence does not seem to be very helpful in reaching a consensus regarding the direction of the potential bias. Gibbons and Chevalier (2008) find that teacher assessments are upward biased in favour of low-achieving students, whereas Burgess and Greaves (2013) and Hanna and Linden (2012) find evidence that teachers discriminate against minorities in the UK and India, respectively. Unfortunately, we do not have data to rule out negative teacher biases towards those students affected by paternal job loss as a potential driver of the negative results found in Section 5. However, it seems unlikely that teachers would start to more negatively evaluate those students coming from families that are struggling due to the Great Recession. If the contrary is true and teachers favour (in terms of grades) those students affected by father's job loss, then estimates of ρ would be downward biased in absolute terms. The true impact of father's job loss on average grades would be more negative in this more reasonable scenario.

Finally, estimates in this paper could be downward bias if the school performance in the control group is negatively affected by the recession. Even if students in the control group are not exposed to parental job loss during the period under analysis, their parents could have suffered wage cuts or, in general, feel a higher degree of job insecurity.

5 Results

5.1 The impact of father's job loss on children's school performance

Table 5 presents different estimates of the effect of father's job loss on the standardised average grade, using the analytic sample of 178 students. Standard errors are clustered at the family level in this and all subsequent tables (there are 137 clusters in the main analytic sample). As pointed out in Section 3, standardisation is not performed at the year level or at the year and cohort level, because the number of observations available for each group would be rather small. Instead, the analysis uses the average grade standardised based on the mean and standard deviation of all students in the sample, with all the models controlling for year and stage of education dummies.[21]

The results of an OLS regression are shown in Column 1. Omitting student fixed effects, father's job loss (FJL from now onwards) does not have a significant effect on the average grade. However, by augmenting the model to take into account individual fixed effects (see Column 2) the coefficient of the FJL variable becomes negative and significant at the 10% level. After father's job loss, students suffer a decrease in average grades of 12.7% of a standard deviation. In Column 3, a dummy variable is added to control for repetition of grades (this variable equals 1 if the student is retaking that particular grade). The point estimate barely changes after the inclusion of this additional explanatory variable.[22] Column 4 shows the results of estimating a random effects model instead. The point estimate is negative and more similar to the fixed effects results shown in Columns 2 and 3 than to the OLS regression shown in Column 1. This is in line with the results shown in the bottom part of the table. The individual-specific component of the error (α_i) is much more important than the idiosyncratic error (ϵ_{it}).[23].

Compared to the OLS model, the fixed effect estimator controls for all the characteristics of the student (and the father/mother/family) that are time-constant. The zero effect found in Column 1 is driven by those fathers who had a lower attachment to the job market prior to job loss.[24] If we restrict the sample to those fathers with at least three (or six) years of tenure in 2008, prior to job loss, the OLS estimate becomes negative and bigger in magnitude than the FE estimates. This is in line with several papers in the job loss literature which have found that workers with longer tenure prior to job loss suffer more after job loss in terms of income declines and employment probabilities (see Jacobson et al. (1993), Farber (2011) or Couch and Placzek (2010)). We will address this point later in the section. Column 3 is the preferred specification used in subsequent tables. The previous results are based on the restricted sample, i.e., the one resulting after applying the sample restriction criteria outlined in Section 3. As a robustness check, Column 5 presents results using the full sample of students whose fathers lived at home, and are enrolled in grades below post-compulsory education. The point estimate in Column 5 is slightly smaller (in absolute terms) than the ones shown in Columns 2 and 3, but the results point in same direction.

[21]Even if results are not shown, the results in this section are very similar to those obtained when using the percentile rank of the students in their cohort as a dependent variable. The percentile rank is not used as the main measure in this paper for two reasons. First, we can only construct the percentile rank of the student in her cohort using the whole sample of students that answered to the questionnaire (we do not have data for the whole population in the school, which would be the ideal scenario). Second, the average grade has been used in other studies in the literature (Rege et al., 2011), and using it here will be useful to compare the results in this paper to the ones obtained by these authors.

[22]Note that it is not clear that this variable should be included as a control since it could potentially be considered an outcome variable. However, in both cases less than 1% of the students are observed as repeating a grade. Additionally, the results do not differ if the repetition variable is defined somewhat differently (equal to 1 from the moment the student has repeated a grade).

[23]See the section in Wooldridge (2002) on the relationship between the random effects (RE) and fixed effects (FE) estimators

[24]Years of tenure in the job in 2008 is one of this time-constant variables picked up in the individual fixed effect.

Tables 6 and 7 suggest that the effects found in Table 5 are likely to be of a causal nature. First, Column 1 in Table 6 shows the results of a placebo test. Future job losses (i.e. job losses that will happen later in the period under analysis) should not have an impact on the average grade of affected students prior to job loss. Column 1 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). The estimate for the main variable of interest is highly imprecise and not significantly different from zero. This finding provides evidence against the possibility that changes in household's unobservables simultaneously drive FJL and school performance of their offspring, since otherwise we would expect to see significantly worse school performance prior to father's job loss. Moreover, Column 2 suggests that the lack of significance of future FJL on school performance is not driven by the fact that we use a cross-section instead of a panel to run the placebo test. Using the 2012 cross-section, the results in Column 2 show that students that by 2012 have been affected by FJL suffer a significant decrease in school performance. The former placebo test indicates that future paternal job losses do not significantly affect grades prior to father's job loss. This evidence does not guarantee that the grades of treated students were already suffering a decline prior to father's job loss. However, the evidence shown in Section 4 does, given that Figure 3 showed that there are no existing negative trends in school performance for treated students prior to treatment.

Another way to partially address this issue is to check whether the impact of father's job loss is mainly driven by those students whose fathers had a lower labour market attachment prior to job loss. One potential way of defining labour market attachment is to use the information on years of tenure at the firm before losing the job. Those workers with lower tenure prior to job loss might have been on a different (negative) trajectory prior to losing their job during the Great Recession, and this could, in turn, have affected the grades of their offspring. In order to verify this we consider only those students whose fathers in 2008 had at least three (or six) years of tenure in their jobs, respectively. Results are shown in Column 1 (and 2) of Table 7. The estimates show that the impact of FJL remains negative and significant in all cases. It is interesting to note that the more years of tenure prior to FJL, the larger are the point estimates in absolute value. That is, the negative effect of FJL does not seem to be driven by those students whose fathers had lower tenure at the firm prior to job loss, but rather, by those students whose fathers had a more stable situation prior to losing the job. This is in line with several papers in the job loss literature that have found that workers with longer tenure prior to job loss suffer more after job loss in terms of income declines and employment probabilities.[25] In this sense, these children would suffer a bigger shock after paternal job loss than those children whose fathers had, prior to job loss, a lower labour market attachment. Column 3 uses an alternative definition for labour market attachment based on the type of contract the father had prior to job loss. In this model we exclude from the sample those students whose fathers had a

[25] See, for instance, Jacobson et al. (1993) or Farber (2011). These papers argue that these results are consistent with the destruction of job or industry specific human capital when a long-term job ends.

temporary contract in 2008.[26] The results are very similar to those shown in Columns 1 and 2 and point towards the same conclusions. Additionally, suffering multiple job losses during the period under analysis might also indicate a rather unstable attachment to the labour market. Column 4 restricts the sample to exclude those students whose fathers have experienced more than one job loss in the period. Stevens (1997) studied the effects of multiple job losses on earnings, and found that much of the persistence in the earnings losses can be explained by additional job losses in the years following an initial displacement. Initial displacements predict future displacements and thus, subsequent displacements might not be exogenous (in the sense that they might no longer be attributed to the combination of the Great Recession and fixed effects). Multiple job losses could be due to unobserved time varying heterogeneity that could bias the estimates. By excluding from the sample those students whose fathers experienced multiple job losses during the period under analysis, the estimate remains negative and very similar to the other point estimates in Table 7. All in all, the evidence in Tables 6 and 7, together with Figure 3, suggests that treated students were not on a different (negative) trend prior to father's job loss.

However, even if treated students do not seem to be on a different trend prior to father's job loss, a further potential concern already raised in Section 4 is that estimates might be driven by negative trends in school performance for particular groups of students. For instance, one could envisage that students from low socioeconomic backgrounds, even in the absence of father's job loss, would have experienced a different evolution of grades. To make sure that the estimates do not simply reflect differential group trends, Table 8 shows the results of different regressions where the original model is augmented by interacting the year dummies with certain group specific characteristics measured prior to job loss (in the 2008 academic year). The year dummies are interacted with a variable that is equal to 1 if the father has a high level of education (beyond high school); a variable that equals 1 if the father was classified in the high-income category in 2008 and a dummy that equals 1 if the father owned a business in 2008 (as opposed to working for a firm). The year dummies are also interacted with dummies for the industry the father was employed in 2008 (3 industry categories are used: manufacturing, construction and services), whether the household lives in a house that is fully paid and student's gender.[27] The last model includes all the group specific trends in Columns 1 to 6 together. The point estimates shown in Table 8 are all very similar to those of Column 3 in Table 5 (all the

[26] The main difference between temporary and permanent contracts in Spain during the period under analysis is given by differences in firing costs. Once the temporary contract reaches the end date, the employer can decide whether to renew the contract or not. If the employer does not want to offer a renewal, she does not face any firing costs. Permanent workers are more expensive to lay off, especially if the layoff is considered unfair. For more information on the characteristics of permanent and temporary workers in Spain at the beginning of the Great Recession, see Bentolila et al. (2008).

[27] In the case that the house is not fully paid, this means that the household either lives in a rented house or has mortgage payments pending. Unfortunately, this information is only available for 2012, although ideally we would want this to be measured in 2008 values. However, it seems very unlikely that those families that are renting or paying a mortgage in 2012 would have had a fully paid house in 2008. Changes in housing status during the Great Recession in Spain are more likely to go from paying a mortgage to renting and the other way around. The way the housing variable is defined, therefore, could be seen as a good proxy for housing status in 2008.

coefficients are significant at the 10% level except in Columns 2 and 7, although in these two cases the p-value is 0.109). This evidence suggests that the estimates presented so far do not simply reflect differential group trends.

5.2 The role of mother's job loss and differential effects by gender

Column 1 in Table 9 shows the results when the impact of mother's job loss (MJL) on her children's school performance is analysed. The same analytic sample used so far is employed here as well, but further excluding those mothers that were unemployed at the beginning of the period. The MJL variable is defined in the same way as FJL. It is equal to 1 from the (academic) year that the mother loses her job. The results in Column 1 show that there is no significant effect of MJL, on average, on her children's school performance. These results do not seem to be driven by the fact that women in a country like Spain have a lower labour market attachment. As it was shown in Table 2, 81% of the mothers in the analytic sample were employed in 2008.

This paper differs from almost all other papers in the literature in the sense that job losses happen during a deep economic crisis rather than being the result of firm downsizes or plant closures for reasons other than an economic recession. Thus, it could be that the Great Recession is also provoking job losses for mothers, and if mother and father job losses are somehow correlated (which is indeed the case in this sample), then the effect of FJL could also be capturing the impact of MJL on the average grades of their offspring.

The results in Column 2, suggest that this is not the case, since the coefficient of the FJL variable retains its sign and magnitude after including the MJL variable. Moreover, the MJL coefficient, which is considerably smaller in absolute size, is not significantly different from zero. These average effects could be hiding heterogeneous effects of both FJL and MJL depending on student's gender. In their test for differential effects of FJL on school performance across boys and girls, Rege et al. (2011) find no significant differences among these two groups. However, the difference in magnitudes suggested a larger negative effect for girls. The difference in magnitudes here suggests the opposite (see Columns 3 and 4 in Table 9). The negative effect of FJL is concentrated on males. Given this result, it could be the case that even if mother's job loss does not have a significant effect on school performance on average, it has an effect on either boys or girls. However, repeating the same exercise but using the MJL variable instead, we find that mother's job loss does not have a significant effect on either boys or girls (see Columns 5 and 6). The estimates, albeit imprecise, would suggest that if anything, MJL might have a negative impact on the school performance of female children. These latter results seem to be in line with the findings of several papers in social psychology. For instance, Barling et al. (1998) found that identification with the parents works as a moderator when assessing the impact of parental job insecurity on children's work attitudes and beliefs. In other words, if sons identify themselves more with fathers than is the case for daughters, male students would then be more distracted cognitively by paternal job insecurity. This could be behind the differential effect of father's and mother's job loss, although more conclusive research is needed. Finally, mothers could react to father's job loss by going back to work (in the case that they were unemployed prior to FJL). The results shown in Column 7 barely change when augmenting the specification with a dummy variable that equals 1 whenever the mother is employed, and 0 otherwise.

The findings in this section could partly be explained by the results in recent papers in health economics that have found that men suffer more negative health related consequences after job loss than women. For instance, Kuhn et al. (2009) find that job loss significantly increases expenditures for antidepressants and related drugs, as well as hospitalizations due to mental health problems for men, but not for women. Eliason and Storrie (2009a) find that job loss produces a twofold short-run increase in suicides and alcohol-related mortality for both sexes. However, overall mortality risk among men increased by 44 percent during the first four years following job loss while there was no impact in the longer run or on female overall mortality. Eliason and Storrie (2009b) also find that job loss significantly increases the risk of hospitalization due to alcohol-related conditions, among both men and women, and due to traffic accidents and self-harm among men only. In terms of earnings decline after job loss, both men and women suffer substantial decreases in the probability of being observed in the high income category (a decline of 31% and 24% for men and women respectively). The bigger contribution of fathers to household income could also be behind these results. Whereas 65% of the fathers were observed in the high income category in 2008, only 24% of mothers reported to be in the high income category. Findings reported by social psychologists suggest that there are detrimental effects of job insecurity (something that is likely to be positively related to job loss) on financial anxiety for men but not for women (Lim and Sng, 2006). As Rege et al. (2011) point out, sociological theories of social roles could be behind the results in this section: social norms and historical patterns have allowed women to develop a greater range of non-employment related roles. Future research would benefit from a wider range of data collected on time use and mental health in household surveys that usually link parents to their children.

5.3 Alternative treatment definitions and the role of long term unemployment

So far, given the reasons stated in Section 4, the treatment variable has been defined as an absorbing state (i.e. it equals 1 from the moment the father loses the job, irrespective of his employment situation afterwards). However, it is interesting to see what happens if we vary the treatment definition to allow those fathers finding a job after job loss to switch treatment status. Table 10 shows the results of experimenting with two different treatment definitions in Columns 1 and 2. FJL (1) is a dummy variable that equals 1 the year the father loses the job and the years after job loss as long as the father remains unemployed, and it equals 0 when the father is employed. FJL (2) is a dummy variable that equals 1 the year the father loses the job (as long as he does not find a job the same year), and the years after job loss as long as the father remains unemployed. As for FJL (1), it equals 0 when the father is employed. The only difference between FJL (1) and FJL (2) is that FJL (1) considers fathers during the year of job loss as treated, whereas FJL (2) only considers them as treated as long as they do not find a job during the same year. In this sense, FJL (2) would be capturing the effect of long term unemployment spells, whereas FJL (1) would be capturing the impact of father's job loss and long term unemployment. The results in Columns 1 and 2 of Table 10, suggest that the negative impact of father's job loss on the average grade is mainly driven by those fathers that stay unemployed for at least one academic year.

The restricted sample size does not allow for an in-depth dynamic analysis of the effects of job loss. The results in Column 3 are a first attempt at trying to disentangle contemporaneous from past effects. This is done by decomposing the effect of the FJL variable into a contemporaneous effect (with a dummy variable that equals 1 the year the job loss happens) and the impact of job losses that occurred in previous years. Both contemporaneous and past paternal job losses seem to affect the average grade of students.[28] However, a larger dataset, both in terms of observations and periods, is needed to provide a more in-depth dynamic analysis of the effects of FJL on children's school performance.

5.4 Additional robustness checks

A series of additional robustness checks are presented in Table 11. First, Column 1 only uses the information corresponding to the academic years 2008, 2010 and 2012. As described in Section 3, by restricting the sample to these periods we do not need to make any assumptions with regards to the exact date of job loss for some of the observations. Estimates in Column 1 show that the coefficients of the FJL variable are also negative and significant, and slightly bigger in magnitude. Second, for sample size reasons, the original FJL variable includes in the treatment group those students whose fathers have closed their own business or are observed as being unemployed for at least one year during the period, but the reason they state for their labour market status change lies within the voluntary or other reasons categories. The *FJL strict* variable shown in Column 2 does not consider these students as treated (as in our main analysis), but as part of the control group instead. The point estimates are very similar to those in the preferred specification (Table 5, Column 3). Third, given the small sample size, it is important to verify that outliers are not the main drivers of the results. In order to address this concern, Column 3 shows the FJL estimate when we drop observations at the extremes of the grade distribution. We calculate the average change in the average grade between the academic years 2008 and 2012 and we run the main specification excluding observations for which the average change falls in the the 5th and 95th percentile. Applying these restrictions has almost no effect on the estimate of FJL. Fourth, we calculate the percent of students whose fathers sufferd a job loss in the same grade and year, and also in the same grade, year and class, as a way to control for peer effects. Again, introducing these variables in the main specification (see Columns 4 and 5) barely changes the original point estimates of FJL shown in the preferred

[28] Given the results in Columns 1 to 2, we would expect that the negative and significant estimates associated with FJL in previous years are concentrated on those children whose fathers suffer long unemployment spells after job loss.

specification in Table 5. Moreover, the peer group effect coefficients are always not significantly different from zero. Finally, Column 6 examines the role of job loss of the main earner in the household. As pointed out in Section 3, if parental job loss leads to separation or divorce and the father moves out during the period under analysis, the sample will not register these cases. Therefore, the results shown so far are constrained to the sample of students whose parents have stayed together during the period under analysis. In Column 6, *JL main earner* is defined in the same way as the FJL variable, but taking into account the job losses of the mother when the father is not present in the household. The results barely change.

5.5 Heterogeneous effects

Following the literature, we analyse whether the impact of father's job loss is heterogeneous across different subgroups in Table 12. The results need to be interpreted with caution given the limitation posed by the sample size (standard errors tend to be large), but nevertheless they potentially add new suggestive evidence on the likely mechanisms operating behind the detrimental effect of father's job loss. Column 1 reproduces the results of the preferred specification (Column 3, Table 5). The subsequent models in the table interact the FJL variable with one characteristic at a time. The results suggest that the effects of FJL are concentrated on those students whose fathers have low levels of education (in Column 2, Table 12, the p-value for the interaction is 0.113).[29,30] The results also suggest that those students whose fathers lost their jobs because their own businesses closed suffer a more detrimental effect of FJL (Column 3). However, standard errors for the interaction term are too big to draw any strong conclusions. Additionally, FJL does not seem to have a differential impact for older students in Column 4 (classified as those enrolled in secondary education in 2012). Column 5 shows that the effect of FJL is mainly concentrated on those students whose families either rent or have a mortgage (as opposed to households that fully own their property).[31] Finally, the results in Column 6 show that the negative effect of FJL seems to be more detrimental for those students whose families moved during the period. This could be related to the results in Column 5, if the families that moved during the period are mainly those that were paying a mortgage or renting in 2008.

Several papers in the literature have documented a considerable reduction in earnings after job loss. For instance, Jacobson et al. (1993) reported that high-tenure workers separating from distressed firms suffer long-term losses averaging 25% per year. Accordingly, Column 1 in Table 13 shows that after job loss, the fathers in the sample are 31 percentage points less

[29]People with low levels of education are less likely to find a job, as could be seen by using data from the Spanish Labour Force survey. Even if according to this data low educated fathers have a higher probability of suffering long unemployment spells after job loss, the results in Section 5.3 are not stemming from the same group of students. The correlation between a dummy variable for low educated fathers and a dummy variable indicating long term unemployment is not significant and close to zero.

[30]Even if not shown, the impact of FJL seems to be concentrated on poorer households, as given by father's net income in 2008. However, standard errors are very big in this case.

[31]Ideally, all the variables interacted with FJL should be measured in 2008 values. For certain variables the data was not available and the 2012 has been used as an approximation of the 2008 value.

likely to be observed in the high-income category. The remaining models in Table 13 explore whether the heterogeneous effects shown in Table 12 could be due to differential reductions in income by group. This is done by regressing the FJL variable on a dummy variable that equals 1 if the father is observed in the high income category, controlling for individual fixed effects. The order of the columns is the same as in Table 12. The evidence partly suggests that those groups with a smaller decrease in average grades are also those groups with a smaller decrease in income, although standard errors of the FJL variable are rather big and the interactions are highly insignificant in most cases. An exception is Column 5, where the results indicate that those fathers living in owned households experience a significantly lower reduction in income after job loss (given by a higher probability of being observed in the high income category). The different income reductions across groups could be suggesting that income is one of the mechanisms driving the negative effect of paternal job loss on the school performance of their offspring. However, it is important to note that these results are obtained for students who are enrolled in the same school during the five periods of observation. The observed reduction in income cannot be linked, therefore, to changes in the school attended after job loss. Reductions in income could partly explain the evidence found in this paper if fathers decrease hours of extra help with homework (or other extra school activities) after job loss or decrease consumption that could be related to school performance. Additionally, income reductions after father's job loss could entail higher stress or financial anxiety and uncertainty for affected individuals and households, as some papers in social psychology and health economics have suggested (see, for instance, Lim and Sng (2006) and Kuhn et al. (2009)). Unfortunately, the data does not allow us to test these alternative channels. They merit, though, consideration for future research.

6 Conclusion

The available evidence on the effects of job loss has shown that affected individuals suffer important earning losses when re-employed, deteriorating physical and mental health and an increase in the likelihood of getting a divorce, among other negative consequences.[32] These negative consequences have a direct effect on some of the inputs that are generally seen as affecting the production function for cognitive achievement. Accordingly, several studies have shown that parental job loss has a negative impact on children's educational outcomes. In doing so, they have used plant closures or local labour market conditions as a way to circumvent the endogeneity of parental job loss (see Section 2). As Kalil (2013) noted in her review of the effects of the Great Recession on child development, we know very little about the Great Recession's impacts on children. This paper has contributed to this literature by looking at the intergenerational impact of labour market shocks (parental job loss) on school performance during the Great Recession in Spain. 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 variables (i.e. finding a source of exogenous variation for parental job loss) and the scarcity of appropriate

[32]See, for instance, Jacobson et al. (1993), Kuhn et al. (2009) and Eliason (2012).

data. This paper has addressed both of these concerns by exploiting the recent developments in the Spanish labour market (using job losses due to the Great Recession) and by using fixed effect models that allow exploitation of within individual variation in school performance. This has been possible on account of a panel dataset of children in compulsory education that was specifically designed to address this question.

The results in this paper imply that father's job loss entails an average decrease in children's average grades of about 13% of a standard deviation, although the effects are larger for particular subgroups. Compared to Rege et al. (2011), who find an average effect of father's plant closure on average GPA of 16 year olds of about 6.3% of a standard deviation, the results in this paper show that the effects of father's job loss on the average grade of their offspring during a deep economic crisis are bigger in magnitude.[33] Rege et al. (2011) compare their estimates with the results summarised by Hanushek (2006) about the STAR experiment. Hanushek notes that 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 quite sizable.

Given the panel nature of the dataset used, we have performed placebo tests that show that school performance prior to father's job loss is not affected by future job losses. Additionally, the negative effect of paternal job loss does not seem to be driven by those students whose fathers had a lower labor market attachment prior to job loss. On the contrary, and in line with Jacobson et al. (1993), the negative impact of father's job loss seems to be driven by those fathers who had a more stable labour market situation prior to losing their jobs (measured as those with more years of tenure or holding a permanent contract prior to job loss). This evidence suggests that treated students were not on a different (negative) trend prior to father's job loss. Moreover, the average grade does not exhibit a negative trend prior to treatment, and the results are robust to the inclusion of differential group specific trends.

The average impact of mother's job loss on school performance is close to zero and non-significant. Additionally, the effect of father's job loss retains its sign and magnitude after controlling for mother's job loss. These results are in line with those reported by Rege et al. (2011). They argue that the disparate effect of job loss across fathers and mothers is consistent with recent empirical studies documenting that the mental distress experienced by displaced workers is generally more severe for men than women (see, for instance, Kuhn et al. (2009)). Moreover, the average results found in this paper mask important differential impacts across different subgroups. The negative impact of father's job loss on school performance is mainly

[33]However, it is important to note some important differences between both papers. First, students in Rege et al. (2011) are generally older (16 years old) whereas students in our sample are aged 8 to 16 in the academic year 2012. Second, the estimation strategies used by the two papers differ. While Rege et al. (2011) use a pooled cross-section of 10th graders and job losses coming from plant closures, this paper uses within-individual variation to analyse job losses that are mostly due to the Great Recession in Spain. Moreover, we cannot rule out the possibility that the bigger magnitude of the results is due to particularities of the Spanish economy (different welfare and protection systems after job loss, for instance).

driven by those fathers who suffer longer unemployment spells. Related to this, the effect of father's job loss appears to be largely concentrated among children of already disadvantaged families in terms of the educational level of the father.

We find evidence of different income reductions across groups that might suggest that income is one of the mechanisms driving the negative effect of paternal job loss on the school performance of their offspring. However, it is important to note that these results are obtained for students that during the five periods of observation are enrolled in the same school. The observed reduction in income can therefore not be linked to changes in the school attended after job loss. Reductions in income could partly explain the evidence found in this paper if fathers decrease hours of extra help with homework (or other extra school activities) after job loss or decrease consumption that could be related to school performance. Additionally, income reductions after father's job loss could entail higher stress or financial anxiety and uncertainty for affected individuals and households, as some papers in social psychology and health economics have suggested (see, for instance, Lim and Sng (2006) and Kuhn et al. (2009)). Unfortunately, the data do not allow us to test these alternative channels. They merit, though, consideration for future research. Research in this area would also benefit from more detailed data on parental labour market status, time use and school performance. An initial descriptive analysis with a cross-section of Spanish time use data indicates that mothers spend more time taking care of their children independently of their labour market status, but conditional on being unemployed mothers increase their time with children more than is the case with fathers. Looking at differences by education level, unemployed fathers with a level of education beyond high school spend more hours with children compared to unemployed fathers with a lower level of education. This very preliminary exercise with cross-section data suggests that the more detrimental impact of paternal job loss for children of low educated fathers could be partly explained by divergences in the time spent with children when unemployed, and it could also be behind the differential effects of father's and mother's job loss. However, more data is needed to perform a rigorous analysis of the mechanisms behind the effects of paternal and maternal job loss.

Given the massive employment destruction that has been taking place in several advanced economies during the Great Recession, the present study underlines the importance of understanding the mechanisms behind the negative and sizable effect of father's job loss on children's school performance. Moreover, the present study has looked at the short-term impact of parental job loss on school performance. As data becomes available, future research should look at more long-term effects: does parental job loss leave permanent scars on individuals? In particular, does parental job loss during childhood affect later educational and labour market outcomes? Besides the importance of the question in terms of granting equality of opportunity to individuals in society, there are also important implications for the economy as a whole, given the paramount importance of human capital for economic growth.

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Figures and tables

Figure 1: Unemployment rates

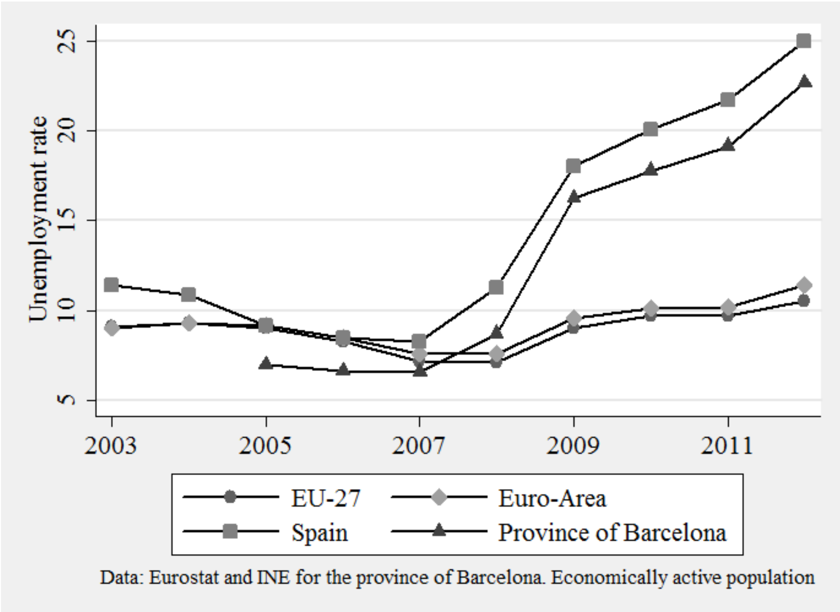


Figure 2: Average grade pre- and post-treatment

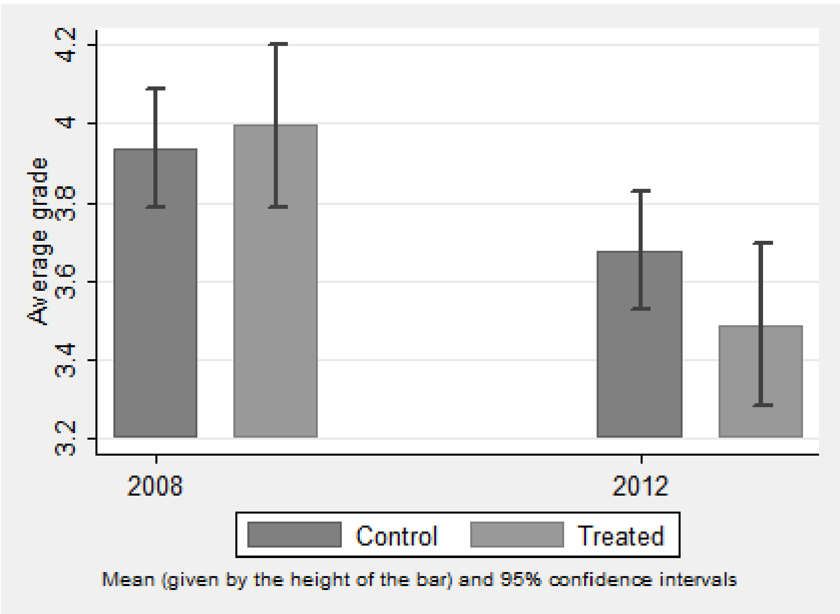


Figure 3: Differences in the average grade between control and treated students in 2008 (pre-treatment)

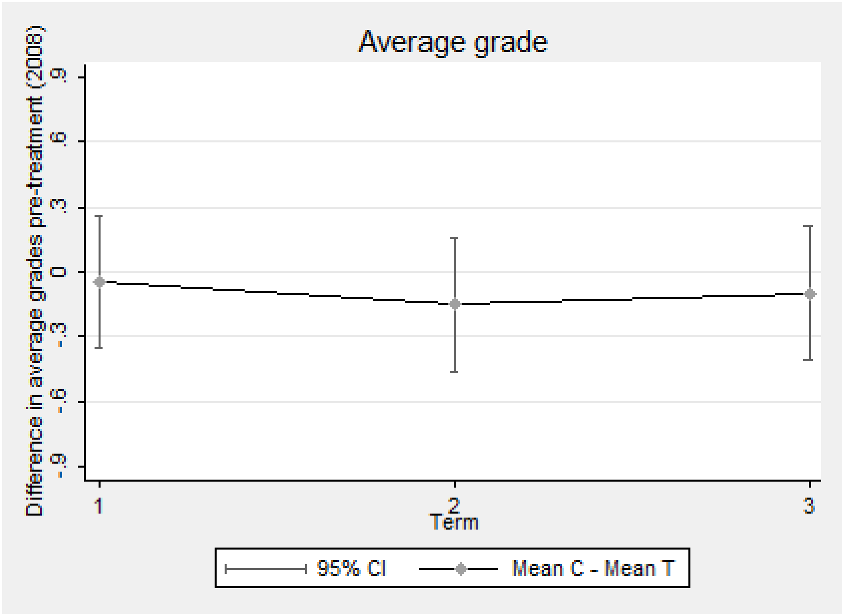


Table 1: **Summary of studies of parental job loss and the educational outcomes of their offspring (in the economic literature)**

Paper	Source and Years	Country	Age children	Treatment	Outcome variable	Estimates are...	Results
Use of the data: Cross-sectional (outcome variable observed once for a given individual)							
Kalil and Wightman (2011)	PSID, 1968:2005. Those born & turning 21 within panel	USA	21	Head ever reported involuntary JL by time child is 21	Any postsecondary educ by age 21	OLS and probit estimates	Parental JL ↓ prob of postsecondary education by 10pp
Gregg et al (2012)	BCS: panel of indiv born April 1970	UK	16	Fathers in industries with 20% employment loss in 80s recession...	GCSE attainment	OLS estimates with a mesure of prior attainment	↓ 18 grade points less, or half a GCSE at grades A^*-C
Pan and Ost (2014)	PSID: use indiv in the panel born between 1970 and 1985	USA	18 to 20	Parental layoff at ages 15-17 (treatment) vs 21-23 (control)	Higher education (HE) enrollment	Linear probab estimates (some include family FE)	Parental JL ↓ prob of HE enrollment by 0.10 pp
Use of the data: Repeated cross sections (outcome variable observed once for a given individual. Authors pool different cross-sections)							
Rege et al (2011)	Admin data, 2003:2007	Norway	16 (year 10)	JL (in school years 8 to 10) from PC	Summary measure of 10 subjects	Pooled OLS	FJL ↓ average grade 6.3% SD. No effect MJL
Coelli (2011)	SLID: use 4 panels from 1993 to 2007	Canada	16 to 20	JL (at ages 16 to 18) due to perm layoff or employer closing	College enrollment	Linear probab estimates	JL main income earner ↓ prob univ enrollment by 0.10 pp
Hilger (2014)	Admin tax records: from 2000 to 2009	USA	18 to 22	Father's layoffs (taking up UI) before college	College enrollment	DD: uses time of JL in control and survivor sample	Father's layoff ↓ annual college enrollment by 1%
Use of the data: Panel data (outcome variable observed more than once for a given individual)							
Kalil and Ziol-Guest (2008)	SIPP: Panel of 1996	USA	5 to 17	Involuntary JL (24 months prior to measure outcome)	Grade retention	Logit estimates with lagged dependent vble	FJL doubles odds of grade retention. No effect MJL
Stevens and Schaller (2011)	SIPP: panels of 1996-2001-2004	USA	5 to 19	Involuntary JL of HH (after wave 1)	Grade retention (and expulsion)	FE estimates	Grade retention ↑ 15% after JL from head
THIS PAPER	Own data collection: 2008:2012	Spain	3 to 16	Involuntary JL during Great Recession	Summary measure: average grade	FE estimates	FJL ↓ average grade by 13% SD No effect MJL

Acronyms used: JL: Job Losses; FJL: Father's job losses; MJL: Mother's job losses; BCS: British Cohort Study; GCSE: General Certificate of Secondary Education; SIPP: Survey of Income and Program Participation (USA), SLID: Survey of Labour and Income Dynamics (Canada); PSID: Panel Study of Income Dynamics (USA); PC: Plant closure; UI: Unemployment insurance benefits. HH: Head of the household; DD: Difference in differences; FE: Fixed effects; pp: percentage points. Note: papers might study other outcomes too (like earnings), but focus of the summary is on educational outcomes.

Table 2: **Descriptive statistics. Children and household characteristics in 2008**

	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)
Age	8.306	8	8.213	0.306
	(2.697)	(2.503)	(2.636)	(0.71)
First child	0.548	0.481	0.528	0.0669
	(0.500)	(0.504)	(0.501)	(0.82)
Ever repeated	0	0.0185	0.00562	-0.0185
a grade	(0)	(0.136)	(0.0750)	(-1.52)
Household characteristics				
Number of children	1.935	2.093	1.983	-0.157
	(0.506)	(0.759)	(0.596)	(-1.39)
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)
Mother has a job	0.798	0.852	0.815	-0.0535
	(0.403)	(0.359)	(0.390)	(-0.84)
Family lives close	0.589	0.519	0.567	0.0702
to school	(0.494)	(0.504)	(0.497)	(0.87)
Language spoken at home:	0.589	0.537	0.573	0.0517
Spanish	(0.494)	(0.503)	(0.496)	(0.64)
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)
N	124	54	178	

First (second) line for each variable corresponds to its mean (standard deviation -SD-). *, **, *** 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. Values shown are for the academic year 2008. Values shown are for the academic year 2008, except for the *Household Size* and *House dummies* variables (information for these variables was not collected for 2008, so values shown correspond to 2012).

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 high school	(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 year:	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 (second) line for each variable corresponds to its mean (standard deviation -SD-). *, **, *** 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. Values shown are for the academic year 2008. *Big firm* equals 1 if in 2008, the father worked in a firm with more than 50 workers. High motivation equals 1 if in 2008 the father had a level of motivation at work of 4 or 5 (measured in a scale of 1 to 5, where 5 means very motivated).

Table 4: **Characteristics of treated fathers in the first and second period after job loss. All job losers**

	2009-2010	2011-2012	All FJL	Diff and t-test
Father's educ	0.304	0.270	0.292	0.0341
beyond high school	(0.464)	(0.450)	(0.457)	(0.36)
Father's age	40.80	41.43	41.02	-0.635
	(5.155)	(6.589)	(5.674)	(-0.55)
Father works in	0.768	0.676	0.736	0.0924
a firm in 2008	(0.425)	(0.475)	(0.443)	(1.02)
Sector: Industry	0.359	0.306	0.340	0.0538
	(0.484)	(0.467)	(0.476)	(0.54)
Sector: Construction	0.359	0.389	0.370	-0.0295
	(0.484)	(0.494)	(0.485)	(-0.29)
Sector: Services	0.281	0.306	0.290	-0.0243
	(0.453)	(0.467)	(0.456)	(-0.25)
N	69	37	106	

First (second) line for each variable corresponds to its mean (standard deviation -SD-). *, **, *** denote significance at 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. There are 6 missing values in the dummy variables describing the sector of activity (we observe 64 individuals in period 2009-2010, and 36 in period 2011-2012). Values shown are for the academic year 2008.

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

	C.1	C.2	C.3	C.4	C.5
	OLS	FE	FE	RE	FE-All
Dependent variable: Average grade					
FJL	0.014	-0.127*	-0.133*	-0.115	-0.097*
	(0.140)	(0.071)	(0.071)	(0.073)	(0.059)
Mean	0.011	0.011	0.011	0.011	0.041
SD	0.942	0.942	0.942	0.942	1.002
N	890	890	890	890	1360
Students		178	178	178	332
σ_ϵ		0.350	0.348	0.348	0.397
σ_α		0.835	0.841	0.749	0.808
ρ		0.851	0.854	0.822	0.805

FJL (father's job loss): dummy equal to 1 from the year the father loses the job. Average grade scaled to mean zero with $SD = 1$ based on entire population of 358 students. *, **, *** denote significance at the 10%, 5% and 1% levels. Clustered robust standard errors at the family level in parentheses. All models include year dummies, and dummies for stage of education. Columns (3) to (5) additionally include an indicator for whether the student is re-taking that particular grade. σ_α gives the SD of the individual effect (α_i); σ_ϵ gives the SD of the idiosyncratic error (ϵ_{it}), and ρ is the intraclass correlation of the error.

Table 6: **Placebo: Average effect of FJL on the cross-section of 2008**

	C.1	C.2
	Cross-section 2008	Cross-section 2012
Dependent variable: Average grade		
Father suffers job loss	0.015	-0.223*
in the period	(0.117)	(0.131)
Mean	0.290	-0.087
SD	0.898	0.968
N	178	178

Father suffers job loss in the period: equals 1 for those students whose father suffers a job loss in the period under analysis (treated students). Average grade scaled to mean zero with $SD = 1$ based on entire population of 358 students. *, **, *** denote significance at the 10%, 5% and 1% levels. Robust standard errors in parentheses. All models include gender, quarter of birth and stage of education dummies, and whether the father has reached a level of education beyond high school.

Table 7: **Excluding fathers that in 2008 had a lower labour market attachment**

	C.1	C.2	C.3	C.4
Dependent variable: Average grade				
FJL	-0.178**	-0.183**	-0.156**	-0.161*
	(0.086)	(0.087)	(0.079)	(0.083)
Mean	-0.004	-0.005	0.001	-0.021
SD	0.960	0.961	0.962	0.960
N	760	710	840	830
Students	152	142	168	166
Proportion treated	25.00%	26.76%	26.19%	25.30%
Subsample	More than 3	More than 6	Only fathers with	Exclude fathers with
	years of tenure	years of tenure	perm contract	multiple job losses

FE estimates. FJL (father's job loss): dummy equal to 1 from the year the father loses the job. Average grade scaled to mean zero with $SD = 1$ based on entire population of 358 students. *, **, *** denote significance at the 10%, 5% and 1% levels. Clustered robust standard errors at the family level in parentheses. All models include year dummies, dummies for stage of education and an indicator for whether the student is re-taking that particular grade. Except for C.4, all the sample restrictions are based taking into account 2008 data.

Table 8: **Robustness check: Group specific trends**

	C.1	C.2	C.3	C.4	C.5	C.6	C.7
Dependent variable: Average grade							
FJL	-0.131*	-0.118	-0.126*	-0.130*	-0.137*	-0.134*	-0.123
	(0.070)	(0.073)	(0.072)	(0.074)	(0.070)	(0.074)	(0.076)
Mean	0.011	0.011	0.011	0.011	0.011	0.011	0.011
SD	0.942	0.942	0.942	0.942	0.942	0.942	0.942
N	890	890	890	890	890	890	890
Students	178	178	178	178	178	178	178
Group specific	Father's	Father's	Father owned	Father's	Mortgage or	Student's	All previous
trends (δ_{tj})	education	income	business	industry	rent	gender	

FE estimates. FJL (father's job loss): dummy equal to 1 from the year the father loses the job. Average grade scaled to mean zero with $SD = 1$ based on entire population of 358 students. *, **, *** denote significance at the 10%, 5% and 1% levels. Clustered robust standard errors at the family level in parentheses. All models include year dummies, dummies for stage of education and an indicator for whether the student is re-taking that particular grade. All variables interacted with the year dummies are measured in 2008, except the mortgage/rent indicator, that is only available for 2012.

Table 9: **Impact of mother's job loss (and labour market status) on school performance**

	C.1	C.2	C.3	C.4	C.5	C.6	C.7
Dependent variable: Average grade							
MJL	-0.043	-0.013			0.057	-0.150	
	(0.095)	(0.095)			(0.121)	(0.152)	
FJL		-0.132*	-0.272**	-0.042			-0.121*
		(0.073)	(0.111)	(0.090)			(0.071)
Mother works							0.116
							(0.080)
Mean	0.006	0.011	-0.195	0.184	-0.195	0.184	0.014
SD	0.944	0.942	1.017	0.837	1.017	0.837	0.940
N	835	890	405	485	405	485	889
Students	167	178	81	97	81	97	178
Proportion treated	29.94%		27.16%	32.99%	27.16%	32.99%	
Subsample	Excl mother unemp in 2008	All restricted	Males	Females	Males	Females	All restricted

FE estimates. FJL/MJL (father's/mothers job loss): dummy equal to 1 from the year the father loses the job. Mother works is a dummy that equals 1 in the years the mother is observed working. Average grade scaled to mean zero with $SD = 1$ based on entire population of 358 students. *, **, *** denote significance at the 10%, 5% and 1% levels. Clustered robust standard errors at the family level in parentheses. All models include year dummies, dummies for stage of education and an indicator for whether the student is re-taking that particular grade. Proportion treated is shown when only one of the variables (FJL or MJL/Mother works) is included in the model.

Table 10: **Alternative treatment definitions and the role of long term unemployment**

	C.1	C.2	C.3
Dependent variable: Average grade			
FJL (1)	-0.089*		
	(0.053)		
FJL (2)		-0.269***	
		(0.094)	
FJL contemp			-0.138*
			(0.074)
FJL prior			-0.129*
			(0.075)
Mean	0.011	0.011	0.011
SD	0.942	0.942	0.942
N	890	890	890
Students	178	178	178

FE estimates. FJL (1): dummy equal to 1 the year the father loses the job and the years after job loss as long as the father remains unemployed. FJL (2): dummy equal to 1 the year the father loses the job (as long as he does not find a job the same year), and the years after job loss as long as the father remains unemployed. FJL (father's job loss): dummy equal to 1 from the year the father loses the job. Average grade scaled to mean zero with $SD = 1$ based on entire population of 358 students. *, **, *** denote significance at the 10%, 5% and 1% levels. Clustered robust standard errors at the family level in parentheses. All models include year dummies, dummies for stage of education and an indicator for whether the student is re-taking that particular grade.

Table 11: **Other robustness checks**

	C.1	C.2	C.3	C.4	C.5	C.6
Dependent variable: Average grade						
FJL	-0.196***		-0.166***	-0.119*	-0.133*	
	(0.073)		(0.057)	(0.072)	(0.074)	
FJL strict		-0.152**				
		(0.060)				
% FJL in grade-year				-0.006		
				(0.004)		
% FJL in grade-year-class					-0.001	
					(0.001)	
JL main earner						-0.123*
						(0.067)
Mean	0.045	0.011	0.109	0.011	0.013	0.003
SD	0.957	0.942	0.893	0.942	0.941	0.939
N	534	890	800	890	882	1000
Students	178	178	160	178	178	200
Robustness check	Using only 2008-2010-2012	Strict FJL definition	Outliers: Excl 5th/95th perc	Peer effects in same grade	Peer effects in same class	Job losses main earner

FE estimates. FJL (father's job loss): dummy equal to 1 from the year the father loses the job. Average grade scaled to mean zero with $SD = 1$ based on entire population of 358 students. *, **, *** denote significance at the 10%, 5% and 1% levels. Clustered robust standard errors at the family level in parentheses. All models include year dummies, dummies for stage of education and an indicator for whether the student is re-taking that particular grade.

Table 12: **Heterogeneous effects**

	C.1	C.2	C.3	C.4	C.5	C.6
Dependent variable: Average grade						
FJL	-0.133*	-0.189**	-0.238**	-0.162*	-0.243***	-0.338***
	(0.071)	(0.090)	(0.092)	(0.085)	(0.080)	(0.098)
FJL*Father's educ beyond HS		0.187 (0.117)				
FJL*Father worked in a firm in 2008			0.154 (0.122)			
FJL*Older students (in secondary 2012)				0.063 (0.109)		
FJL*owning house in 2012					0.264** (0.118)	
FJL*household not moving in the period						0.237** (0.118)
Mean	0.073	0.073	0.073	0.073	0.073	0.069
SD	0.931	0.931	0.931	0.931	0.931	0.934
N	890	890	890	890	890	880
Students	178	178	178	178	178	176

FE estimates. FJL (father's job loss): dummy equal to 1 from the year the father loses the job. Average grade scaled to mean zero with $SD = 1$ based on entire population of 358 students. *, **, *** denote significance at the 10%, 5% and 1% levels. Clustered robust standard errors at the family level in parentheses. All models include year dummies, dummies for stage of education and an indicator for whether the student is re-taking that particular grade.

Table 13: **Income reductions across different subgroups**

	C.1	C.2	C.3	C.4	C.5	C.6
Dependent variable: Father's income (=1 if father has high income)						
FJL	-0.318***	-0.354***	-0.332*	-0.366***	-0.470***	-0.553*
	(0.099)	(0.117)	(0.181)	(0.133)	(0.135)	(0.308)
FJL*Father's		0.111				
educ beyond HS		(0.210)				
FJL*Father owned			0.021			
business in 2008			(0.214)			
FJL*Older students				0.103		
(in secondary 2012)				(0.148)		
FJL*owning house					0.342**	
in 2012					(0.171)	
FJL*household not						0.248
moving in the period						(0.325)
Mean	0.647	0.647	0.647	0.647	0.647	0.654
SD	0.478	0.478	0.478	0.478	0.478	0.476
N	829	829	829	829	829	819
Students	169	169	169	169	169	167

FE estimates. High income is defined as having monthly net income in the 2 highest categories in the survey (more than 1500 euro net). 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 family level in parentheses. All models include year dummies. Missing observations due to missing values in the income variable (additional missing values in M.7 related to moving information).

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

This appendix presents a simple theoretical framework to provide some intuition on how parental job loss could affect the school performance of affected children. Consider a student in general education who 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 is 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 labour supply model, but here the student chooses the level of effort to maximise her utility:

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

Subject to the grade production function:

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

The first order condition for an interior solution is given by Equation 3 and states that students will choose the level of school 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 (1999). Card inserts heterogeneity into 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, we will assume that the marginal rate of return to school effort, $g'(e)$, and the marginal cost of school effort, $d'(e)$, are linear functions with person-specific intercepts and homogeneous slopes:

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

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

$$k_1 \geq 0, k_2 \geq 0 \quad (6)$$

As Card (1999) 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 parameterised 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 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 of the paper, the empirical evidence has shown that people experiencing job loss suffer from income reduction, worse family environment, deteriorated physical and mental health, etc. (see Jacobson et al. (1993), Kuhn et al. (2009) and Eliason (2012) among others). 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. For instance, Todd and Wolpin (2003) point out the lack of consensus on the effect of maternal employment on school achievement.

Parental job loss could also distort the taste 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 five years of age, children understand such concepts as pay, labour 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 experience 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 taste for effort. However, 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 better performance at school. In this sense, the empirical evidence shows that, in general, children choose more education when the labour market is weak (Betts and McFarland, 1995). In this case, parental job loss would introduce a positive distortion in the taste for effort.[34]

Therefore, both b_i and r_i could potentially be affected by parental job loss, and we will express this by writing both of them as a function of parental job loss (JL): $b(JL)_i$ and $r(JL)_i$,

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

respectively. Optimal level efforts are then determined according to:[35]

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

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 and these are, as mentioned above, theoretically ambiguous.[36]

Appendix B. More details on the data

This appendix is a summary of Chapter 1 in Ruiz-Valenzuela (2014). The sections in this appendix briefly describe the survey and item non-response, the representativeness of the data and the format of school outcomes.

B1 Survey and item non-response

There were 931 children (distributed over 700 families) that were enrolled at the school where the data was collected during the academic year 2011-2012. Some children were not present at the school the day the questionnaires were handed out, but we were able to distribute the questionnaires to children from 630 families. A total of 313 families returned the questionnaires. Since there could be more than one child enrolled at the school for each family, this data corresponded to 436 children distributed throughout all the grades. The response rate is, therefore, close to 50% of the questionnaires delivered. After receiving, coding and revising the questionnaires, three typologies of answers emerged. First, a total of 242 families returned the questionnaires completed (there were some minor cases of item non-response, but in general the answers were complete and consistent). Second, some inconsistency was found for the answers of either the father or the mother in 58 families. In order to correct these inconsistencies, the school allowed us to contact these 58 families again. 21 of those families returned the questionnaire corrected. Finally, out of the 313 returned questionnaires, 13 of them presented a substantial number of questions unanswered. These 13 families have been disregarded from the analysis. Additionally, 8 families did not provide the name of the children in the returned questionnaires, and therefore it was impossible to match the parental data provided with their children's grades. Taking this into account, the final sample consists of 408 students in 292 families (358 of them were enrolled in compulsory education grades in 2012). Item non-response is very low for almost all questions in the household and individual questionnaires. Importantly, there is almost no missing data regarding the labour market status of the father or the mother after following up with respondents to correct mistakes.

[35] Where a necessary condition for the equilibrium to exist with non-negative levels of effort is that $b(JL)_i \geq r(JL)_i$.

[36] Even if not included here, it might 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 would still be theoretically ambiguous.

B2 Representativeness

This section assesses the ability of the final sample to reproduce the characteristics of the population. Different population definitions will be used to achieve this goal. First, we will use the population of 6th graders in primary School in Catalonia in different academic years. Second, we will use the school population during the academic year 2011-2012 (year of data collection). Third, we will use the Spanish Labour Force Survey (LFS) to extract a sample of children aged 0 to 20 in Spain, Catalonia and the province of Barcelona, in the first quarter of 2012.

The variables analysed in Subsections B2.2 and B2.3 below have answers whose options are mutually exclusive and exhaustive. This is needed in order to perform a test of goodness of fit, namely, the Pearson Chi Square test.

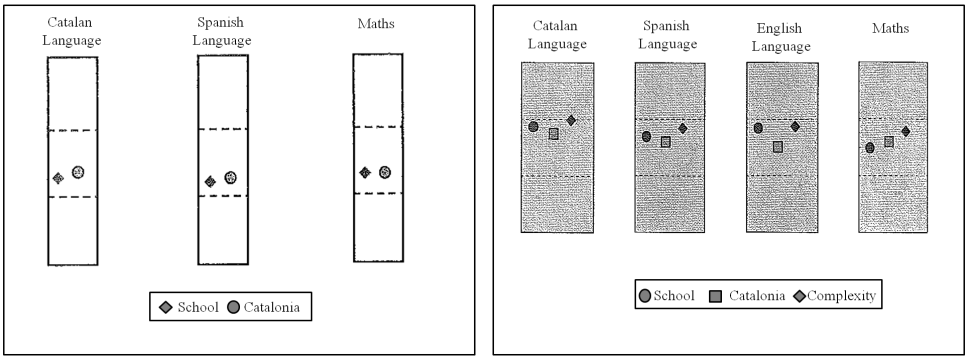
B2.1 The school within the Catalan school system

The school where the data has been collected is a concerted school in the province of Barcelona. A concerted school is a private school, typically owned by the Catholic Church (80% of them are including this particular school), that signs a long-term concert or agreement with the government by which it becomes fully subsidised in exchange for implementing a state school-like admission policy (Arellano and Zamarro, 2007). Neither public nor concerted schools, in principle, charge fees because they are both funded by the taxpayers. However, in practice the cost of attending concerted schools may be three times larger than for state schools, but in either case these are much smaller amounts than those faced by the small fraction of parents that send their children to non-concerted fee-paying private schools (Arellano and Zamarro, 2007).[37] For this particular school, the fees vary according to parental income, but for kindergarten and compulsory schooling ages, it is below or around 100 euros per month.

Figure B1 provides a description of the position of the school in the Catalan education system in terms of the achievement of its students. The information comes from a test designed and organised by the Education Department of the Catalan Government that all 6th graders (primary school) must take regardless of school type. The first test was administered in the academic year 2008-2009 and evaluated core competencies in Catalan, Spanish and Mathematics. From the next academic year it also tested the English knowledge of 6th graders. The results of these tests are not publicly available, but the schools receive a document with information about how their students performed compared to the average school in Catalonia, and this is what is shown in Figure B1 for the academic years 2008-2009 and 2011-2012.

[37] According to the data for the academic year 2011-2012 offered by the Ministry of Education, 68.2% of the students in general (non-vocational) education were enrolled in public schools, 25.4% were enrolled in concerted schools and 6.4% attended private schools. Source: Datos y Cifras, Curso Escolar 2012-2013, Ministerio de Educación, Cultura y Deporte.

Figure B1: Position of the school in the Catalan Education system



Source: Primary school evaluation, 2008-2009 (left panel) and 2011-2012 (right panel). Education Department, Generalitat de Catalunya (Catalonian Government).

The results divide the level of core competencies into three categories: low (0 to 70), average (70 to 90) and high (90 to 100). The results for the academic year 2008-2009 of 6th graders in the school where the data has been collected are very close to the average results in Catalonia for the three tested subjects. The same can be stated about the academic year 2011-2012 on average, although they performed slightly worse in English and slightly better in Maths. The school does not have the data needed to compute whether the differences between the school and the Catalan average results are significantly different from each other. Nevertheless, these results seem to suggest that, in terms of academic results, the school is very close to the average Catalan school.

B2.2 How representative is the sample of the school population?

The school granted us access to the data that they had in electronic format for the population of all children enrolled at the school during the academic year 2011-2012. In particular, we got data related to the distribution of students by grades, their birth dates and the postcodes associated with the household residence for all students enrolled at the school during the academic year 2011-2012. In general, there are no remarkable differences between the sample and the school population regarding neighborhood, month of birth and distribution of the students across different grades (cohorts). The results of the Pearson Chi-Square tests indicate that there are no significant differences between the frequency distribution in the sample and the school population for any of these variables. We also got access to data on school outcomes for the school population. Unfortunately, this data was not available in electronic format for all the school population, but just for some groups (e.g. for some subjects, grades and classes). Therefore, when assessing representativeness using outcome data we use the data of those students enrolled in grades for which we also observe the final outcomes of the school population. The data for both the sample and the school population refers to the third term of the academic year 2011-2012. For both Maths and Catalan, there are not significant differences between the frequency distribution in the sample and the school population for both primary and secondary school students with Spanish-like surnames (if taking into account the whole sample, students in the sample tend to perform better; but this is no longer the case when students without Spanish-like surnames are excluded from both the sample and the population). If interested, the reader can find graphical evidence and the results of the Pearson-Chi Square tests described here in Chapter 1 of Ruiz-Valenzuela (2014).

Unfortunately, the data available for the whole population of students in the school in 2012 does not allow me to discern respondents from-non respondents. We can therefore not analyse whether some of the available characteristics (postcode, month of birth, etc.) play an important role in the decision to fill out the questionnaire. However, the previous comparison of the available data for the school population with the sample data seems to suggest that the sample is representative of the school population as long as students with an immigrant background are excluded from both the sample and school population. Therefore, our fundamental working assumption is that conditional on the immigration status of their parents, students from non-respondent households are missing at random or $f(G|I) = f(G|I, D = 1)$ (see Little and Rubin (1987)), where G is the outcome variable of interest (i.e. a measure of school performance), I is a dummy variable equal to 1 if the father has Spanish nationality, and $D = 1$ indicates participation in the survey.

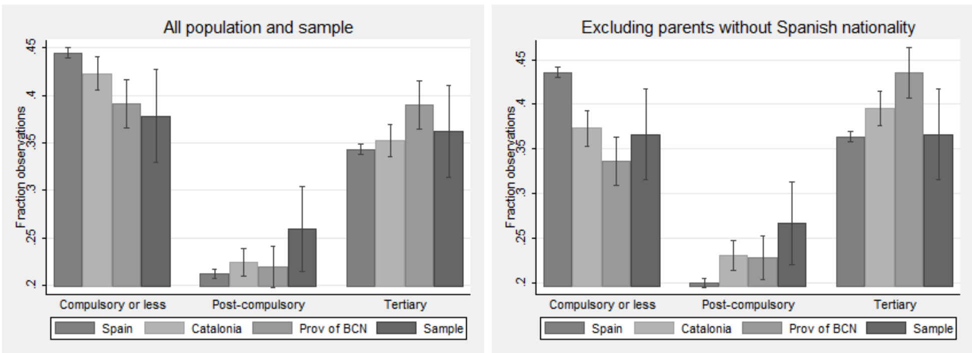
B2.3 The characteristics of the sample compared to the population in the Spanish Labour Force Survey

In this section we use the data of the Spanish Labour Force Survey (LFS) to assess how the distribution of some key characteristics of the individuals in our sample compares to the distribution of these same characteristics in the Spanish, Catalan and (province of) Barcelona population. Even if we do not claim that our sample is representative of these populations, it is nonetheless interesting to see if the distribution of some parental characteristics in our sample resembles the distribution of these same characteristics in the populations defined above.

In order to do so, we have used the LFS data produced by the Spanish National Institute of Statistics (INE) corresponding to the 1st quarter of 2012, and we have extracted the subsample of individuals aged 0 to 20. Since the age data is given in five year interval age groups, and given that the individuals in our sample have ages ranging from 3 to 18, this is the closest we can get to the population of our sample using the LFS data. Using the information on family relationships, we have matched these individuals with the information of their parents (this information is available as long as they live in the same household).

The distribution of father's education, father's labour market status and father's firm sector of activity are shown in Figures B2, B3 and B4, respectively. In general, there is a higher fraction of fathers in the sample with post-compulsory (non-tertiary) education if compared to any of the three different populations extracted from the LFS, and whether we use all the population (left figure) or we restrict the sample to include only children from Spanish citizens (right figure). Nonetheless, the results of Pearson square tests indicate that the frequency distribution of education levels for fathers in the sample resembles that of fathers in Catalonia and Barcelona when the whole population is considered, and that of Catalonia when we restrict the sample to Spanish nationals. Figure B3 presents the distribution of father's labour market status, divided into three categories: own a business, work for a firm or unemployed. The sample distribution when the entire population is considered is almost identical to the distribution in Spain, Catalonia and the province of Barcelona. The results of the Pearson chi square tests show that there are no significant differences in the frequency distribution of father's labour market status between the sample and these populations. However, once we restrict the sample to include only those individuals with Spanish parents, the null hypothesis cannot be rejected only at the Spanish level. For those fathers that are working, the distribution regarding the sectors of activity of the firm are plotted in Figure B4. Both for the whole population and for the restricted one, the frequency distribution of the sectors in the sample resembles that of Catalonia.[38]

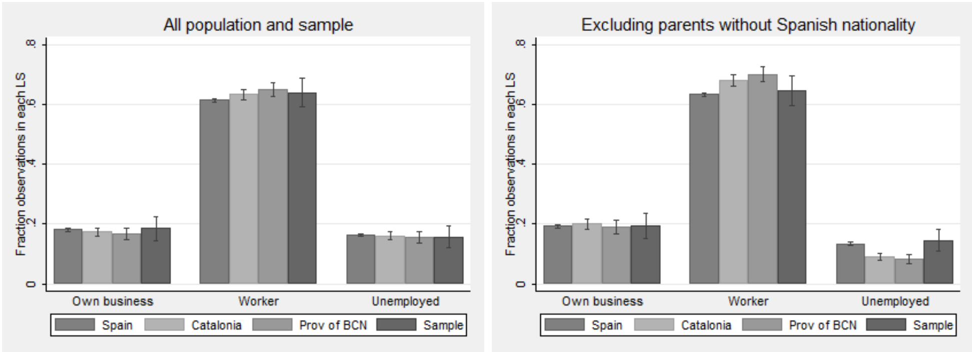
Figure B2: Father's education



Mean (given by the height of the bar) and 95% confidence intervals. Population data refers to the first quarter of 2012 of the Spanish LFS. Weights have been used for the LFS data.

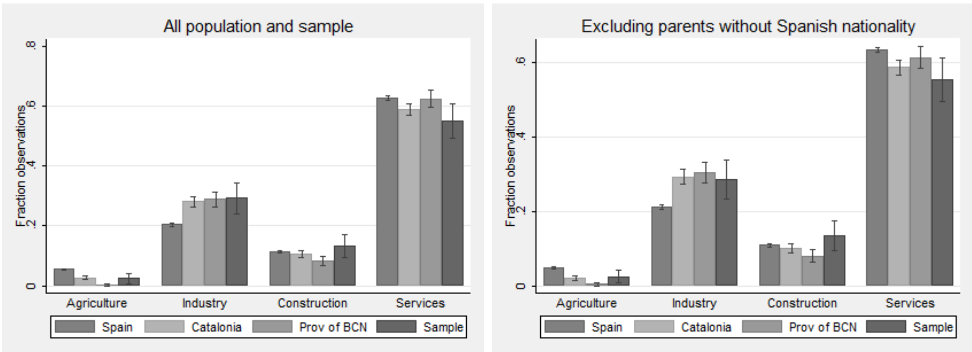
[38]Data on the frequency distribution of other household variables and mother's characteristics can be found in Chapter 1 of Ruiz-Valenzuela (2014).

Figure B3: Father's labour market status



Mean (given by the height of the bar) and 95% confidence intervals. Population data refers to the first quarter of 2012 of the Spanish LFS. Weights have been used for the LFS data.

Figure B4: Father's sector of the firm



Mean (given by the height of the bar) and 95% confidence intervals. Population data refers to the first quarter of 2012 of the Spanish LFS. Weights have been used for the LFS data.

The descriptive analysis in this section suggests that the sample, even if restricted in terms of size and concentrated in only one school, is sufficiently diverse to reproduce some of the most representative characteristics of the population with children aged 0 to 20 (as given by the data in the Spanish LFS).

B3 The data on school outcomes

The different stages in the Spanish education system are as follows. Kindergarten is divided into a first stage (children from ages 0 to 3) and a second stage (children from 3 to 6 years of age). Even if kindergarten is not compulsory, 98% of three-year-olds were enrolled in the second stage of kindergarten in the academic year 2008.[39]. Compulsory education in Spain begins the year the child turns six until the year the child turns sixteen, and is divided in two stages: primary school, with a total of six grades (until the year the child turns twelve) and secondary school,

[39]Source: Datos y Cifras, Curso Escolar 2012-2013, Ministerio de Educación, Cultura y Deporte

comprising four additional grades. After completing compulsory education successfully, students can choose to enrol in high school (bachillerato) for two additional years or in vocational training. The data collected in this project refers to children aged 3 to 18, that are enrolled in either the second stage of kindergarten, primary school, secondary (compulsory) school or high school.

Grades' formats differ across stages of education. In the school where the data comes from, grades in secondary school and high 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 grades can take on five different values: (1) Fail, (2) Pass, (3) Good, (4) Very Good and (5) Excellent. Secondary school grades can be translated into this five value scale following the traditional convention in the school: Grades 1 to 4 in secondary school were assigned a grade of Fail (1). A grade of 5 or 6 in secondary school corresponds to Pass (2) or Good (3), respectively. Grades 7 or 8 correspond to Very Good (4). Finally, grades 9 or 10 are translated into a grade of Excellent (5). In the school analysed, the student in primary, secondary or high school receives a report with her grades 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 short sentences. These short sentences can be clearly positive (ex: the child can count from one to five, the child can write her name, etc.), clearly negative (ex: the child cannot count from one to five, the child cannot write her name, etc.), or improving-type of sentences (child's counting has improved, etc.). In order to translate these sentences into a numeric grade a value of 1 is assigned to positive and improving sentences, and a value of 0 to negative sentences. After doing this, we computed a simple average of the points obtained in each subject 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 five scale values with the same criteria outlined for secondary school grades. Based on this information, we constructed a summary measure of each student's performance during the academic year. The main measure used throughout the analysis is the average grade obtained each academic year by each student. This measure is obtained by averaging the student's grades in all subjects and terms in a given academic year. Therefore, it is the average of the results in four subjects in the kindergarten stage, nine to ten subjects in the primary stage, and between eleven and fifteen in secondary (compulsory) schooling (the number depends on the grade the students is enrolled in).

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