R&D restructuring during the Great Recession and Young Firms

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Abstract

In this paper, I examine whether the Great Recession of the late 2000s (henceforth abbreviated as GR) had an effect on the organization of R&D in young versus older firms. Using a difference-in-difference approach and propensity score reweighting estimator, for a panel of more than 12,000 Spanish firms from 2005 to 2014, I compare young firms with older firms before and after the GR. I show that young firms implemented three key compositional changes in their R&D policies during the GR as compared to older firms: a) they reduced their R&D employment by firing medium and low-skilled R&D workers; b) they hired high-skilled R&D workers; and c) they increased their capital investments for R&D. These changes in R&D policies suggest that, during the GR, young firms substituted medium and low-skilled R&D workers by high-skilled workers and machines. These effects are mediated by the firms' financial health.

Keywords: Young firms; Great Recession; Firm performance; R&D; Innovation; Automation/Mechanization of R&D; Skill-upgrading; Job polarization.

JEL classification: L26; D22; L25; O32

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1. Introduction

R&D is a fundamental driver of productivity, firm dynamics, market reallocations and, ultimately, economic growth. Investments in R&D depend on economic conditions, which is why recessions are crucial events. As Schumpeter (1923/1939) argues "…there is more brain in business at large during recession than there is during prosperity" (p.143). Therefore, studying the organizational changes that firms undertake in their R&D policies during recessions – the main topic of this paper – is important for understanding job creation, growth potential and aggregate fluctuations.

The economic literature shows that during recessions labour is often relocated and firms tend to reorganize their production and innovation methods (Davis and Haltiwanger 1992; Aghion and Saint-Paul 1998; Manso et al. forthcoming). Recent literature suggests that one way to reduce costs in recessions is through automation by substituting medium-skilled workers with machines and simultaneously hiring a small number of high-skilled workers that complement these machines (Brynjolfsson and McAfee 2011; Autor 2015; Morin 2016).[1] Moreover, during recessions, firms can hire from a larger pool of high-skilled workers (Bewley 1999; Mueller 2017).

The process of skill-upgrading and automation or mechanization is particularly important for the R&D department and for young firms.[2] Human capital contributes crucially to firms' technological activities. Moreover, young firms are highly adaptable to the hiring environment

[1] Along these lines, Hershbein and Kahn (2018) find that skill requirements increased during the last recession and are correlated with an increase in capital investments. This mechanism might partly explain the jobless recovery in routine occupations after the last recession as highlighted by Cortes et al. (2017) and Jaimovich and Siu (2020), among others, for US firms and also the decline in participation rates of workers in routine occupations (Grigoli et al., 2020). An alternative explanation for the jobless recovery is the effect of import competition that might have reduced employment by relocating labour-intensive industries abroad (Fort et al. 2018).

[2] Automation refers to use of machines or technology that enables to substitute human input by capital. Examples of automation are the use of robots, AI or computer-assisted machines (Acemoglu and Restrepo, 2018, 2019a). Mechanization also implies the replacement of humans by machines or technologies, but they are less self-controlling than in the case of automation (Groover, M. *Encyclopedia Britannica*).

(Geurts and Van Biesebroeck 2016). One of the reasons is that young firms have lower labour adjustment costs than old firms because severance payments typically rise with tenure and the average worker tenure is small in young firms.

The main contribution of this paper is to provide evidence of the mechanization and skill-upgrading of R&D for young firms during the Great Recession of the late 2000s (henceforth abbreviated as GR).[3] I compare young firms with older firms before and after the Great Recession in a difference-in-difference framework and use a propensity score reweighting estimator. I examine whether the GR influenced the organization of R&D in young versus older firms. I find that young firms adjusted their R&D employment during the GR. I show that young firms implemented three key compositional changes in their R&D policies during the GR as compared to older firms: a) they reduced their R&D employment by firing medium and low-skilled R&D workers; b) they hired high-skilled R&D workers; and c) they increased their capital investments for R&D. These changes in R&D policies suggest that, during the GR, young firms substituted medium and low-skilled R&D workers by high-skilled workers and machines. These effects are mediated by the firms' financial health.

I use a panel dataset of more than 12,000 Spanish firms from 2005 to 2014. This dataset is uniquely suitable for my purposes because it contains detailed information of the R&D inputs of the firm as well as firm-level financial information. Thereby, I can measure, at the firm level, changes in the composition of the R&D labour force and R&D investments during the GR.

[3] My measure of mechanization is "R&D expenditures in machinery, equipment and software used in order to generate product and process innovations." This variable is more general than automation since it might include equipment or systems that are not self-regulated. Examples of machinery, equipment and software for R&D include computer hardware, software, data processing equipment, and also laboratory equipment.

Moreover, in Spain, as in many European countries, firing costs rise with tenure,[4] which makes young firms in the sample more likely to adjust their labour force than older firms because of their lower firing costs. My results contribute to the understanding of the changes in the internal organization of firms' R&D during an economic cycle. In particular, I show that the GR particularly affected the reorganization of the R&D of young firms.

The GR was an unexpected shock (Aghion et al. 2021). Most economies experienced financial restrictions, large declines in their domestic demand, and drops in employment at all educational levels (Farber 2015). There is evidence that R&D activities are time-dependent and procyclical (Beneito et al. 2015; Fabrizio and Tsolmon 2014) and that the distress of the banking sector during the GR negatively affected firm innovation (Spatareanu et al. 2019). However, some of the research that is conducted during recessions seems to be more radical than during non-recession times. For example, Manso et al. (forthcoming) show that innovative activities are explorative during recessions and exploitative during booms. Lebdi and Hussinger (2016) study the pattern of innovations of startups founded at different times of the business cycle. Their results suggest that startups founded during the crisis introduce fewer product innovations but of higher novelty compared to the products introduced by startups founded during non-crisis periods. These results are consistent with my finding that startups skill-upgraded their R&D labour force during the GR. A major difference with respect to previous studies on R&D during the business cycle is that I document the changes in R&D inputs during the GR and find that there is mechanization in R&D. My results also suggest that young firms, with similar characteristics to older firms before

[4] In Spain, severance pay for redundancy dismissal of a worker with one year of tenure is equal to 2.9 weeks, with five years of 14.3 weeks and with ten years of tenure is 28.6 weeks. This relationship between firing costs and tenure is also positive for other European countries like France, Germany, Greece or United Kingdom (Source: World Bank 2018).

the GR, become more efficient in the way they conduct their R&D during the crisis as compared to older firms.

This paper also contributes to the literature on empirical studies of the performance of young firms. Sedláček and Sterk (2017) analyse the potential of young firms over the business cycle. They find that firms founded during periods of economic growth grow larger than firms founded during recessions. Piergiovanni (2010) finds that young firms, during their first six years, grow faster than older firms. Haltiwanger et al. (2013) show that, conditional on survival, young firms grow faster than older firms and they are also more volatile. In this line, García-Quevedo et al. (2014) find that young firms are more erratic in their R&D policies than older firms. As Coad et al. (2016) show for a sample of Spanish firms, a possible reason is that young firms invest more in riskier R&D activities than older firms.[5] Compared to these papers my paper identifies the R&D policies that young firms undertake during the GR that might contribute to the differences in performance between younger and older firms.

The rest of the paper is organized as follows. In Section 2, I discuss the relevant theory. In section 3, I describe the dataset and the main variables. In Section 4, I explain the econometric specification. Section 5 presents the baseline results, as well as robustness checks. Section 6 shows additional empirical evidence, investigating heterogeneous effects and the effects of the GR to further innovation inputs, outputs, and firm economic variables. Finally, in Section 7, I summarize the results and conclude.

[5] For a summary of the literature on startups and innovation see Autio et al. (2014). For the relationship between in-house R&D and external R&D and startups see Pellegrino et al. (2012).

2. Theoretical considerations

Recessions are periods of fundamental distress for firms and employment.[6] Evidence suggests that in order to survive in a challenging macroeconomic environment, firms modify their production (Aghion et al. 2021; Bernard and Okubo 2016), they reorganize their employment in a way that complements routine-biased technologies (Hershbein and Kahn 2018),[7] and they invest in explorative innovations (Manso et al. forthcoming).

There are theoretical arguments explaining that recessions influence R&D capital investments and employment. During bad times, firms have incentives to invest in new technologies and R&D equipment or software because the profitability of alternative investments, such as those that are directly related to production, drops during recessions. This generates a decline in the opportunity costs of new technologies or R&D physical investments and software. For example, the model of Aghion and Saint-Paul (1998) shows that technological investments are counter-cyclical if, during recessions, their opportunity costs decline more than their return. The models of Cooper and Haltiwanger (1993), Caballero and Hammour (1994) or Kopytov et al. (2018) also relate the fall in the opportunity costs during bad times with machine replacement or investment in new technologies.

The new machines or technologies reduce employment, but they also generate a productivity effect. Consequently, there might be an overall employment reduction and a change in the labour

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[6] In many countries unemployment rates and firm exit increased dramatically during the GR. For example, data from the World Bank show that in the US the unemployment rate increased from 5 percent to 9.6 percent during the GR; in the United Kingdom the unemployment rose from 5 percent to 8 percent; and in Spain the unemployment rate increased from 8 percent to 20 percent.

[7] Other fundamental changes during recessions are the firing of employees and reduction of working hours. For example, early evidence by Davis and Haltiwanger (1992) shows that job reallocation rate increases during recessions. During the GR, Van Dalen and Henkens (2013) document employment reorganization within European companies. In particular, companies adjusted their labour force by reducing their working hours and offering early retirement packages and buy-outs.

composition of the adopting firms (Acemoglu and Restrepo 2019b). The new technologies tend to reduce employment with routine tasks and increase employment with non-routine tasks and high-qualified employment with skills that can complement the new machines or technologies (Autor et al. 2003, Hershbein and Kahn 2018, Kopytov et al. 2018).

An additional effect that contributes to the positive relationship between recessions and skill-upgrading and investment in machines or new technologies is that, during recessions, there are more highly qualified employees in the job market due to firm exit and firm cost-saving strategies (Bewley 1999; Mueller 2017; Modestino et al. 2020). Consequently, during recessions the cost of hiring highly qualified workers declines. This additionally incentivizes the substitution of medium or low-skill employees by high-qualified employees whose skills and knowledge can complement the new machines or technologies.

These effects are likely to be more important for young than for older firms for several reasons. Young firms can more flexibly fire employees than older firms due to the lower severance payments that they face, which are typically related with tenure. Moreover, employees in young firms might have accumulated less firm-specific human capital than employees in older firms, which also reduces the firing costs of young firms.[8] Hence, during recessions, young firms can fire and skill-upgrade more easily than older firms. Consequently, young firms are more likely to hire qualified employees whose skills complement the new technologies. This, in turn, can affect the likelihood of young firms adopting new machinery, technology or software as compared to older firms. An additional reason for the higher likelihood of young firms adopting new technologies is

[8] Becker (1962) distinguishes between general human capital that can improve the productivity in any firm and firm-specific human capital that increases productivity only in the current firm of the employee.

that their R&D departments tend to be less bureaucratic than those of older firms (Schneider and Veugelers 2010), which makes reorganization easier.

Finally, the financial health of the firm is likely to have a mediating effect on the adoption of new machinery or technology and firing and hiring behaviour. Two fundamental reasons are that less financially healthy firms have reduced access to the credit needed for the acquisition of the new technology and firms with high debts also have a higher risk of default (Giroud and Mueller 2017), which might incentivize them to delay their new hirings until they improve their financial health.

3. The data

My source of firm-level data is a survey of firms operating in Spain (*Panel de Innovación Tecnológica*, *PITEC*), a panel database for 12,827 firms constructed by the Spanish National Institute of Statistics based on annual responses to the Community Innovation Survey (CIS) administered to a representative sample of Spanish firms.[9] The empirical analysis is for the years 2005 to 2014. The panel contains an average of nine observations per firm. Summary statistics of the sample and variable definitions are presented in Table 1.

I identify young firms at the beginning of the sample period. I construct the variable *young* as an indicator variable that takes the value one if the firm has been created during the five years prior to 2005 (from the year 2000).[10] This definition of young firm follows Adelino et al. (2017), Audretsch et al. (2014), García-Macía et al. (2018), and European Commission regulations that

[9]The PITEC survey is specifically designed to analyze R&D and other innovating activities following the recommendations of the OSLO Manual on performing innovation surveys (see OECD 2005). Details on PITEC and data access guidelines can be obtained at https://icono.fecyt.es/pitec/descarga-la-base-de-datos.
[10] The data from PITEC are available from 2004. However, I consider the year 2005 as the beginning of the period in order to include lagged firm characteristics (for the year 2004) as observables for the matching procedure that I will describe in the following section.

consider young firms as firms that are less than six years old.[11] The sample comprises 341 young firms, at the beginning of the period. In 2005, the mean and median age of a young firm is three years while, for the rest, the mean age is 22 years, and the median is 17 years. In the robustness check section, I will explore the sensitivity of the results to an alternative definition of a young firm.

The dataset provides information of some key economic variables such as closure, sales, capital investments, and number of employees. It also includes very detailed information on R&D inputs and innovation output. In Table 2, I present the means of the main variables for the year 2005. In column (1), I show means for young firms and in column (2) means for older firms. Young firms are smaller in terms of the number of employees, capital and sales, although they spend more on R&D. Young firms also have higher sales and employment growth, and more product and process innovations, as well as more patents than older firms. This suggests that young firms might behave differently than the average firm during the GR because there are significant differences between young firms and older firms in terms of growth, R&D expenditures and innovation at the beginning of the period.

In Table 3, I present the number of observations and percentage of young firms by sectors of activity. There are young firms in all sectors. Half the sectors have more than 2% of young firms. The sector with the largest percentage of young firms is "R&D services, software and technological analysis" (8.5%), followed by the "Agricultural" sector (3.7%), which is an important industry in the Spanish economy, and "Transport and storage" (3.5%).

4. Econometric specification and description of independent variables

[11] See the General Block Exemption Regulation (GBER) of the European Commission available at http://ec.europa.eu/competition/state_aid/legislation/block.html, addressed 20.09.2021.

My main goal is to analyse organizational changes that young firms undertake in their R&D units during the GR. For these purposes, I consider the following difference-in-difference model (DID). The difference between before and after the GR performance of young firms relative to the control group of older firms can be expressed as:

$$Ln(y_{it}) = \alpha_i + \beta\, Young_i + \theta Young_i \times GR_t + \vartheta GR_t + g_i t + \delta_t + \lambda_{jt} + \epsilon_{it}, \qquad (1)$$

where the variable y_{it} represents the outcome; $Young_i$ is a dummy variable that takes the value of one if firm *i* is a young firm in 2005 (i.e., at most five years old), GR_t denotes the years of the Great Recession which, in Spain, lasted from 2007 to 2013 (see for example Almunia et al. 2018), α_i and δ_t are firm and year fixed effects, λ_{jt} are industry fixed effects that might be time variant and ϵ_{it} is the error term. In the robustness section, I report an alternative specification in which I present results with a different definition of the GR variable.[12] The interaction of interest is $Young_i \times GR_t$, namely whether a young firm performs differently during the GR than an older firm. As shown in Table 2, young firms are different from older firms at the beginning of the period and it is possible that they also might grow faster than older firms. First, to deal with the issue of uncommon trends, I include idiosyncratic firm trends in the model (e.g., Bøler et al. 2015), where g_i is a firm-specific trend coefficient.

I take first differences of equation (1). This yields the following equation, which I estimate by OLS with firm fixed effects:

$$\Delta Ln(y_{it}) = \theta \Delta (Young_i \times GR_t) + \vartheta \Delta GR_t + g_i + \Delta \delta_t + \Delta \lambda_{jt} + \Delta \epsilon_{it}, \qquad (2)$$

[12] Similar to Almunia et al. (2018), as an alternative measure of the GR in Spain I consider changes in local demand by measuring the number of new vehicles in a given region.

Second, to address the potential selection bias generated by young firms being different than old firms at the beginning of the sample period, 2005, I estimate equation (2) using a propensity score reweighting estimator. This technique implies calculating the predicted probability of being a young firm in 2005 or propensity score in terms of observable characteristics and use the propensity scores as weights in the DID regression. To calculate the propensity score, I conduct a probit estimation for the probability of being a young firm as a function of the lagged natural logarithm of capital; lagged natural logarithm of employment; lagged labour productivity; and lagged natural logarithm of number of researchers, distinguishing by educational level. I also include the lagged values of the variables product innovations, process innovations and number of patents to control for lagged innovation outputs.[13] The propensity scores estimates are transformed into weights and yield consistent estimates (see, for example, Guadalupe et al. 2012 or Stiebale 2016). The analysis is conducted for the firms with common support.[14]

To summarize, the econometric model that I use is a conditional DID model with firm fixed-effects and propensity score reweighting estimator, which essentially absorbs differences between firms' characteristics before the GR, and differences in trends.

As discussed in the introduction, young firms might be more likely to automatize or mechanize during the GR than older firms because they are more flexible in various ways, including the ability to fire workers, to reduce salaries and to attract talent. This flexibility during the GR is particularly important in the R&D department because firms need to adapt their products and

[13] I estimate the propensity score separately for three main sectors of activity (high-tech, medium-tech and low-tech). The classification of industries follows the Eurostat/OECD classification (https://www.oecd.org/sti/ind/48350231.pdf for manufactures and for services https://www.oecd-ilibrary.org/science-and-technology/revision-of-the-high-technology-sector-and-product-classification_134337307632, addressed 20.09.2011).
[14] This econometric approach has been recently used by Aghion et al. (2018) and Jaravel et al. (2018). Matching is carried out with STATA command pscore by Becker and Ichino (2002). The caliper used is equal to 0.001.

processes to quickly find new potential markets and to reduce their costs.[15] To examine this mechanism, I analyse several variables that account for changes in the organization of R&D. I consider variables related to R&D personnel and R&D expenditures in machinery. The dataset provides information on the *total number of R&D employees* and the R&D employment by education level as follows: employees *with a PhD*, employees *with five-year (or more) BA degree or MSc degree* (labelled as *5 or more year degree*), employees *with a four- or three-year BA degree* (labelled as *4 or less year degree*), and employees *without higher education*.[16] This allows me to study changes in the skill mix and human capital upgrading of R&D employees.

The dataset also includes the variable *R&D expenditures in machinery, equipment and software used to generate product and process innovations*. With this variable, I analyse whether there has been an increase in the investments of machines for R&D during the GR. If young firms mechanize more than older firms during the GR, I should expect a decline in R&D workers and an increase in expenditures of machinery and equipment for R&D.

5. Results

5.1. Baseline results

In this section, I analyse the differences in R&D employment and capital investment for R&D between young and older firms during the GR. Before presenting the results of the estimations, I show, in Table A1, the balancing test comparing observable characteristics for the reweighted sample for the treated (young firms) and control group (older firms). The table indicates that, for

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[15] For example, Gupta (2020) shows that firms with high R&D levels before the GR are more resilient because of their capability to introduce new products to the market.

[16] The higher-education degrees in the survey are classified as follows: a) PhD degree, labelled as *with PhD*; b) degrees of more than 240 European credit transfer systems (ECT) corresponding to Medicine, Odontology, Pharmacy, and Veterinary; in addition to "licenciaturas" or "ingenierías", and MScs, labelled as *5 or more year degree*; c) degrees of 240 ECTS, "diplomatura" and "arquitectura o ingeniería técnica", labelled as *4 or less year degree*.

the reweighted group, young and old firms have very similar observable characteristics at the beginning of the sample period.

In Table 4, I present the baseline results from the DID propensity score reweighting estimation with firm fixed effects. I also include in all regressions industry and year fixed effects. I show the estimated coefficient of interest corresponding to the interaction between young and GR. This coefficient measures growth elasticities. In column 1, I report results for *total R&D personnel*. In columns 2 to 5, I show estimates for changes in R&D personnel distinguishing by educational level. Finally, column 6 displays estimations for *R&D expenditures on machinery, equipment, and software*.[17]

In column 1, the estimate of the interaction between *young* and *GR* is negative and significantly different from zero. The estimated coefficient is equal to -0.143. This indicates that, during the GR, young firms reduced their R&D employment by 12.0% compared to older firms with similar pre-GR characteristics.[18] Distinguishing by education level, column 2 documents that there is an increase in R&D personnel at the highest educational level (employees with a PhD). This increase is equal to 27.0%. Column 3 shows a decline of 26.0% for personnel with a five-year, or more, degree, although this effect is not significant at standard statistical levels. Column 4 shows an increase in the proportion of the employees with medium-low qualification, which is equal to 41.1%. For the lowest category of employment, column 5 shows a decline in the proportion of employment, which is equal to 56.4%.[19] This suggests that, during the GR, young firms have

[17] In this last specification, in order to control for the potential dynamics of this variable, I include as control the lagged stock of capital in R&D. I use a depreciation rate of 15 percent, as it has been traditionally suggested in the literature (Li and Hall, 2020), although the results remain unchanged when I use higher depreciation rates such as 20 or 25 percent.

[18] This is calculated as (0.023-0.143)*100 based on the average R&D employment growth for the control group before the GR and the estimated coefficient in Table 4.

[19] These numbers are calculated based on the average R&D employment growth for the control group before the GR and the estimated coefficients in Table 4. They are as follows: For the R&D personnel with a PhD: (0.0028+0.267)*100;

simultaneously reduced R&D personnel and increased the average skill of the R&D labour force as compared to older firms. In column 6, I show estimations for R&D expenditures on machinery, equipment and software. The interaction term is positive and significant at standard statistical levels. The estimated coefficient is equal to 0.533. This represents an increase in machinery for R&D equal to 52.0%.[20]

Next, I assess the sensitivity to sample size of previous R&D employment estimates by educational level. In Table 5, I consider the same sample of firms as in column (1) of Table 4 and I re-estimate columns (2) to (5). In order to include the zeros of the dependent variables, I add one to the dependent variables before calculating their natural logarithm.[21] The findings from this estimation are similar to those in Table 4 and show that young firms adjusted their R&D department during the GR as compared with older firms. In particular, young firms dismissed employees with medium and low levels of education and hired employees with very high educational levels.

Overall, the results from this section suggest that young firms, during the GR, reduced their R&D employment and increased their expenditures in machines and equipment as compared with older firms, which is consistent with mechanization in the R&D department. Moreover, on average, young firms increased the educational level of their R&D employees by substituting medium and low skill employees with highly educated employees. In the next subsection, I assess the sensitivity of the baseline results.

5.2. Robustness checks

for R&D personnel with five-year or more degree (0.010-0.27)*100; for R&D personnel with four-year or less degree: (-0.027+0.438)*100; for R&D personnel without higher education (0.190-0.754)*100.

[20] This is calculated as (-0.013+0.533)*100 based on the average growth of R&D expenditures on machinery, equipment and software for the control group before the GR and the estimated coefficient in Table 4.

[21] The addition of one to the dependent variable is an arbitrary transformation used in the literature for innovation variables to include the zeros of the dependent variables in the regressions (e.g. Bloom et al., 2016; Haucap et al. 2019).

In this section, I complement the baseline results with four robustness tests that I document in the Appendix, including an alternative definition of the GR, an alternative definition of young firm, longer pre-treatment trends, and a placebo test.

An identification assumption in my approach is that the GR has hit all firms in the same way. This assumption is likely to be violated since some firms might have been more exposed to the GR than others. To address this issue, I use a firm-variant variable that captures the GR. A possible candidate is changes in local demand as a measure for the differential impact of the GR across firms located in different regions. Similar to Almunia et al. (2018), I measure changes in local demand by changes in the number of vehicles in a region.[22] Figure A1 in the Appendix plots average growth of vehicle registration over time. The figure shows that, on average, the number of vehicles dramatically dropped at the beginning of the GR and recovered from the year 2013 onwards. The identification comes from the assumption that firms in regions with a large decline in local demand, measured as the changes in the number of vehicles newly registered, were more affected by the GR than firms located in regions where the local demand did not decline that much. In Table A2 in the Appendix, I show results using the lag of one minus the growth of regional number of registered vehicles,[23] which I denote as *alternative GR*, instead of the GR dummy variable.

In all regressions in Table A2, the results are consistent with previous estimations and support the conclusion that young firms reduce their total employment in R&D, upgrade their skills

[22] The source for the number of registered vehicles by region is from the Spanish Registry of Motor Vehicles (Dirección General de Tráfico, DGT) at http://www.dgt.es/es/seguridad-vial/estadisticas-e-indicadores/parque-vehiculos/tablas-estadisticas/, addressed 20.09.2021.

[23] The dataset does not provide the address of the company. It only provides information about the region where the R&D employment is located. To identify the main region for the R&D activity of the firm, I consider a 50% threshold. In other words, I identify the region where the main R&D activities of the firm are produced as the region where at least 50% of the R&D employment is located.

and increase their expenditures for machinery for R&D. This suggests that the results are not biased by the potential differential effect of the GR across firms.

A possible concern with the baseline estimations is that some young firms at the beginning of the period (the year 2005) were not young at the beginning of the GR. As previously reported, in 2005 the mean and median age of a young firm is three years. This implies that many of the firms I have defined as young, still qualify as young in 2007 following European Commission regulations. Nevertheless, to assess the sensitivity of the results to this issue, I consider an alternative measure of young firms, where "alternative young" is defined as a firm that is, at most, five years old in the year 2007. I present results for the balancing test using this alternative measure of young firms in Table A3 and the estimated coefficients of interest in Table A4. The results are less precisely estimated to those reported in Table 4, but they are consistent with the decline in total R&D employment and the increase in R&D machinery in young firms.

Next, I present DID results from an alternative propensity score specification, where I control for longer common pre-existing trends by including in the matching procedure variables lagged one and two years before the GR.[24] In Table A5, I present the balancing test for the alternative procedure. I conduct the DID estimations with the alternative propensity score estimation. The results reported in Table A6 are, again, similar to those of previous specifications. The key messages remain unchanged. This suggests that my results are not biased by longer pre-existing trends.

The identification strategy considers that skill-upgrade and mechanization is undertaken more by young firms due to, among other reasons, their lower firing costs and flexibility, compared to

[24] In this case, I calculate the predicted probability of being a young firm in 2006.

older firms. One implication of this identification strategy is that there should not be an effect of the GR when the DID is performed among randomly selected old firms because, for this sample, there should not be systematic differences in firing costs or flexibility. To test this implication, I perform a placebo test, where I randomly assign a young firm to an older firm and I drop younger firms from the sample. In Table A7, I present the results of the balancing test for the matching procedure and in Table A8 the results from this placebo test. The estimated coefficients are all statistically equal to zero. This exercise provides support for the view that young firms were more affected in their R&D organization decisions by the GR than older firms.

To conclude, the analysis in this section suggests that, after controlling for an alternative definition of the GR, an alternative definition of young firm, longer pre-treatment trends, and a placebo test, there is evidence that young firms, during the GR, mechanize their R&D department relatively more than older firms. In addition to this, I show that young firms increased the educational level of their R&D employees. In the next two sections, I study the time trends before the GR to provide evidence of parallel trends before the treatment for the reweighted sample. In order to do this, first, I analyse the time trends of the dependent variables. Second, to provide further evidence that support the mechanization hypothesis during the GR, I also study time trends and present evidence of the effect of the GR on the ratio of R&D expenditures on machinery over R&D employment.

5.3. Pre-GR trends of the dependent variables

An identification assumption for the DID propensity score reweighting estimator is that, for the reweighted sample, control and treated firms have similar dependent variable trends before the GR. One concern is that, in the reweighted sample, young firms might grow faster than older firms and, rather than the GR itself, time might increase the gap. To test whether this is the case, I use pre-GR data (2005 and 2006) to estimate differential trends in R&D employment and R&D machinery for the reweighted sample, as in the following specification:

$$\Delta Ln(y_{it}) = \theta Young_i + \Delta\delta_t + \Delta\epsilon_{it}, \qquad (3)$$

I present the results in Table 6.[25] The estimated coefficients for the pre-GR trends are not significantly different from zero in all cases with the exception of column 5 for R&D personnel without higher education. In this case, the estimated coefficient is positive and significant at standard statistical levels. This contrasts with the corresponding estimated coefficient in Table 4, which is negative. Therefore, for this variable, there is a change in the sign of the slope of the trend that materialized during the GR. For the other variables, one can conclude that, for the reweighted sample, both groups were on a similar pre-trend.

5.4. Ratio of R&D expenditures on machinery over R&D employment

Next, I provide additional support for the finding that the GR increases the mechanization of young firms as compared to older firms. In this section, I present estimates for the ratio of R&D expenditures on machinery, equipment and software over R&D employment. Note that an increase in this ratio indicates a rise in mechanization for the R&D department. I estimate equation (2) with the original propensity score and interact the treatment indicator with time dummies including the years before the GR, as in the following equation:

$$\Delta y_{it} = \sum_{\tau=2006}^{2014} \theta_\tau \Delta Young_i + g_i + \Delta\delta_t + \Delta\epsilon_{it}, \qquad (4)$$

[25] Note that for this specification it is not possible to include firm fixed effects because there is only one period in increments per firm for the pre-GR years.

where y_{it} is the ratio of R&D expenditures on machinery, equipment, and software over R&D employment and θ_τ measures the difference between young and older firms for the reweighted sample in year t.[26] The results are summarized in Figure 1. The differences in the ratio before the GR (the year 2006 and the baseline year 2005) for younger and older firms are small and insignificant at standard statistical levels. The difference in the ratio increases and becomes statistically significant in the years 2007 and 2008, and it declines and becomes statistically insignificant for 2009, the ratio rises and becomes significantly different from zero in 2012 and 2013 (the years of the Spanish sovereign debt crisis and the crisis of its semi-public banks)[27] and declines for 2014. This indicates that, for the years before the GR, young and older firms have a similar mechanization trend. The pattern shown in Figure 1 is consistent with an increase in mechanization of young firms during the peak of the GR (years 2007 and 2008) and during the Spanish sovereign debt crisis.

6. Additional empirical evidence on the effect of the GR for young firms

In this section, I first explore the mediating effect of firm financial health on young firm mechanization during the GR. Second, I study changes in R&D labour costs. Finally, I analyse the effects of the GR for young firms on total R&D expenditures and innovation outputs, as well as other firm economic variables.

6.1. Allowing for heterogeneous effects: Firm financial health

[26] Note that the ratio variable is not in logs in order to preserve the variability of the data. This specification is convenient for isolating, year by year, the differential effect of young versus older firms.
[27] The European debt crisis affected several Southern European countries. Between 2011 and 2012, Spain experienced a large increase of its debt/GDP ratio and on its spreads of sovereign bonds. Moreover, semi-public banks (where many small firms traditionally obtained their funds) were highly indebted and were unable to borrow money (Lane 2012).

In this section, I examine firm heterogeneity in the effects reported in Table 4. A key element for investments in capital is that firms have financial funds or that firms would be able to obtain external financial resources to acquire machinery for their R&D activities (Gorodnichenko and Schnitzer, 2013). The interest is to identify whether there is a differential effect of the GR between young and older firms for firms with different levels of financial health. I base my measure of financial health on Mohnen and Röller (2005). In the dataset the firms report whether the lack of funds within the firm or from sources outside the firm has been an obstacle to their innovation. I construct a dummy variable that takes the value of one if the firm reports that the lack of funds was an important obstacle for its innovation. I denote this variable as *low financial health*. I include this variable lagged by one year to alleviate concerns with reverse causality. In the model, I am interested in the triple interaction $Young_i \times GR_t \times low\ financial\ health_{it-1}$ and double interaction $Young_i \times GR_t$.[28] The triple interaction measures whether the mechanization of R&D and skill-upgrading is weaker for firms with low financial health. I present the results in Table 7.

The results in columns (1) to (5) of Table 7 show that none of the estimated coefficients for the triple interaction term are significantly different from zero at standard statistical levels. The only coefficient for the triple interaction that is significant is machinery and equipment for R&D in column (6). In this column, the estimated coefficient is negative. The double interactions in the table remain similar to the baseline case in Table 4. This suggests that less financially healthy young firms, that already had R&D personnel, reduced their R&D employment similarly to more financially healthy firms. Moreover, on average, young firms mechanized more during the GR than older firms, but this effect is mediated by a firm's financial health. Specifically, during the GR, less

[28] In the model, I include the interaction between GR and less financially health, and the variable less financially health in addition to the triple and double interaction explained above.

financially healthy young firms acquired less machinery for their R&D activities than more financially healthy young firms.

In Table 8, I include firms that might not have all types of R&D employment. In particular, I re-estimate the effects for R&D employment by educational levels (columns 2 to 5 of Table 7) considering the zeros. I take the sample of firms with R&D personnel (column 1 of Table 7). As in Table 5, I add one to the regressors before taking the natural logarithm of the variables.

The estimates for the triple interactions are significantly different from zero for all types of R&D personnel with educational levels below those with a PhD. In contrast, the estimates for double interaction are only significantly different from zero for R&D employees with a PhD (column 1) and are not precisely estimated for employees with a four-year or less degree (column 3). These results indicate that, as compared to older firms, all young firms increased their R&D employment with the highest educational level during the GR. However, only financially constrained young firms decreased the number of middle-high and low R&D employment and increased the middle-low R&D employment. Overall, the estimates from Table 8 suggest that the decline in R&D employment for firms with low financial health is concentrated in employees with middle-high and low levels of education, while less financially constrained firms seemed to have reduced their middle-low R&D employment. A note of caution is warranted, however, given that the last effect is not precisely estimated.

6.2. Labour costs in the R&D department

In this section, I study the changes in the labour costs in the R&D department. In Table 9, I document results for salaries of researchers (column 1); for technicians (column 2); average salary per researcher (column 3); and average salary per technician (column 4) working in R&D. In both columns 1 and 2 the estimated coefficients of the interaction term are negative and significantly different from zero. This implies that young firms reduced their expenditures on salaries during the GR as compared to older firms. This reflects the firing of R&D labour force documented in Table 4. However, column 3 shows that the average salary per researcher increased while the estimated coefficient for the average salary per technician is small and not significantly different from zero at standard statistical levels.

Overall, the findings suggest that young firms reduced their R&D labour costs (in terms of savings coming from salaries of both researchers and technicians, columns 1 and 2) during the GR as compared to older firms. Moreover, we know from Table 4 and the different robustness checks that there has been skill-upgrading, which is consistent with an increase in the average salaries of researchers. These findings suggest that young firms changed the composition of their researchers and were able to take advantage of the new hiring environment during the GR. The results are consistent with young firms hiring more qualified employees for their R&D department than older firms.

6.3. R&D expenditures, innovation outputs and firm performance

In the previous sections, I showed that young firms undertook fundamental changes in their R&D department during the GR by reducing employment, labour costs, and increasing skill-upgrading and investments in R&D machinery, equipment, and software. These results suggest that young firms become more efficient during the GR than older firms. In this section, I consider alternative firm level input and output measures that provide further evidence to this possible efficiency improvement.

In Table 10, column (1), I present results for *total R&D expenditures*; in columns (2) and (3), the dependent variables are indicators that take the value of one if a firm has *product (process) innovations* in the current and following two years; in column (4), the dependent variable is the *number of patents* in the current and following two years; in column (5), I consider *closure*, which is an indicator that takes the value of one if the firm permanently or temporarily stops its economic activity; and, finally, in column (6), I study firm *sales.*

The evidence in Table 10 suggests that young firms became very efficient regarding the management of their R&D. In column (1), the estimated coefficient for total R&D expenditure is negative and highly significant. This reflects the large decline in R&D labour costs documented in the previous section, which were not compensated by the increasing expenditures in machinery and equipment for R&D. So overall, during the GR, young firms saved costs in their R&D units as compared to older firms. Moreover, columns (2) to (4) indicate that young firms, during the GR, significantly increased their innovation outputs, particularly in terms of product innovations (in column 2) and number of patents (in column 4).

Finally, I analyse additional economic variables outside the R&D units. In column (5), I observe the effect on closure. The estimated coefficient is negative and highly significant at standard statistical levels. This implies that young firms were less likely to shut down either permanently or temporarily than older firms during the GR. The effects for sales in column (6) strongly suggest that young firms increased their sales. Therefore, these findings suggest that young firms with similar characteristics before the GR performed better during the crisis than older firms. The overall conclusion from these estimations is that young firms became more efficient in the use of their resources and more resilient during the crisis than older firms with similar pre-crisis characteristics.

7. Summary and concluding remarks

Young firms are fundamental drivers of innovations and economic growth and it is, therefore, important to understand how they perform under recessions. In this paper, I studied the behaviour of young Spanish firms during the Great Recession of 2007. I find evidence that, during the GR, young firms with similar characteristics to older firms before the crisis reacted more flexibly to the economic conditions than older firms and, therefore, they were more resilient to economic fluctuations than older firms.

My results suggest that young firms became more efficient in the management of their R&D than older firms during the GR. I find that young firms reduced their R&D employment. In particular, there was a reduction of the number of R&D employees with medium and low-skills, and an increase in high-skill R&D workers. At the same time, the results indicate that capital investments for R&D increased, which suggests that there is a substitution of R&D employees by R&D machines. These results are consistent with the theoretical argument of a decline in the opportunity cost of the new machines or technologies (Aghion and Saint-Paul 1998) and an increase of automation during recessions. Moreover, the results suggest that the introduction of the new machineries and technologies are labour reducing for young firms. This is in line with the results of Acemoglu and Restrepro (2020) on the decline of employment after the introduction of industrial robots. My results suggest that firm financial health was an important factor contributing to the mechanization of the R&D department and skill-upgrading for young firms during the crisis. The increase in machinery and software for R&D is more important for firms in good financial health than for those with poor financial health. This finding has policy implications. It suggests that an important R&D policy is to enable young firms access to external funding during a crisis.

Although this study provides relevant insights, I acknowledge some limitations. First, given the number of young firms, it was only possible to match young firms within three main industrial categories. Therefore, it is possible that the calculated propensity scores used for the estimations are not accurately considering the industrial dimension of the firm. The regressions include industry and firm fixed effects and there are young firms in all sectors of activity. However, it is not completely possible to control for the fact that some young firms operate in highly growing specific sectors, where there are few older firms to compare with. Second, I do not have information about R&D employees' tasks and precise firm technologies. Hence, I am not able to know the exact reason why older firms retain more R&D employees than younger firms during recessions. One plausible possibility is the differences in severance payments between young and older firms and another possibility is that R&D employees working in older firms have accumulated specific knowledge and experience about their firm's technologies. This specific human capital might be difficult to replace and, therefore, older firms might have less incentives to dismiss employees than younger firms. Finally, it is possible that the differences between young and older firms, that I have shown, are mediated by different institutional and cultural settings. For example, entrepreneurs of young firms from countries where bankruptcy laws are very strict might have limited incentives to modify their R&D department during recessions given the associated risk to R&D investments. Young firms in areas where there are social norms on employment security might tend to retain their R&D employees. These are questions that are interesting avenues for future research.

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TABLES

Table 1: Descriptive statistics of the main variables

Variable	Mean	SD	Observations
Young	0.024	0.153	116,415
Closure	0.005	0.071	116,415
Sales growth	-0.025	0.541	100214
Capital growth	-0.088	1.663	60148
Labour growth	-0.033	0.336	100330
R&D growth	-0.019	0.988	52201
Product innovation	0.462	0.499	91694
Process innovation	0.480	0.500	91694
Number of patents	0.478	5.862	91694
R&D personnel growth	0.014	0.493	43203
Share of R&D personnel growth with			
PhD	-0.001	0.080	90739
5 or more year degree	-0.011	0.205	90739
4 or less year degree	-0.007	0.147	90739
Without higher education	-0.004	0.137	90739
Salaries to R&D personnel growth			
to researchers	0.040	0.811	43080
to technicians	0.034	0.814	32270
Machinery, equipment & software for R&D	-0.064	1.475	6550
Alternative GR	1.032	0.151	54859

Notes: The data include observations from firms in PITEC dataset for the period 2004-2014. *Young* is an indicator that takes the value one if the firm has been newly created before the Great Recession: This is a firm that in 2005 has been created during the previous five years (from the year 2000); *Closure* is an indicator that takes the value one if a firm permanently or temporarily stops its economic activity; *Sales growth* is the growth of all sales of a firm; *Capital growth* is the growth of the capital of a firm; *Labour growth* is the growth of the total employment of a firm; *R&D growth* is the growth of all R&D expenditures of a firm; *Product (process)* innovation is a dummy variable that takes the value one if the firm has undertaken product (process) innovations; *Number of patents* is the number of patents of a firm in a given year; R&D personnel growth is the growth of the personnel working in R&D of a firm; *Share of R&D personnel growth* for different educational levels is the percentage of R&D personnel with different educational levels; *Salaries to R&D personnel growth to researchers (to technicians)* is the growth of the salaries for researchers (technicians) working in R&D. *R&D expenditures in machinery, equipment & software* is the growth of the R&D expenditures in machinery, equipment and software used in order to generate product or process innovations. *Alternative GR* is one minus the growth of regional registration of vehicles (Source: Dirección General de Tráfico).

Table 2: Comparison between young firms and older firms in 2005

	Young firms	Older firms
	(1)	(2)
Sales (logs)	13.339	15.767
	(2.424)	(2.079)
Capital (logs)	11.370	12.375
	(2.309)	(2.401)
Number of employees (logs)	2.525	4.164
	(1.440)	(1.644)
R&D expenditures (logs)	12.206	12.138
	(1.624)	(1.686)
Sales growth	0.189	0.030
	(1.548)	(0.560)
Capital growth	0.134	-0.043
	(1.869)	(1.563)
Labour growth	0.096	0.003
	(0.533)	(0.328)
R&D expenditures growth	0.140	0.164
	(1.214)	(1.062)
Product innovations	0.614	0.491
	(0.488)	(0.500)
Process innovations	0.556	0.511
	(0.498)	(0.500)
Number of patents	0.635	0.482
	(1.676)	(5.173)
Number of firms	341	12,486

Notes: Standard deviations are in parenthesis. The variable definitions are in Table 1 and in the main text.

Table 3: Descriptive statistics for the proportion of young firms by sector

	No. of observations	Percentage of young firms in the sector
	(1)	(2)
Agriculture	1,496	3.7%
Mining and extractive industries	6,650	1.4%
Food and tobacco	7,588	2.3%
Textiles, printing and wood	10,456	1.3%
Chemicals	5,862	2.0%
Pharmaceuticals	1,636	2.4%
Manufacturing of non-metallic products	6,947	1.0%
Manufacturing of basic metals	10,458	1.1%
Manufacturing of electrical and optical equipment	10,950	2.2%
Manufacturing of transport equipment	3,492	1.0%
Wholesale and retail trade	9,195	0.9%
Transport, storage and communication	8,370	3.5%
Financial intermediation	2,451	0.4%
Real estate, renting and business services	8,507	3.4%
R&D services, software and technical analysis	9,575	8.5%
Other services	12,782	1.8%
Total	116,415	2.4%

Notes: Column (1) shows the number of observations per sector. Column (2) shows the ratio between the number of young firms within a sector over the number of observations per sector.

Table 4: R&D personnel and machinery for R&D during the Great Recession

Dependent variable		*R&D personnel*				*Machinery, equipment & software for R&D*
	R&D personnel	*with PhD*	*with 5 or more year degree*	*with 4 or less year degree*	*without higher education*	
	(1)	(2)	(3)	(4)	(5)	(6)
Young x GR	-0.143**	0.267***	-0.270	0.438*	-0.754**	0.533**
	(0.072)	(0.084)	(0.186)	(0.225)	(0.320)	(0.224)
Observations	26,289	5,267	18,952	11,983	13,425	3,086
R-squared	0.508	0.720	0.535	0.392	0.770	0.433
Industry, year and firm FEs in all regressions						

*Note: Fixed effects-OLS with propensity score reweighting estimations. R&D personnel is the number of full time employees working in research. Columns (2) to (5) refer to types of R&D employees by educational level. Machinery, equipment and software for R&D is the growth of the R&D expenditures in machinery, equipment and software used for product and process innovations. For exact definitions and sources of all variables see Table 1 and main text. Estimated robust standard errors are in parentheses. * Significant at 10%;** Significant at 5%; *** significant at 1%.*

Table 5: R&D personnel for R&D during the Great Recession. Accounting for zeros

Dependent variable	*R&D personnel +1*			
	with PhD	*with 5 or more year degree*	*with 4 or less year degree*	*without higher education*
	(1)	(2)	(3)	(4)
Young x GR	2.399**	-4.942*	1.214	-8.292***
	(1.068)	(2.979)	(4.450)	(2.006)
Observations	26,289	26,289	26,289	26,289
R-squared	0.498	0.298	0.559	0.620
Industry, year and firm FEs in all regressions				

*Note: Fixed effects-OLS with propensity score reweighting estimations. R&D personnel is the number of full time employees working in research by educational level. For exact definitions and sources of all variables see Table 1 and main text. Estimated robust standard errors are in parentheses. * Significant at 10%;** Significant at 5%; *** significant at 1%.*

Table 6: Pre-GR trends of the dependent variables

Dependent variable	*R&D personnel*	*R&D personnel with PhD*	*R&D personnel with 5 or more year degree*	*R&D personnel with 4 or less year degree*	*R&D personnel without higher education*	*Machinery, equipment & software for R&D*
	(1)	(2)	(3)	(4)	(5)	(6)
Young	0.455	0.233	1.154	-0.197	3.257**	-1.887
	(0.313)	(0.154)	(0.860)	(0.230)	(1.266)	(1.333)
Observations	7,419	584	2,852	1,765	1,790	1,152
R-squared	0.045	0.039	0.106	0.013	0.298	0.153
Industry and year FEs in all regressions						

*Note: Fixed effects-OLS with propensity score reweighting estimations. R&D personnel is the number of full time employees working in research. Columns (2) to (5) refer to types of R&D employees by educational level. Machinery, equipment and software for R&D is the growth of the R&D expenditures in machinery, equipment and software used for product and process innovations For exact definitions and sources of all variables see Table 1 and main text. Estimated robust standard errors are in parentheses. * Significant at 10%;** Significant at 5%; *** significant at 1%.*

Table 7: R&D personnel and machinery for R&D during the Great Recession by firm financial health

Dependent variable	*R&D personnel*	*R&D personnel*				*Machinery, equipment & software for R&D*
		with PhD	*with 5 or more year degree*	*with 4 or less year degree*	*without higher education*	
	(1)	(2)	(3)	(4)	(5)	(6)
Young x GR x low financial health	0.101	-0.158	-0.120	0.315	0.189	-0.933***
	(0.205)	(0.278)	(0.392)	(0.242)	(1.543)	(0.140)
Young x GR	-0.509**	0.826***	-0.980*	0.217	-2.728*	2.668***
	(0.242)	(0.201)	(0.574)	(0.347)	(1.482)	(0.161)
Observations	26,289	5,267	18,952	11,983	13,425	3,086
R-squared	0.117	0.066	0.341	0.021	0.536	0.203
Industry, year and firm FEs in all regressions						

*Note: Fixed effects-OLS with propensity score reweighting estimations. R&D personnel is the number of full time employees working in research. Columns (2) to (5) refer to types of R&D employees by educational level. Growth of R&D expenditures in machinery, equipment and software is the growth of the R&D expenditures in machinery, equipment and software used for product and process innovations For exact definitions and sources of all variables see Table 1 and main text. Estimated robust standard errors are in parentheses. * Significant at 10%;** Significant at 5%; *** significant at 1%.*

Table 8: R&D personnel and machinery for R&D during the Great Recession by firm financial health. Accounting for zeros

Dependent variable	*R&D personnel+1*			
	with PhD	*with 5 or more year degree*	*with 4 or less year degree*	*without higher education*
	(1)	(2)	(3)	(4)
Young x GR x low financial health	0.241	-7.289**	7.660**	-11.257***
	(0.648)	(3.688)	(3.783)	(3.892)
Young x GR	2.023**	1.658	-4.978	1.075
	(0.974)	(4.572)	(3.424)	(4.013)
Observations	26,289	26,289	26,289	26,289
R-squared	0.365	0.188	0.399	0.477
Industry, year and firm FEs in all regressions				

*Note: Fixed effects-OLS with propensity score reweighting estimations. R&D personnel is the number of full time employees working in research. Columns (2) to (5) refer to types of R&D employees by educational level. Growth of R&D expenditures in machinery, equipment and software is the growth of the R&D expenditures in machinery, equipment and software used for product and process innovations. For exact definitions and sources of all variables see Table 1 and main text. Estimated robust standard errors are in parentheses. * Significant at 10%;** Significant at 5%; *** significant at 1%.*

Table 9: R&D labour costs during the Great Recession

Dependent variable	*Salaries to researchers*	*Salaries to technicians*	*Salary per researcher*	*Salary per technician*
	(1)	(2)	(3)	(4)
Young x GR	-0.167*	-0.158*	0.210***	-0.032
	(0.098)	(0.084)	(0.078)	(0.058)
Observations	26,234	20,729	26,234	20,729
R-squared	0.614	0.823	0.604	0.819
Industry, year and firm FEs in all regressions				

*Note: Fixed effects-OLS with propensity score reweighting estimations. Salaries to researchers (technicians) is the R&D expenditures for the salaries of researchers (technicians) working in R&D. Salary per researcher (technician) is the average salary per researcher (technician) working in R&D. For exact definitions and sources of all variables see Table 1 and main text. Estimated robust standard errors are in parentheses. * Significant at 10%;** Significant at 5%; *** significant at 1%.*

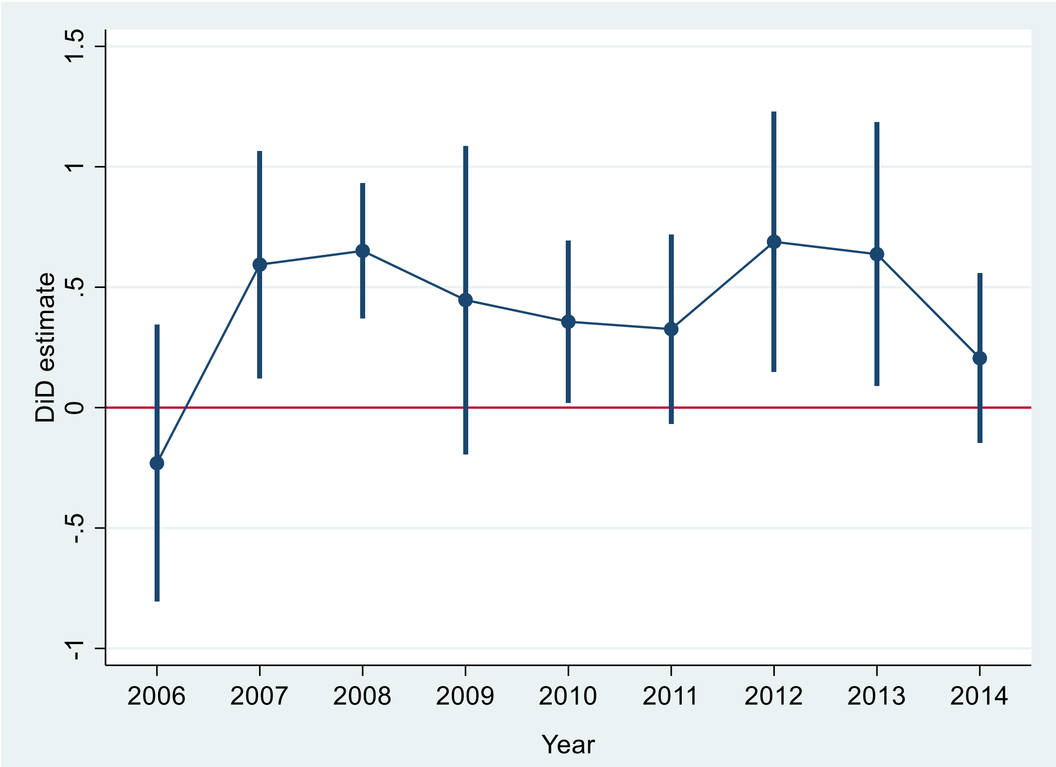
Table 10: Innovation input, outputs and further outcomes during the Great Recession

Dependent variable	*R&D*	*Product innovation*	*Process innovation*	*Patents*	*Closure*	*Sales*
	(1)	(2)	(3)	(4)	(5)	(6)
Young x GR	-0.378*	0.219**	-0.004	0.422**	-0.002***	0.160***
	(0.196)	(0.088)	(0.032)	(0.195)	(0.001)	(0.061)
Observations	34,562	30,580	30,580	26,695	38,765	34,539
R-squared	0.758	0.497	0.226	0.032	0.008	0.391
Industry, year and firm FEs in all regressions						

*Note: Fixed effects-OLS with propensity score reweighting estimations. R&D is the total R&D expenditures of the firm. Product (process) innovation is a dummy variable that takes the value one if the firm undertakes product (process) innovation. Patents is the growth in stock of number of patents of a firm. Closure is the temporary or permanent shutdown of a firm. Sales are the total sales of the firm. For exact definitions and sources of all variables see Table 1 and main text. Estimated robust standard errors are in parentheses. * Significant at 10%;** Significant at 5%; *** significant at 1%.*

Figure

Figure 1: DiD estimates for the ratio of machinery for R&D over R&D personnel



APPENDIX

TABLES

Table A1: Balancing property for the reweighted sample

	Mean			t-test	
	Treated	Control	% diff	t	p>|t|
Employment$_{t-1}$	2.77	2.82	-2.8	98.0	0.800
Physical capital$_{t-1}$	6.81	6.88	-2.8	95.6	0.812
Labor productivity$_{t-1}$	6.70	6.68	1.7	97.9	0.888
Product innovation $_{t-1}$	0.85	0.83	3.6	96.2	0.737
Process innovation $_{t-1}$	0.63	0.69	-13.9	49.5	0.242
Number of patents $_{t-1}$	0.76	0.73	0.8	94.9	0.931
R&D personnel $_{t-1}$					
…with PhD	0.56	0.52	3.5	70.4	0.902
…with 5 or more year degree	0.87	0.80	6.0	73.6	0.667
…with 4 or less year degree	0.66	0.44	18.9	6.7	0.317
…without higher education	0.35	0.31	3.4	0.2	0.869
Machinery, equipment & software for R&D$_{t-1}$	0.49	0.43	12.8	67.1	0.323

Note: For exact definitions and sources of all variables see Table 1 and main text. The t-test indicates the balancing of the variables

Table A2: R&D personnel and machinery for R&D during the GR with alternative GR measures

Dependent variable	*R&D personnel*	*R&D personnel* with PhD	*with 5 or more year degree*	*with 4 or less year degree*	*without higher education*	*Machinery, equipment & software for R&D*
	(1a)	(2a)	(3a)	(4a)	(5a)	(6a)
Young x Alternative GR	-1.163**	1.085***	-1.300*	0.109	-3.051**	1.963***
	(0.526)	(0.279)	(0.778)	(0.661)	(1.390)	(0.483)
Observations	26,138	5,204	18,827	11,887	13,327	2,810
R-squared	0.388	0.680	0.362	0.182	0.632	0.123
Industry, year and firm FEs in all regressions						

*Note: Fixed effects-OLS with propensity score weighting estimations. Alternative GR is one minus the growth of regional vehicle registration. R&D personnel is the number of full time employees working in research. Columns (2) to (5) refer to types of R&D employees by educational level. For exact definitions and sources of all variables see Table 1. Estimated robust standard errors are in parentheses. * Significant at 10%;** Significant at 5%; *** significant at 1%.*

Table A3: Balancing property for alternative definition of young firm for the reweighted sample

	Mean			t-test	
	Treated	Control	% diff	t	p>|t|
Employment$_{t-1}$	2.511	2.465	2.80	0.17	0.866
Physical capital$_{t-1}$	6.846	6.594	10.70	0.63	0.529
Labor productivity$_{t-1}$	6.499	6.467	2.50	0.12	0.904
Product innovation $_{t-1}$	0.831	0.814	3.70	0.24	0.812
Process innovation $_{t-1}$	0.644	0.746	-20.50	-1.20	0.234
Number of patents $_{t-1}$	0.593	1.102	-19.70	-1.05	0.294
R&D personnel $_{t-1}$					
…with PhD	0.505	0.663	-12.30	-0.32	0.754
…with 5 or more year degree	0.934	0.692	19.20	1.12	0.264
…with 4 or less year degree	0.860	0.520	31.20	1.18	0.242
…without higher education	0.448	0.227	18.60	0.79	0.434
Machinery, equipment & software for R&D$_{t-1}$	0.424	0.441	-3.60	-0.18	0.854

Table A4: R&D personnel and machinery for R&D during the GR with alternative definition of young firm

Dependent variable	*R&D personnel*	*R&D personnel* with PhD	*with 5 or more year degree*	*with 4 or less year degree*	*without higher education*	*Machinery, equipment & software for R&D*
Panel A						
	(1a)	(2a)	(3a)	(4a)	(5a)	(6a)
Alternative Young x GR	-0.480*	0.686***	-0.279	0.467***	0.437	0.315**
	(0.287)	(0.223)	(0.273)	(0.147)	(0.315)	(0.132)
Observations	27,903	5,706	20,171	12,625	14,254	3,511
Industry, year and firm FEs in all regressions						

*Note: Fixed effects-OLS with propensity score weighting estimations. Alternative Young is a firm that has been founded less than 5 years before the GR. R&D personnel is the number of full time employees working in research. Columns (2) to (5) refer to types of R&D employees by educational level. For exact definitions and sources of all variables see Table 1. Estimated robust standard errors are in parentheses. * Significant at 10%;** Significant at 5%; *** significant at 1%.*

Table A5: Balancing property for longer pre-trends for the reweighted sample

	Mean			t-test	
	Treated	Control	% diff	t	p>|t|
Employment$_{t-1}$	2.86	2.84	1.80	0.19	0.849
Physical capital$_{t-1}$	7.00	7.12	-5.30	-0.50	0.620
Labor productivity$_{t-1}$	6.69	6.96	-22.20	-1.99	0.048
Product innovation $_{t-1}$	0.70	0.77	-13.60	-1.29	0.199
Process innovation $_{t-1}$	0.63	0.58	9.20	0.81	0.416
Number of patents $_{t-1}$	0.82	0.72	3.60	0.46	0.649
R&D personnel $_{t-1}$					
…with PhD	0.27	0.82	-48.00	-1.97	0.052
…with 5 or more year degree	0.95	0.90	4.00	0.31	0.753
…with 4 or less year degree	0.93	0.43	43.80	2.67	0.008
…without higher education	0.46	0.34	10.00	0.62	0.538
Machinery, equipment & software for R&D$_{t-1}$	0.18	0.20	-6.40	-0.58	0.561
Employment$_{t-2}$	2.79	2.82	-2.20	-0.23	0.820
Physical capital$_{t-2}$	6.97	6.97	-0.10	-0.01	0.992
Labor productivity$_{t-2}$	6.75	6.84	-5.70	-0.69	0.489
Product innovation $_{t-2}$	0.87	0.79	19.90	1.97	0.050
Process innovation $_{t-2}$	0.66	0.56	21.10	1.87	0.062
Number of patents $_{t-2}$	0.72	0.58	4.50	0.68	0.498
R&D personnel $_{t-2}$					
…with PhD	0.49	0.53	-3.50	-0.14	0.886
…with 5 or more year degree	0.86	0.81	4.60	0.37	0.713
…with 4 or less year degree	0.68	0.49	16.80	1.10	0.271
…without higher education	0.27	0.34	-6.50	-0.40	0.689

Note: For exact definitions and sources of all variables see Table 1 and main text.

Table A6: R&D personnel and machinery for R&D during the GR with longer pre-trends in the propensity score weighting

Dependent variable	*R&D personnel*	*R&D personnel with PhD*	*R&D personnel with 5 or more year degree*	*R&D personnel with 4 or less year degree*	*R&D personnel without higher education*	*Machinery, equipment & software for R&D*
	(1)	(2)	(3)	(4)	(5)	(6)
Young x GR	-0.188***	0.272***	-0.250**	0.235	-1.283***	0.536**
	(0.052)	(0.100)	(0.126)	(0.169)	(0.297)	(0.219)
Observations	27,357	5,807	19,927	12,555	14,152	3,438
Industry, year and firm FEs in all regressions						

*Note: Fixed effects-OLS with propensity score weighting estimations. R&D personnel is the number of full time employees working in research. Columns (2) to (5) refer to types of R&D employees by educational level. For exact definitions and sources of all variables see Table 1 and main text. Estimated robust standard errors are in parentheses. * Significant at 10%;** Significant at 5%; *** significant at 1%.*

Table A7: Balancing property for placebo test for the reweighted sample

	Mean: Treated	Mean: Control	% diff	t-test: t	t-test: p>|t|
Employment$_{t-1}$	4.24	4.17	4.60	0.14	0.892
Physical capital$_{t-1}$	7.96	7.96	-0.10	0.00	0.998
Labor productivity$_{t-1}$	7.79	7.41	37.90	1.42	0.156
Product innovation $_{t-1}$	0.56	0.75	-39.40	-1.38	0.168
Process innovation $_{t-1}$	0.56	0.69	-27.20	-0.89	0.374
Number of patents $_{t-1}$	0.33	0.57	-9.70	-0.29	0.773
R&D personnel $_{t-1}$					
…with PhD	-0.46	0.10	-69.30	-1.16	0.247
…with 5 or more year degree	0.71	0.56	14.50	0.41	0.684
…with 4 or less year degree	0.35	0.40	-5.10	-0.12	0.903
…without higher education	0.75	0.38	30.40	0.80	0.423
Machinery, equipment & software for R&D$_{t-1}$	0.33	0.50	-38.40	-1.00	0.319

Note: For exact definitions and sources of all variables see Table 1 and main text.

Table A8: Placebo test. Random assignment of young firms

Dependent variable	*R&D personnel*	*R&D personnel*				*Machinery, equipment & software for R&D*
		with PhD	*with 5 or more year degree*	*with 4 or less year degree*	*without higher education*	
	(1)	(2)	(3)	(4)	(5)	(6)
Random young x GR	0.079	-0.008	0.326	-0.052	0.205	-0.013
	(0.073)	(0.033)	(0.228)	(0.108)	(0.173)	(0.127)
Observations	25,608	5,195	18,483	11,835	13,342	3,121
R-squared	0.017	0.081	0.029	0.013	0.029	0.044
Industry, year and firm FEs in all regressions						

*Note: Fixed effects-OLS with propensity score weighting estimations. R&D personnel is the number of full time employees working in research. Columns (2) to (5) refer to types of R&D employees by educational level. For exact definitions and sources of all variables see Table 1 and main text. Estimated robust standard errors are in parentheses. * Significant at 10%;** Significant at 5%; *** significant at 1%.*

FIGURES

Figure A1: Average regional growth of vehicles' registration over time