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# R&D restructuring during the Great Recession and young firms

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GEP

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Abstract

In this paper, I provide evidence of automation and skill-upgrading of R&D for young firms during the Great Recession of the late 2000s (henceforth abbreviated as GR). Using a difference-in-difference approach and propensity score matching, for a panel of more than 12,000 Spanish firms from 2005 to 2014, I examine if the GR had an effect on the organization of R&D in young versus older firms. I find that young firms adjust 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-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-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; 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) argued "…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 labor is often relocated and firms tend to reorganize their production methods (Davis and Haltiwanger 1992; Aghion and Saint-Paul 1998; Manso et al. 2017). 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 are able to hire from a larger pool of high-skilled workers (Bewley 1999; Mueller 2017).

The process of skill-upgrading and automation is particularly important for the R&D department and for young firms. Human capital contributes crucially to firms' technological activities. Moreover, young firms are highly adaptable to the hiring environment (Geurts and Van Biesebroeck 2016). One of the reasons is that young firms have lower labor adjustment costs than

[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 (forthcoming) among others for US firms, and also the decline in participation rates of workers in routinizable occupations (Grigoli et al., 2020). An alternative explanation for the jobless recovery is the effect of trade (Fort et al. 2018).

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 automation and skill-upgrading of R&D for young firms during the Great Recession of the late 2000s (henceforth abbreviated as GR). Using a difference-in-difference approach and propensity score matching, I examine if the GR had an effect on the organization of R&D in young versus older firms. I find that young firms adjust 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-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-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 am able to measure, at the firm level, the changes in the composition of the R&D labor force and R&D investments during the GR. Moreover, in Spain, as in many European countries, firing costs rise with tenure,[2] which makes young firms in the sample more likely to adjust their labor force than older firms because of their lower firing costs. My results contribute to the understanding of the changes in the internal

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[2] 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).

organization of the R&D of the firm during the economic cycle. In particular, I show that the GR particularly affected the reorganization of R&D of young firms.

The GR was an unexpected shock (Aghion et al. 2017). 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). However, the research that is conducted during recessions seems to be more radical than during non-recession times. For example, Manso et al. (2017) who show that innovative activities are explorative during recessions and exploitative during booms. Lebdi and Hussinger (2016) study the pattern of innovations of startups founded in 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 labor 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 job polarization and automation in R&D. My results also suggest that young firms 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 on young firms and performance. Sedláček and Sterk (2017) analyse the potential of young firms over the business cycle. They find that firms that are founded during periods of economic growth grow larger than firms founded during recessions. 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.[3] A further major difference to these papers is that 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 describe the dataset and the main variables. In Section 3, I explain the econometric specification. Section 4 presents the baseline results, as well as robustness checks. Section 5 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 6, I summarize the results and conclude.

## 2. The data

My source of firm-level data is a survey of firms operating in Spain (*Panel de Innovación Tecnológica, PITEC*). It is a panel database for 12,827 firms constructed by the Spanish National Institute of Statistics on the basis of annual responses to the Community Innovation Survey (CIS) administered to a representative sample of Spanish firms.[4] 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.

The main variable for my analysis is being a young firm 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

[3] 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).

[4] 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.

created during the five years prior to 2005 (from the year 2000).[5] This definition of young firm follows Adelino et al. (2017), Audretsch et al. (2014), García-Macía et al. (2018), and European Commission regulations that consider young firms as firms that are less than six years old.[6] There are 341 young firms in the sample at the beginning of the period. In 2005, the mean and median age of a young firm is three years, while for the rest of the firms 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 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. They also have higher sales and employment growth, and more product, 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.

## 3. Econometric specification and description of independent variables

My main goal is to analyze 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

[5] 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.

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

(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:

$$Ln(y_{it}) = \alpha + \beta_1\, Young_i + \beta_2 Young_i \times GR_t + \beta_3 GR_t + \delta_t + \epsilon_{it}, \qquad (1)$$

where the variable $y_{it}$ represents the outcome, $\alpha$ is the constant; $Young_i$ is a dummy variable that takes the value one if a firm $i$ is a young firm in 2005 (i.e., at most 5 years old); and $GR_t$ denotes the years of the Great Recession, which in Spain lasted from 2007 to 2013 (see for example Almunia et al. 2018). In the robustness section, I report an alternative specification in which I present results with a different definition of the GR variable.[7] The interaction of interest is $Young_i \times GR_t$, namely whether a young firm performs differently during the GR than an older firm; $\delta_t$ are year fixed effects; and $\epsilon_{it}$ is the error term.

The empirical strategy presented above is based on the assumption that young and older firms are equivalent before the GR and they have a common trend. These assumptions might not hold in this case. As I have 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. To deal with these issues I include idiosyncratic firm trends in the model:

$$Ln(y_{it}) = \alpha + \gamma_i \times trend_t + \beta_1\, Young_i + \beta_2 Young_i \times GR_t + \beta_3 GR_t + \delta_t + \epsilon_{it}, \, (2)$$

where $\gamma_i$ are firm fixed-effects and the rest of the variables are as in equation (1).

Differentiating equation (2), I can estimate with firm fixed effects the following equation (e.g. Bøler et al. 2015):

[7] 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.

$$\Delta Ln(y_{it}) = \gamma_i + \beta_2 \Delta(Young_i \times GR_t) + \beta_3 \Delta GR_t + \Delta\delta_t + \epsilon_{it}, \tag{3}$$

Second, in order to address the potential selection bias, I estimate equation (3) using a matching procedure. This econometric approach has been recently used by Aghion et al. (2018) and Jaravel et al. (2018). With this methodology, I obtain a group of young and older firms that are observationally equivalent at the beginning of the period. Regarding the matching procedure, I use a propensity score reweighting estimator.[8] 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; the lagged natural logarithm of employment; lagged labor productivity and the lagged natural logarithm of number of researchers.[9] 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.

To summarize, the econometric model that I use is a conditional DID model with firm fixed-effects and propensity score weighting, 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 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

[8] Matching is carried out with STATA command pscore by Becker and Ichino (2002). The caliper used is equal to 0.001.

[9] In the following section, as a robustness check, I include additional variables as controls. In particular, I include the the lagged values of the variables *product innovations*, *process innovations* and *number of patents* to control for lagged innovation outputs.

important in the R&D department because firms need to adapt their products and processes in order to find new potential markets fast and to reduce their costs.[10] To examine this mechanism, I analyze several variables that account for changes in the organization of R&D. In particular, 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 a 5-year BA degree*, *employees with a 3-year BA degree* and *employees without higher education*.[11] 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 in order to generate product and process innovations*. With this variable, I analyze whether there has been an increase in the investments of machines for R&D during the GR. If young firms automatize more than older firms during the GR, I should expect a decline in R&D workers and an increase in expenditures of machineries and equipment for R&D.

## 4. The results

### *4.1. Baseline results*

In this section, I analyze 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 young

[10] For example Gupta (2018) shows that firms with high R&D levels before the GR are more resilient because their capability to introduce new products to the market.
[11] This is a standard way of classification of undergraduate degrees in Spain, where a 5-year BA degree is denominated as “licenciatura” or “ingeniería” in Spanish; and a 3-year BA degree is denominated as “diplomatura” or “ingeniería técnica”.

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

In Table 3, I present the baseline results from the conditional DID estimation with firm fixed effects. In the table, 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*.[12]

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 -0.580. This indicates that, during the GR, young firms reduced their R&D employment by 55.7% compared to older firms with similar pre-GR characteristics.[13] 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 53.08%. Column 3 shows a decline of 45.5% for personnel with a 5-year BA degree. Column 4 shows an increase in the proportion of the employees with medium-low qualification, which is equal to 44.2%.[14] For the lowest category of employment, the changes in the proportion of employment are statistically the same between young firms and older firms. This suggests that, during the GR, young firms have simultaneously reduced R&D personnel and increased the average skill of the R&D labor force as compared to older firms. The results also

[12] 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.

[13] This is calculated as (0.023-0.580)*100 based on the average R&D employment growth for the control group before the GR and the estimated coefficient in Table 3.

[14] 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 3. They are as follows: For the R&D personnel with a Ph.D: (0.0028+0.528)*100; for R&D personnel with 5-year degree (0.010-0.465)*100; for R&D personnel with 3-year degree: (-0.027+0.469)*100.

suggest that the R&D labor structure of young firms have become more polarized during the GR than for old 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 0.328. This represents an increase in machinery for R&D equal to 31.5%.[15] Overall, the findings indicate that young firms have adjusted their R&D department during the GR as compared with older firms. In particular, young firms have dismissed medium-skill workers, hired very high-skill workers and low-medium skill workers and an increased expenditures in machines and equipment, which is consistent with automation in the R&D department. In the next section, I assess the sensitivity of the baseline results.

*4.2. Robustness checks*

In this section, I complement the baseline results with five robustness tests that I present in the Appendix, including an alternative definition of the GR, an alternative definition of young firm, longer pre-treatment trends, pre-GR 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.[16] Figure A1 in the Appendix plots

[15] This is calculated as (-0.013+0.328)*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 3.
[16] 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/.

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 that it 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, 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, 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 of Table 3 and support the conclusion that young firms reduce their total employment in R&D, there is skill-upgrading and an increase in the expenditures in 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 our 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 the majority of the firms that 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 it is at most 5 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 more precisely estimated and very similar to those reported in Table 3, which implies that the results are robust to the definition of being a young firm.

An identification assumption for the DID is that control and treated firms have similar trends before the GR. I tackle this issue in two ways. First, I present DID results from an alternative matching 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. Second, I show that young and older firms where in a similar trend before the GR. In Table A5, I present the balancing test for the alternative matching procedure. I conduct the DID estimations with the alternative matching 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.

Next, I estimate differential time trends 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 automation for the R&D department. I estimate equation (3) for the original matched sample and interact the treatment indicator with time dummies including the years before the GR. The results are summarized in Figure A2. 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)[17] and declines for 2014. This indicates that there is no difference in the slope of automation trend between young and old firms before the GR. These findings are consistent with automation of young firms during the peak of the GR (years 2007 and 2008) and during the Spanish sovereign debt crisis.

[17] 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).

The identification strategy considers that young firms skill-upgrade and automatize more than older firms due to their lower firing costs and their flexibility. One implication of this identification strategy is that there should not be an effect of the GR when the DID is performed among random 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 older firms 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, with the exception of *R&D personnel without higher education*, which is negative. This is in contrast to the corresponding estimated coefficient in Table 3, which is positive. 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.

## 5. 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 automation during the GR. Second, I study changes on R&D labor costs. Finally, I analyze the effects of the GR for young firms on total R&D expenditures and innovation outputs, as well as other firm economic variables.

### *5.1. Allowing for heterogeneous effects: Firm financial health*

In this section, I examine firm heterogeneity in the effects reported in Table 3. A key element for automation 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 et al. (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 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 the double interaction $Young_i \times GR_t$.[18] The triple interaction measures whether the automation of R&D and skill-upgrading is weaker for firms with low financial health. I present the results in Table 4.

The results in column (1) of Table 4 suggest that less financially healthy young firms reduce their R&D personnel less than more financially healthy firms, although this effect is not significant at standard statistical levels. In column (2), the estimated coefficient for the triple interaction term for the variable R&D personnel with a PhD is negative but it is again statistically insignificant. The only coefficients for the triple interaction that are significant at standard levels are R&D personnel with 5-year degree in column (3) and machinery and equipment for R&D in column (6). In both columns the estimated coefficients are negative. The double interactions in the table remains very similar to the baseline case in Table 3. This suggests that on average younger firms automatize more during the GR than older firms, but this effect is mediated by a firm's financial health.

*5.2. Labor costs in the R&D department*

In this section, I study the changes in the labor costs in the R&D department. In Table 5, I document results for salaries for 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

[18] 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.

columns 1 and 2 the estimated coefficients of the interaction term are negative and significantly different from zero. This implies that young firms reduce their expenditures on salaries during the GR as compared to older firms. This is a reflection of the firing of R&D labor force documented in Table 3. However, columns 3 and 4 show that the estimated coefficients for the interaction term when I focus on the average salary per either researcher or technician the coefficients are small and not significantly different from zero at standard statistical levels.

Overall, the findings suggest that young firms reduce their R&D labor costs (in terms of savings coming from salaries of both researchers and technicians) during the GR as compare to older firms. Moreover, we know from Table 3 and the different robustness checks that there has been skill-upgrading but, as Table 5 suggests, the average salaries have not been affected. This findings suggest that young firms are 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 at lower salaries than older firms.

### *5.3. R&D expenditures, innovation outputs and firm performance*

In the previous sections, I showed that young firms, with similar characteristics than older firms before the GR, undertook fundamental changes in their R&D department during the GR by reducing employment, labor costs, and increasing skill-upgrading and automation. 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 outputs measures that provide further evidence to this possible efficiency improvement.

In Table 6, column (1), I present results for *total R&D expenditures*; in columns (2) and (3), the dependent variables are indicators that take the value 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 one if the firm permanently or temporarily stops its economic activity; and finally in column (6), I study firm *sales.*

The evidence in Table 6 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 labor 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 process innovations (in column 3) and number of patents (in column 4).

Finally, I analyze 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, with similar characteristics than older firms before the GR, 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 increased their sales. Therefore, these findings suggest that young firms performed better during the crisis than older firms with similar characteristics before the GR. 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.

## 6. 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 that older firms before the crisis reacted more flexibly to the economic conditions than older firms, and as a consequence, 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-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 was an increase in automation in the R&D units. Firm financial health was an important factor that contributed to the automation of the R&D department and skill-upgrading for young firms during the crisis. This finding has policy implications. It suggests that an important R&D policy is to enable young firms access to external funding during crisis.

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## TABLES

**Table 1: Descriptive statistics of the main variables**

| Variable | Mean | SD | Observations |
|---|---|---|---|
| Young | 0.027 | 0.161 | 141097 |
| Closure | 0.084 | 0.278 | 141097 |
| Sales growth | -0.025 | 0.541 | 100214 |
| Capital growth | -0.088 | 1.663 | 60148 |
| Labor 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-year undergraduate degree | -0.011 | 0.205 | 90739 |
| 3-year undergraduate 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; *Labor 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 |
|---|---|---|
| Variables: | (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) |
| Labor 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: R&D personnel and machinery for R&D during the GR**

| *Dependent variable* | *R&D personnel* | *R&D personnel* | | | | *Machinery, equipment & software for R&D* |
|---|---|---|---|---|---|---|
| | | *with PhD* | *with 5-year degree* | *with 3-year degree* | *without higher education* | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Young x GR | -0.580** | 0.528** | -0.465* | 0.469*** | -1.160 | 0.328** |
| | (0.254) | (0.264) | (0.247) | (0.133) | (1.207) | (0.133) |
| Observations | 27,878 | 5,705 | 20,152 | 12,617 | 14,239 | 3,507 |
| 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. 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 4: R&D personnel and machinery for R&D during the GR by firm financial health**

| *Dependent variable* | *R&D personnel* | *R&D personnel* | | | | *Machinery, equipment & software for R&D* |
|---|---|---|---|---|---|---|
| | | *with PhD* | *with 5-year degree* | *with 3-year degree* | *without higher education* | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Young x GR x low financial health | -0.227 | -0.100 | -0.562* | 0.187 | -1.155 | -0.399* |
| | (0.174) | (0.345) | (0.302) | (0.165) | (0.925) | (0.209) |
| Young x GR | -0.332** | 0.617** | -0.070 | 0.249 | 0.067 | 0.634** |
| | (0.166) | (0.284) | (0.288) | (0.206) | (0.682) | (0.264) |
| Observations | 27,878 | 5,705 | 20,152 | 12,617 | 14,239 | 3,507 |
| 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. 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 5: R&D labor costs during the GR**

| *Dependent variable* | *Salaries to researchers* | *Salaries to technicians* | *Salary per researcher* | *Salary per technician* |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Young x GR | -0.829*** | -0.651*** | -0.041 | -0.085 |
| | (0.308) | (0.163) | (0.089) | (0.157) |
| Observations | 27,817 | 21,889 | 27,817 | 21,889 |
| Industry, year and firm FEs in all regressions | | | | |

*Note: Fixed effects-OLS with propensity score weighting estimations. All independent variables are in terms of growths. Growth of expenditures on salaries to researchers (technicians) is the growth of the R&D expenditures for the salaries of researchers (technicians) working in R&D. Salary per researcher (technician) growth is the growth of the average salary per researcher (technician) working in R&D. 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 6: Innovation input, outputs and further outcomes during the GR**

| *Dependent variable* | *R&D* | *Product innovation* | *Process innovation* | *Patents* | *Closure* | *Sales* |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Young x GR | -0.747** | 0.067 | 0.069** | 0.727*** | -0.002** | 0.593*** |
| | (0.316) | (0.050) | (0.032) | (0.250) | (0.001) | (0.193) |
| Observations | 30,499 | 31,367 | 31,367 | 31,367 | 41,172 | 40,711 |
| Industry, year and firm FEs in all regressions | | | | | | |

*Note: Fixed effects-OLS with propensity score weighting 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%.*

**FIGURES**

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

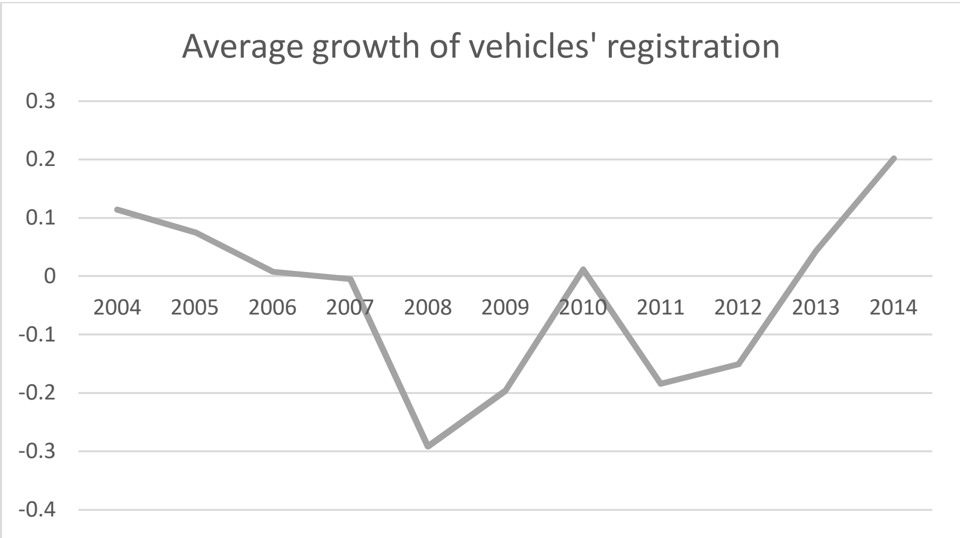
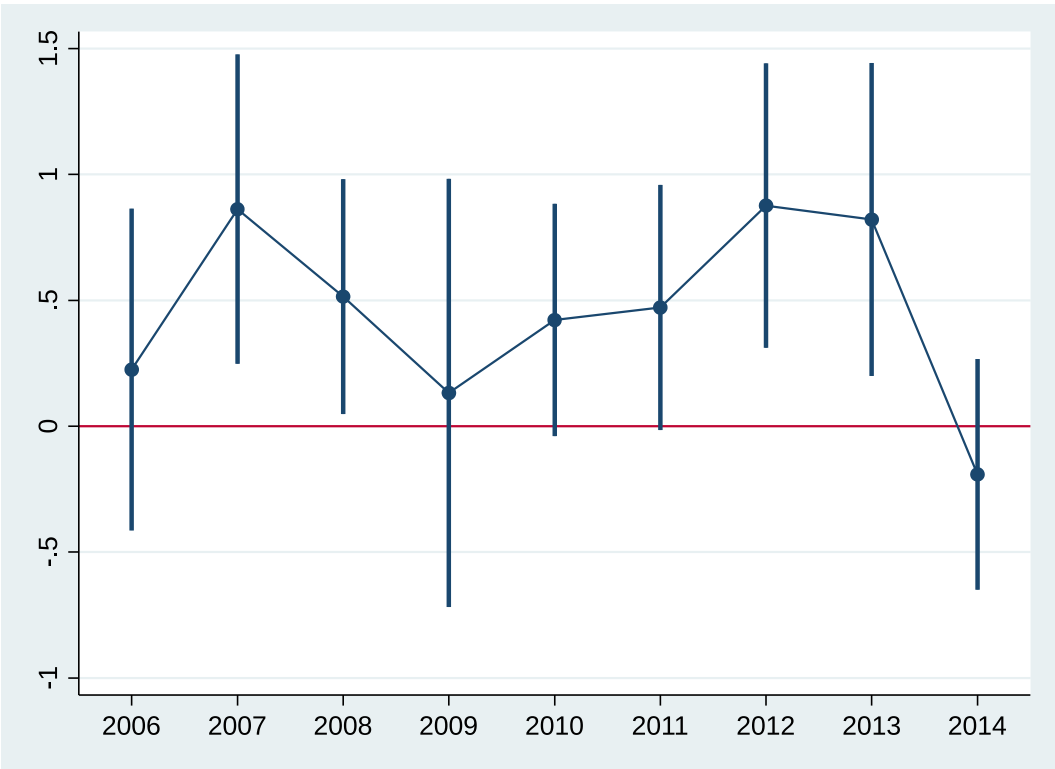



**Figure A2:**



## APPENDIX

**Table A1: Balancing property**

| | Mean | | | t-test | |
|---|---|---|---|---|---|
| | Treated | Control | % diff | t | p>\|t\| |
| Panel A: Variables used in the matching procedure | | | | | |
| R&D personnel$_{t-1}$ | 8.481 | 7.357 | 5.9 | 0.92 | 0.358 |
| Machinery, equipment & software for R&D$_{t-1}$ | 0.486 | 0.546 | -12.5 | -1.14 | 0.254 |
| Researchers in R&D$_{t-1}$ | 3.879 | 3.941 | -8.4 | -0.85 | 0.397 |
| Employment$_{t-1}$ | 2.694 | 2.785 | -5.8 | -0.59 | 0.556 |
| Physical investment$_{t-1}$ | 6.834 | 7.129 | -12.8 | -1.29 | 0.198 |
| Labor productivity$_{t-1}$ | 6.625 | 6.616 | 0.7 | 0.07 | 0.941 |
| Panel B: Variables not used in the matching procedure | | | | | |
| Product innovation $_{t-1}$ | 0.847 | 0.779 | 15.5 | 1.64 | 0.103 |
| Process innovation $_{t-1}$ | 0.648 | 0.657 | -2.0 | -0.19 | 0.847 |
| Number of patents $_{t-1}$ | 0.864 | 0.575 | 9.7 | 1.02 | 0.307 |
| R&D personnel $_{t-1}$ | 5.773 | 5.230 | 3.6 | 0.34 | 0.734 |
| …with PhD | 35.532 | 30.460 | 16.2 | 1.52 | 0.130 |
| …with 5-year degree | 13.338 | 15.562 | -11.5 | -0.93 | 0.353 |
| …with 3-year degree | 11.918 | 9.580 | 12.8 | 1.22 | 0.224 |
| …without higher education | 0.847 | 0.779 | 15.5 | 1.64 | 0.103 |

*Note: For exact definitions and sources of all variables see Table 1 and main text. This table presents mean values of the variables used for the matching procedure and other variables not used in the matching procedure. 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* | | | | *Machinery, equipment & software for R&D* |
|---|---|---|---|---|---|---|
| | | *with PhD* | *with 5-year degree* | *with 3-year degree* | *without higher education* | |
| Panel A | | | | | | |
| | (1a) | (2a) | (3a) | (4a) | (5a) | (6a) |
| Young x Alternative GR | -1.318** | 1.603** | -1.187** | 0.049 | -0.769 | 2.057*** |
| | (0.671) | (0.648) | (0.558) | (0.570) | (1.701) | (0.789) |
| Observations | 27,707 | 5,634 | 20,016 | 12,515 | 14,137 | 2,992 |
| 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. 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. 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**

| | Mean | | | t-test | |
|---|---|---|---|---|---|
| | Treated | Control | % diff | t | p>\|t\| |
| R&D personnel$_{t-1}$ | 8.214 | 8.729 | -2.7 | -0.16 | 0.873 |
| Machinery, equipment & software for R&D$_{t-1}$ | 0.414 | 0.400 | 3.0 | 0.17 | 0.865 |
| Researchers in R&D$_{t-1}$ | 3.926 | 3.887 | 5.3 | 0.32 | 0.746 |
| Employment$_{t-1}$ | 2.393 | 2.604 | -13.1 | -0.81 | 0.419 |
| Physical investment$_{t-1}$ | 6.656 | 6.974 | -13.7 | -0.83 | 0.408 |
| Labor productivity$_{t-1}$ | 6.512 | 6.298 | 16.8 | 1.10 | 0.271 |

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

**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* | | | | *Machinery, equipment & software for R&D* |
|---|---|---|---|---|---|---|
| | | *with PhD* | *with 5-year degree* | *with 3-year degree* | *without higher education* | |
| Panel A | | | | | | |
| | (1a) | (2a) | (3a) | (4a) | (5a) | (6a) |
| Alternative Young x GR | -0.783*** | 0.800*** | -0.522** | 0.425** | 0.707*** | 0.327** |
| | (0.227) | (0.155) | (0.210) | (0.200) | (0.259) | (0.134) |
| Observations | 27,878 | 5,705 | 20,152 | 12,617 | 14,239 | 3,507 |
| 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. 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. Estimated robust standard errors are in parentheses. * Significant at 10%;** Significant at 5%; *** significant at 1%.*

**Table A5: Balancing property for longer pre-trends**

| | Mean | | | t-test | |
|---|---|---|---|---|---|
| | Treated | Control | % diff | t | p>\|t\| |
| R&D personnel$_{t-1}$ | 1.722 | 1.674 | 4.5 | 0.40 | 0.687 |
| Machinery, equipment & software for R&D$_{t-1}$ | 7.422 | 7.270 | 0.7 | 0.08 | 0.940 |
| Researchers in R&D$_{t-1}$ | 3.898 | 3.996 | -13.7 | -1.35 | 0.177 |
| Employment$_{t-1}$ | 2.742 | 2.818 | -5 | -0.53 | 0.599 |
| Physical investment$_{t-1}$ | 6.961 | 7.089 | -5.5 | -0.53 | 0.595 |
| Labor productivity$_{t-1}$ | 6.738 | 6.666 | 4.8 | 0.59 | 0.555 |
| R&D personnel$_{t-2}$ | 1.722 | 1.674 | 4.5 | 0.40 | 0.687 |
| Machinery, equipment & software for R&D$_{t-2}$ | 7.248 | 8.193 | -4.4 | -0.40 | 0.689 |
| Researchers in R&D$_{t-2}$ | 3.884 | 3.924 | -5.5 | -0.51 | 0.608 |
| Employment$_{t-2}$ | 2.599 | 2.775 | -11.4 | -1.19 | 0.234 |
| Physical investment$_{t-2}$ | 6.957 | 7.014 | -2.5 | -0.23 | 0.816 |
| Labor productivity$_{t-2}$ | 6.581 | 6.542 | 3.2 | 0.26 | 0.795 |

*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* | | | | *Machinery, equipment & software for R&D* |
|---|---|---|---|---|---|---|
| | | *with PhD* | *with 5-year degree* | *with 3-year degree* | *without higher education* | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Young x GR | -0.527** | 0.502* | -1.370** | 0.212 | -3.518*** | 0.533*** |
| | (0.243) | (0.283) | (0.668) | (0.211) | (0.982) | (0.138) |
| Observations | 27,416 | 5,807 | 19,927 | 12,555 | 14,152 | 3,447 |
| 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. 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 A7: Balancing property for placebo test**

| | Mean | | | t-test | |
|---|---|---|---|---|---|
| | Treated | Control | % diff | t | p>\|t\| |
| R&D personnel$_{t-1}$ | 8.750 | 6.000 | 15.0 | 1.06 | 0.300 |
| Machinery, equipment & software for R&D$_{t-1}$ | 0.500 | 0.563 | -12.9 | -0.34 | 0.733 |
| Researchers in R&D$_{t-1}$ | 3.503 | 3.506 | -0.4 | -0.01 | 0.990 |
| Employment$_{t-1}$ | 3.524 | 3.629 | -7.4 | -0.27 | 0.790 |
| Physical investment$_{t-1}$ | 7.547 | 7.846 | -13.7 | -0.53 | 0.597 |
| Labor productivity$_{t-1}$ | 7.141 | 7.205 | -7.2 | -0.30 | 0.765 |

*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-year degree* | *with 3-year degree* | *without higher education* | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Random young x GR | 0.033 | -0.002 | 0.203 | -0.045 | 0.212** | -1.615 |
| | (0.064) | (0.027) | (0.193) | (0.090) | (0.107) | (2.284) |
| Observations | 26,544 | 5,302 | 19,180 | 12,196 | 13,783 | 3,432 |
| 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. 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%.*