Employee Training and Firm Performance: Evidence from ESF grant applications*

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Abstract

As work changes, firm-provided training may be particularly relevant. However, there is little causal evidence about the effects of training on firms. This paper studies a large training grants programme supported by the European Social Fund, contrasting firms in Portugal that received the grants and others that also applied but were unsuccessful. Combining several rich data sets, we compare a large number of potential outcomes of these firms, while following them over several years both before and after the grant decision. Our difference-in-differences models estimate significant positive effects on take up (training hours and expenditure), with limited deadweight; and that such additional training led to increased sales, value added, employment, productivity, and exports. These effects tend to be of at least 5% and, in some cases, 10% or more, and are robust in multiple dimensions.

Keywords: Training subsidies, Productivity, Programme evaluation.

JEL Codes: J24, H43, M53.

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1 Introduction

As technology evolves more rapidly, firm-provided employee training can play an increasingly important role. Training can update and extend the schooling qualifications of workers in their jobs and deliver important private and social benefits. The pandemic crisis may also represent an opportunity for firms to invest in the skills of their workers in the context of growing importance of remote work. However, employee training also faces a number of well-known obstacles. These include worker mobility, namely through poaching by other firms, and credit constraints for firms to fund the direct and indirect costs of training. Such obstacles can lead to sub-optimal levels of this particular type of human capital investment (Leuven 2005).

Even if the obstacles above can be addressed, firms may find it difficult to estimate the returns to their training activities. Training sessions may be more or less effective; and the relationship between human capital improvements and gains in productivity and sales may be difficult to establish, leading to uncertainty that can further discourage training. This point is further underlined by the fact that the academic literature on the firm-level returns to employee training has not yet drawn on experimental or quasi-experimental variation. All approaches adopted so far are based on assumptions about the production technology of firms (Almeida & Carneiro 2009, Mehra et al. 2014, Konings & Vanormelingen 2015), controls for firm heterogeneity, including firm fixed effects (Goux & Maurin 2000, Barrett & O'Connell 2001, Zwick 2006, Dostie 2018) or case studies of single or small numbers of firms (Krueger & Rouse 1998, Lyons 2020). As stated in Fialho et al. (2019), 'it is very difficult to measure the returns to training [for employers] and very few studies have attempted to estimate it' (page 24). Brunello & Wruuck (2020) also highlight this point and argue that a 'more systematic assessment of the benefits [of training for firms] could contribute to explain the heterogeneity in training investment' (page 29).[1]

In contrast to the literature above, this paper is one of the first to provide evidence on the effects of employee training on firm performance based on potentially quasi-experimental variation, even if not drawing on a randomised control trial. The variation in training across firms

[1] See Martins (2021) for a recent review of the literature. Note that, in contrast, the related literature on returns to training provided to unemployed individuals includes several experimental and quasi-experimental contributions (Card et al. 2010) including, very recently, novel analyses using machine learning methods (Cockx et al. 2020, Zimmert 2020). Another important related literature is about the (individual) wage (and employment) returns to training (Leuven & Oosterbeek 2008, Brunello et al. 2012, Goerlitz & Tamm 2016, Dauth 2016).

that we use here is drawn from a large, 200 million euro training grants programme supported by the European Social Fund of the European Union. This programme, FIG, implemented in Portugal, supported the training of employees of different skill levels, from factory workers to managers, and in diverse areas, including innovation, marketing, and international trade (Bloom & Reenen 2007, Bloom et al. forthcoming). FIG involved five annual calls between 2007 and 2011, all studied here, each one receiving applications from about 2,000 firms. As demand exceeded the funding available, less than half of the applicants were selected and funded, receiving a grant of about 30,000 euros on average. While assignment to treatment is not random (and in, that sense, our study is observational), variation in treatment status is influenced by the changing circumstances of each call, namely the funding available, the number of firms applying for support, and the binding (or not) nature of minimum scores, as explained in detail in the next section.

Our analysis is based on matching the administrative data from all applicants in each call to a rich matched employer-employee panel. This allows us to follow both the funded and the rejected firms, using difference-in-differences (Lechner 2011), and drawing on a more comparable (self-selected) set of firms. We follow these firms over a period of up to ten years before their application and up to ten years after the funding was or was not awarded. (Our approach bears some similarity to Holzer et al. (1993), which studies a training programme in Michigan, and Howell (2017), which studies an R&D programme in the US. See also Criscuolo et al. (2019) which studies the effects of an industrial policy in the UK, which can also include worker training components.) Moreover, we consider a very large number of potential firm-level outcomes, all of which collected from the same compulsory surveys across firms and years, to provide a comprehensive analysis of the effects of training. Some of these variables have not been examined before in the training literature. We also examine the effects of training at different times over the business cycle, which strengthens the external validity of our findings.

Our findings indicate that, first, the training grants had a significant positive effect on training activities: both training expenditure and training hours more than double. This increase also involved limited deadweight loss: we estimate that at least 74% of the grant led to additional training and, under some assumptions, cannot rule out some form of crowd-in (whereby the increase in training exceeded the support provided by the programme). Our finding of limited deadweight is in contrast to several studies (Leuven & Oosterbeek 2004, Abramovsky et al. 2011, Schwerdt et al. 2012, Hidalgo et al. 2014) but certainly not all (Holzer et al. 1993, Goerlitz 2010). Our results may be driven by the format of the programme, which required an application by interested parties (where they made their cases about the relevance of the grant) and established levels of co-payment by firms that decreased with the generality of the skills provided.

Second, we find that the additional training driven by the programme led to economically and statistically significant improvements in several dimensions of firm performance. Sales, value added, employment, productivity, and exports increase in the firms that received the training grant compared to the control group of unsuccessful applicants. On the other hand, total (accounting) investment and profits appear to not be positively affected by training, although these variables are subject to measurement error. As to the variables that increase, the effects are typically of around 10%, emerge one or two years after the grant is provided and the training is conducted, and in some cases remain in place for at least ten years. Interestingly, the employment effects we find tend to be stronger in periods of recession. This may correspond to a positive form of training 'lock-in', in contrast to the case of training programmes for the unemployed, which may reduce transitions to employment at least in the short-run.

The large and durable positive effects in several firm performance variables and the relatively low cost of the additional training indicate that there may be significant underprovision of employee training. At the same time, the results highlight the potential of public programmes in addressing at least part of this underprovision. Quasi-experimental evidence may also go some way in informing firms regarding the likely returns from training. Our results also contribute to the evaluation of the 100 billion European Social Fund (Becker et al. 2013), of which FIG was a small component, and towards the design and implementation of the new funding schemes currently under plan to alleviate the pandemic crisis.

The structure of the remaining of the paper is as follows: Section 2 describes the training programme evaluated here. Sections 3 presents the data sets used (and their descriptive statistics) and 4 discusses our methodology. Our main results are presented in Section 5 while a number of additional results are described in Section 6. Finally, Section 7 concludes.

2 The FIG programme

Our evidence on the returns to training is driven from a public programme that offered training grants to successful firms following an application process. This programme, FIG, was launched in Portugal in 2008 and was funded both by the European Social Fund (ESF) and the Government of Portugal.[2] FIG, with a total budget of about 200 million euros, provided grants to support firms in the training of their employees, in particular in the context of technical, technological and organisational changes.

The funding was made available to firms depending on the scoring of their applications, which was conducted by the public agency responsible for the management of FIG (and other ESF programmes). The scoring was based on a number of criteria, each one carrying a specific weight. The main criterion (40% weight) was about the extent to which the training would provide knowledge and skills to workers that were required given technical, technological and organisational changes. The training would have to promote workers' employability, while 'fostering innovation and the production of higher-value added tradable goods and services'.[3] The grant would range between 30% and 80% of total training costs, depending on training type, firm size and region. For instance, general training provided by small firms located in low average GDP regions would receive the highest subsidy rate. Eligible training costs could include also indirect costs (namely the salaries of the workers participating in training, during the period in which the training was taking place). On average, each grant was of about 30,000 euros, as we will see later when we describe our data.

Unlike other ESF programmes, FIG was demand-led, as the grants were given to firms and not training providers.[4] FIG also supported flexible training, including that of a practical nature (in the workplace, not in a classroom, and during normal working hours) and based on

[2]FIG stands for Training for Innovation and Management ('Formação para a Inovação e a Gestão'). The European Social Fund supported several other similar programmes, including the 'New Innovative Entrepreneuship' (Greece), 'Profissional qualifications and counselling for enterprises' (Poland), and the 'Training Aid Framework' in Malta. However, FIG was the only programme of its type in Portugal at the time under analysis.

[3]The remaining criteria involved a focus on smaller firms (20% weight), low-skill workers and certification (10%), training what would increase promotions and quality of life (15%), skills in new technologies (10%), and the promotion of the equality of opportunities (namely in terms of gender; 5%). It is important to note that some of these criteria, in particular the first one, inevitably involve some degree of subjectivity in the resulting evaluations carried out by the public agency.

[4]In practice, many applications may have been intermediated by training providers, which tend to be more knowledgeable about training grants, including the application process, compared to the firms that formally submitted the application and whose employees receive the training. These training providers may also deliver the subsidised training later, in case the application is successful. FIG was the only demand-led programme at the time - the remaining training programmes were supply-led, focused on supporting apprenticeships, traineeships and training directed to unemployed jobseekers.

contents outside the official training 'catalogue', a registry of all certified courses and modules. Training content from this catalogue tends to be more general (as opposed to more firm-specific) but sometimes is regarded to be outdated with respect to firm needs, in particular those firms that are more technologically advanced. Finally, according to its regulations, FIG funding could be used to meet the labour-law mandate in Portugal that firms provide their employees at least 35 hours of training per year.[5]

We study the first five annual calls for applications, between 2007 and 2011, each with a total budget of about 40 million euros. Each call was composed of three regional sub-calls (corresponding to regions of different GDP per capita levels and different grant rates). In all cases, applications had to meet a minimum threshold of 50 points (out of 100) or higher (if demand for funding at the minimum quality level exceeded the budget available). The deadline for the submission of applications in each call was around June (of year zero, in the terminology of our analysis below), while the funding results were released in September and the funding was provided for training that started from January of the following year (year one). The exception was the first, 2007 call that had a later deadline for submissions, release of results and start date.[6]

3 Data

Our empirical analysis is based on combining four different data sets. The first is an administrative and confidential data set made available by the FIG agency. This data set lists all firms that submitted applications to the five calls mentioned above, between 2007 and 2011. This data set also includes information about the score of each application as well as funding and training values requested to and provided by FIG.

The second data set is a matched employer-employee panel census, QP (*Quadros de Pessoal* or Personnel Records). This data set, administered by the Ministry of Employment, has been used extensively in different fields given its richness: it includes detailed firm- and worker-level information on all firms based in Portugal that employ at least one worker in (October of) each

[5]According to the Labour Code, such 35 hours of minimum training per year can be deferred or anticipated by one year, so that they are made available over a period of three years on average. Firms can also opt to offer fewer training hours, but in this case employees are entitled to be paid for the hours in which they worked instead of receiving training.

[6]The amount made available to each successful applicant could also be subject to discretionary downward adjustments by the agency managing FIG. See Table B1 for more details regarding each call and Figure A1 for the distribution of scores (centered in terms of the applicable threshold) and the resulting acceptance rates.

year. Some of the firm-level variables we ue are annual sales, number of employees, industry, and region. At the worker level, QP provides information on several variables including age, gender, schooling, and wages (all regarding the workforce of the firm as of October of each year). Moreover, unique firm (and worker) identifiers allow researchers to conduct longitudinal analyses, as we do in this study. We consider the period between 2002 and 2017, including at least five years before FIG in all calls.

We also draw on a novel component of QP, introduced in 2010, about the training of employees conducted by each firm. This data set provides information on the hours of training of each worker of each firm in each year, broken down in terms of the provider of the training (the firm itself or a different organisation, such as a training provider), where the training was conducted (in or outside the firm) and the timing of the training (during working hours or at a different time). We have access to this data for both 2010 and 2011 but not more recent years.[7]

The third data set, SCIE, provides firm-level information on a large number of accounting and financial variables over the period 2004-2017. This data set covers all firms in the country and is compiled by Statistics Portugal. The variables available include gross added value, sales, investment, profits, and income taxes, all of which we use as potential outcomes. We also use a variable indicating the firm's annual expenditure on staff excluding salaries, which includes training costs, and a variable indicating expenditure on training. While the former variable is available since 2004, the latter is only available from 2010, when FIG is running its fourth call.

Our fourth and last data set, CI, provides detailed firm-level information on the international trade of goods. We focus on the exports of each firm, considering their total value as well as the number of (eight-digit) products exported and the number of countries the firm exports those products to, over the period 2002-2017. Similarly to SCIE, CI is collected by Statistics Portugal and covers all firms in the country.

We constructed the data set that we use by merging the FIG admin data to the QP data set ensuring that the confidentiality of the firms was preserved. Moreover, the QP data

[7]Other studies including QP data include Martins (2019), on the effects of trade union representatives on firm performance and the role of training, Martins & Thomas (2021), which examines training and worker interfirm mobility also from a theoretical perspective, and Martins (2009), on firm performance effects of an employment law reform. Note that QP is also used in the monitoring of compliance with labour regulations by the labour inspectorate and firms are consequently subject to heavy fines if the information registered in QP is incorrect.

(together with the FIG data) was merged to the SCIE and CI data sets using common firm identifiers made available by Statistics Portugal. The final version of the data set used in our analysis thus covers the periods 2002-2017 (QP and CI data), 2004-2017 (SCIE, except its training variable, available between 2010 and 2017) and 2010-2011 (individual-level training data). This data refers to the 9,386 firms that applied to FIG over the 2007-2011 period. This time span allows us to measure their post-FIG outcomes over a period of between six (2012-2017) and ten years (2008-2017). This time coverage also allows us to compare their characteristics up to their applications to FIG over an equivalent period of between six (2002-2007) and ten years (2002-2011). In total, each firm can be followed over a period of up to 16 years (2002-2017).

Note that a number of firms (1,087) apply more than once. In this case, if firms apply multiple times but are always unsuccessful, we keep all their applications in our benchmark results. In our robustness section, we check that the results do not change when dropping these firms. If firms apply multiple times but are successful at least once, then we only keep in the data their first successful application. This may underestimate the total amount of the financial support received by some firms but ensures that firms are not placed in the control group or in the 'before' period when they may have already received a grant.

3.1 Descriptive statistics

Tables 1 and 2 present descriptive statistics of our firms, separately for approved and rejected firms. The tables consider the characteristics of the firms only in the years of each call to which a firm applied (2007-2011), i.e. immediately before the FIG funding is made available in case of success (Table B3 presents descriptive statistics for the full sample of 133,051 firm-year observations over the 2002-2017 period).

We find that the two groups of firms exhibit differences that are in several cases significant but certainly not always. Focusing first on the case of the means of approved firms (those that receive and use the training grants from FIG), we find that they have annual sales of 19m euros, employ 112 workers, have capital equity of 4m euros (89% of which held by domestic private investors), and have been operating for about 21 years. All monetary variables were converted to 2017 euros using the consumers' price index and are expressed in millions except training variables (in thousands of euros) and wages (in euros).[8] Considering the average

[8]Note that several variables exhibit a significant level of skewness, leading to means that can be much larger

size of FIG-supported firms and their number as well as the total size of the workforce in the country (around 3m individuals), we note that, over the five years analysed here, FIG supported firms that accounted for well over 10% of the private sector employment of the country.

As to the means of the remaining variables, gross added value is 5.4m, investment is 1.44m, and profits are 0.88m. Non-salary staff expenditure - which may include a number of diverse items on top of training, such as subsidised meals, health and safety expenses, and recruitment and separation costs - corresponds to 0.66m. In contrast, mean training expenditure (a variable available from 2010) is less than five thousand euros, around 1% of non-salary staff expenditure.[9]

Regarding their FIG applications, approved firms request means grants of 97k euros, while 28k are approved (median 19.2k). Again in terms of means, these grants correspond to 125% of the monthly total wagebill of a firm (median 65%). The number of worker-participations in training (including attendance of multiple training modules by the same worker) ranged between 131 (request) and 112 (approved), while the number of training hours ranged between 3.95k (request) and 3.37k (approved), and were conducted over a period of 11 months. Considering the average number of workers per firm, the approved training hours figure amounts to a mean number of training per worker similar to the 35-hour figure established in labour law but would exceed it in the likely case that not all workers participate in FIG funded training. [10]

As to the observable differences between approved and rejected firms, in the year of their applications, the most important differences concern ownership (approved firms are more likely to be owned by private parties) and gross added value (higher for approved firms).

than the medians. For instance, the median firm size is 36.

[9]The most important industries include wholesale, molds, retail and food (corresponding to over 5% of all firms each), while the North and Centre regions (with lower average GDP per capita and higher FIG subsidy rates) cover by far the largest percentage of firms (nearly 80% in total), given the focus of the ESF in less developed regions in the EU. Exports account for nearly 10m euros and involve over 23 different products and eight destinations.As to the firms' workforce, 36% are women, they are 38 years old, have been with the firm for 7.5 years, 69% have open-ended (permanent) contracts, nine years of schooling and are paid 811 and 952 euros per month (base and total pay, respectively).

[10]We also report descriptive statistics regarding individual-level training data that we aggregated to the firm-level, in this case concerning the years of 2010 and 2011 only (QP data set). We find that mean training hours per firm-year are 1.1k, about one third of the training hours funded by FIG, or an average of about ten hours of training per worker per year. Less than half of total training is flexible (possibly firm-specific and non certified) training content, while external organisations provide more than half, and nearly all is provided during working time. On average, only 22 workers (out of a mean of 112) receive training over the two years considered. Again, these figures on training intensity do not necessarily imply non-compliance with the labour law requirement of 35 hours of training per worker per year as firms may anticipate or delay this training requirement or pay the worker for the time that is not spent under training.

There are also some differences in their sectoral distribution, more concentrated in the leading industries mentioned before in the case of approved firms. Their workforces are somewhat more male, have more tenure and less schooling. As to training, approved firms request and (of course) receive more funding from FIG.[11] However, we also note that, under several variables that we consider as proxies for firm performance (e.g., two measures of sales and the employment count), there are no statistically significant differences between the two groups before treatment. This result supports the comparability of treatment and control group in terms of observable variables and is consistent with our common trends assumptions and results discussed below.

Note also that, considering the year of 2008 alone, while firms applying to FIG represent only 0.89% of all 357k firms with employees in the country, they account for 14.9% of all private sector employment and 16.3% of all sales in the private sector (figures from our analysis of population QP data). Applicant firms are also older (median year of foundation of 1992 as opposed to 1999 in the case of non-applicants). The contrast between applicant and non-applicant firms in these different dimensions highlights the non-representative nature of the FIG firms in terms of the full economy and the potential limitations of the external validity of our findings below.

4 Methodology

This paper seeks to understand the effects of a training subsidy on a number of firm-level outcomes. We conduct a difference-in-differences (DiD) analysis (Lechner 2011) by comparing, over time, firms that apply for and receive the FIG training subsidiy against firms that also apply but do not receive such financial support. Identification in this DiD context in predicated on a number of assumptions, namely common trends, but also several other such as stable unit treatment value, exogeneity of conditioning variables, bias stability, and common support.[12]

[11] The amount approved in the case of rejected firms is not zero because a small number of firms drop out from FIG after having their application approved. We use these firms for additional robustness checks described below. However, approved firms request support for fewer workers and fewer hours of training. Importantly, actual training hours and workers under training in 2010 and 2011 (again, in the years in which they apply) are lower in approved firms.

[12] Figure A2 presents the McCrary (2008) analysis of this distribution. The analysis indicates that the distribution of scores is not continuous at the funding threshold thus discouraging a regression discontinuity approach. According to discussions with the FIG agency, the gap in the distribution at the left of the funding threshold may be driven by the re-analysis of a number of marginal applications, following complaints from

The common trend assumption establishes that differences over time in expected potential outcomes under non-treatment are unrelated to group membership (treatment or control). In our specific case, this assumption requires that, in the absence of treatment, subsidised firms would evolve over time in the same way as non-subsidised firms. As we have multiple observations of each firm before treatment, then the common trends assumption can be tested within the model setting chosen, as we do below (e.g. subsection 5.2).[13] Indeed, as indicated above, our data covers a period of between six and ten years before the relevant moment when the subsidy is or is not provided, a large number of years compared to other research based on difference-in-differences. We thus exploit this relatively large number of years to analysing potential 'effects' before the subsidy was provided, which make the common trends assumption more plausible. Tables B4 and B5 and several related figures, all discussed in detail later, present our analysis of such potential differences in the pre-treatment period, showing that these are not statistically significant until the time when the subsidy is provided to selected firms.[14]

As to the remaining identification assumptions, they are not testable to the extent that they depend on unobservable random variables. However, we believe stable unit treatment value would also apply in our case: despite the significant size of the firms supported, representing around 7% of employment and sales, we believe this figure would not be large enough to induce effects on control group firms. As to exogeneity, we allow the programme to have multiple effects and therefore adopt a minimalistic equation, controlling only for time-invariant variables (industry, original firm size, original workforce profile, etc) through firm fixed effects. Indeed, we exploit our panel data to difference out all influences of time constant (additively separable) confounding factors. Moreover, we adopt a conservative approach and do not control for (within-firm) time-varying variables as they may be influenced by the intervention itself (indeed, we will show later that FIG affects several different variables of

such rejected candidates that were subsequently accepted. Our data does not indicate which firms had their scores revised upwards but we conduct a number of robustness checks around this margin and find that this does not affect our results.

[13] According to **?**, 'The most compelling differences-in-differences-type studies report outcomes for treatment and control observations for a period long enough to show the underlying trends, with attention focused on how deviations from trend relate to changes in policy.'

[14] A threat to identification would involve some form of changes in supported firms that take place just before the treatment starts and are not captured in the data available (more generally, there may have been time-varying unobserved differences between firms applying successfully or unsuccessfully). While we cannot rule this out entirely, we believe this would not apply in our case, given the comprehensive nature of our data, measuring training and other investments over the entire year, and the relatively long duration of time required by investment in physical and even human capital. For instance, training courses can require considerable planning (contents, formats, delivery, etc) and be delivered over many months or even one year.

interest). The large number of periods (and the many groups of observations) is also important as it allows more precise estimation and more reliable inference, on top of the testing for the common trend assumption (Lechner 2011). Moreover, we also partial out year-specific influences on the outcomes of interest. Common support is also strengthened through our analysis exclusively of firms that applied to the programme, while also considering different ranges of application scores in Section 6.[15]

Specifically, the model we consider is as follows:

$$Y_{itj} = \sum_{j=-9}^{10} \delta_j I(t;j) + \sum_{j=-9}^{10} \beta_j FIG_i * I(t;j) + \alpha_i + \tau_t + \epsilon_{itj}, \tag{1}$$

in which Y_{itj} is the log of a given outcome of firm i in calendar year t and relative year j (the latter defined in relation to the call year in which firm i applied to FIG). FIG_i is the treatment dummy variable (equal to one in the case of firms that received FIG funding).

The relative year period ranges between -9 (the year 2002 for firms that applied to the 2011 call) or -7 (in the case of the SCIE variables, which are available from 2004) and +10 (the year 2017 for firms that applied to the 2007 call, which have an 'after' period of ten years). The relative year 0 (which is also the benchmark year) corresponds to 2007, 2008, 2009, 2010 or 2011, depending on the call in which firm i submitted its application. $I(t;j)$ is a dummy variable equal to one when year t corresponds to year j (for instance, $I(t;j) = 1$ for all firms that apply to the 2008 call). The τ_t parameters thus capture systematic differences in the underpinning calendar years (2002-2017) and the α_i (the firm fixed effects) control for time-invariant differences of each firm. Critically, the δ_j pick up differences in the relative years -9 to +10 (with respect to the year of each call).

Finally, the key parameters of interest are the β_j, which indicate any systematic differences in Y_{itj} at each relative year between firms that receive FIG funding and those that do not. In the context of the identification discussion above, β_j will indicate the average treatment effect on the treated. As we consider several outcome variables of interest measured over long periods, we present most of our results graphically, focusing on the point estimate of each β_j parameter and its 95% confidence interval, based on standard errors clustered at the

[15] See Murakozy & Telegdy (2020) for a similar empirical approach, which also includes a theoretical discussion. This discussion involves a linkage between a technology upgrading and TFP growth, that may apply the case of FIG as well, in which subsidies may lead to improvements in capital, output and labor productivity growth and ambiguous employment effects.

firm level. In the appendix, we also present the full regression results for the key variables of interest.

5 Main results

5.1 Training outcomes

Our first analysis concerns the effects of FIG on the training conducted by firms. This is motivated by the findings in Leuven & Oosterbeek (2004), Abramovsky et al. (2011) and Schwerdt et al. (2012) of (very) high levels of deadweight in other training programmes, in which training subsidies essentially do not alter the level of training conducted by supported firms (or individuals). Here we investigate this question from different perspectives, exploiting the complementary training variables available in our data set.

First, we consider the accounting and financial information on non-salary staff expenditure, which is available for each firm between 2004 and 2017. We take this variable as a proxy for training, as the latter is one of its components, even if it may represent a small share of its total value, as we discussed when analysing our descriptive statistics (Table 1). Figure 1 presents the results regarding the β_j coefficients from equation 1 (see also column 4 of Table B4). We find that all coefficients before the year when the application are submitted (year 0) are statistically insignificant from zero, which supports the common trends assumption. Moreover, the results also indicate that as soon as the funding is made available (year 1), there is a marked spike in non-salary staff expenditure, of nearly ten percent and statistically significant from zero. This result is largely unchanged for year two after which the point estimates tend to drop while the confidence intervals tend to increase making the resulting estimates statistically insignificant at the end of the period. This result suggests that training has indeed increased in firms that received the FIG grants, when compared to their counterparts that were not successful in their bids.[16]

Second, we consider the more specific training expenditure variable, which is also available for all firms but only from 2010. Given this restriction, we focus on firms that apply to the last two FIG calls, of 2010 and 2011. In these two cases we can observe the training expenditure of each firm in at least one year before the funding was available (the year of 2010 in the

[16]It also suggests that firms that did not decrease their training, when comparing to other firms, once the funding came to an end, as the coefficients do not become negative after the first two years. In other words, firms do not appear to be frontloading their training expenditure as allowed under employment law.

case of the 2010 call) or as many as two years (2010 and 2011, in the case of the 2011 call). Figure 2 presents the results for each call, considering training expenditure both in logs and levels. We find in all cases large increases in training expenditure precisely in the first period when the FIG funding is provided, as in the analysis with the non-salary staff expenditure. However, when using training expenditure, in contrast to non-salary staff expenditure, the effects are shorter-lasting, coming to an end (becoming insignificant) in the third or fourth year following the submission of the application. Note that the funding typically is made available for training that starts in the first months of period one and lasts around 12 months in total, thus covering both years one and two.[17]

Third, we analyse our detailed individual-level training data available for the years of 2010 and 2011, which we aggregated to the firm level. In this case, we consider only the 2010 call, for which we can compare one year in the 'before' period (2010) and one year in the 'after' period (2011). Table 3 presents our first set of results, focusing on three complementary dependent variables (for each firm and year): training duration in total hours, in average hours, and in log total hours. We also break down total training duration in three non-mutually exclusive components (flexible, non-'catalogue' training; training provided by external organisations, namely training providers; and training conducted during the normal work schedule). We use a simplified version of equation 1, including simply an 'after' dummy (for the year 2011), an interaction of that dummy with a 'treated' dummy (for firms supported by FIG), and firm fixed effects.

The results indicate that, in all specifications and dependent variables, FIG participation leads to an economically and statistically significant increase in training. For instance, when considering the first column (total training duration) of Panel A (total hours, in levels) in Table 3, FIG support leads to an increase of 2,492 hours of training compared to firms that are not supported by FIG. This increase can be compared to the average training hours support provided by FIG for this specific call of 3,359 (as described in Table B2, together with several other statistics for both approved and rejected firms in this call). This results

[17]While these results are consistent with a positive effect of FIG on training, it is not clear if firms register subsidised (reimbursed) training expenditure in the accounting variable we are exploiting here. If they do, the increase in training expenditure is of about 8,000 euros per firm (when summing the coefficients over the years in which they are significant), or less than one third of the 28,000 average grant provided - Table 2. If subsidised (reimbursed) training expenditure is not registered by firms in this variable, then the 8,000 could correspond only to the private co-payment required by FIG which would substantially underestimate the increase in training in these firms. Given the uncertainty above, regarding the interpretation of this variable, we conduct our deadweight analysis using the training hours variable discussed next.

in a ratio between training increase and training support of 74%, indicating a deadweight of 26%. However, we take the latter figure as an upper bound of the true deadweight as our effect is measured over one year only (as our QP training hours data is available only over one year in the 'after' period, 2011) while the FIG support could also take place over the following year (2012 in the case of the 2010 call). Indeed, only 46% of the total funding was made available in 2011. If this reflects the distribution of the training hours across the years, then the average training hours supported by FIG in 2011 is 1,545 (46% of 3,359) and the 2,492 hours of training effect actually corresponds to a crowd-in of 38% (1-1,545/2,492).

We also consider the impact of FIG in terms of the number of employees under training - Table 4, Panel D - as an extensive margin of the programme. While we do not find significant results when considering the number of employees per se (column 1), the effects of FIG are significant in the share of the workforce, the log of the number of employees and the log of the share of the workforce (columns 2, 3 and 4). We also consider the two expenditure variables used before (from the SCIE data set) in the specific context of the 2010 call and for the years of 2010 and 2011 alone (Panels E and F, Table 4). This exercise seeks to assess the extent to which these variables (and, in particular, non-salary staff expenditure, which is available for nearly the full period we cover, 2004-2017) can be satisfactory proxies for training hours. We find that they both lead to statistically significant positive coefficients, even if of a much smaller magnitude in the case of non-salary staff expenditure. These results indicate that, even in the case of non-salary staff expenditure, and despite the small percentage of such expenditure that is devoted to training, those variables are likely to be informative regarding changes in training provision.

We conclude that FIG had a significant positive effect on the training conducted by firms and limited deadweight, of not more than 24%, and possibly much less, involving some crowd-in. This result is in contrast to earlier studies about other training programmes, namely Abramovsky et al. (2011) and Schwerdt et al. (2012). The result is particularly noteworthy given the labour law requirement of a minimum amount of training provision by firms and the fact that FIG did not require supported firms to exceed it. Some of the explanations for the limited deadweight found here may include the targeted nature of the programme. Indeed, FIG focused on firms that could benefit from the training support but that would not necessarily conduct the training investment without the grant, given the uncertainty involved in training because of poaching of workers or the sheer difficulty in estimating its returns (even in a context without poaching). The timing of the programme, coinciding with the financial crisis of 2008/9 and the euro sovereign debt crisis of 2011/13, may also have played a role in the limited deadweight found here, as opportunities for borrowing funds from the financial markets to invest in training became more limited, especially in 2011/13.

5.2 Firm performance outcomes

Having established a positive effect of FIG on training, we now consider the wider firm performance implications of the increased levels of training conducted in treated firms. Improvements in the human capital of the workforce following from training may potentially be observed in multiple dimensions of firms. Fortunately, the richness of the data sets that we put together allow us to conduct an extensive examination of several margins.

We start with the case of (annual log) sales, again using the difference-in-differences model of equation 1. The results are depicted in Figure 3 and presented in detail in Tables B4 and B5, as for other key variables. We find that FIG firms follow the same pattern as firms not supported by the programme up to year -1 (2007 to 2011, depending on the specific call applicable in the case of each firm), with very similar point estimates, always close to zero, and wide confidence intervals. This result supports the common trends assumption underpinning difference-in-differences. In other words, prior to treatment, the two groups of firms do not exhibit marked changes in their performance, which supports the assumption that, absent the intervention, they would continue to perform on similar levels and it is because of FIG support and the increased training that follows from it that they paths suddenly diverge. However, the pattern is changed from year one (the first year in which selected firms received FIG grants), first with a borderline statistically significant positive coefficient, and then with significant coefficients for all following years, between about 5% and 15%. The coefficients of the latter years are subject to wider confidence intervals, possibly reflecting the smaller underlying sample sizes (as only the earlier calls can be followed that far), but are still statistically significant.

Our second variable of interest is (log) employment (the headcount of employees as of October of each year). As far as we know, this is the first study that considers the potential effects of training upon employment. However, employment is a potentially relevant variable in this context, as the increased firm productivity that may follow from training may spur firms to both retain their current workers and hire additional staff. Figure 4 presents our results, which indicate again no significant differences over time between FIG supported and rejected firms up to year -1, thus again supporting the common trends assumption underpinning difference-in-differences. However, this pattern is reversed exactly from year 1, when a significant gap of 4% emerges. This significant gap continues at least year 4, when the point estimates remain similar but less precise and generally not significantly different from zero.[18] One may use this estimate to compute a crude measure of the cost per job created by FIG. If one were to divide the 30,000 euros of the average subsidy above by the extra jobs in the average firm that received a grant (111.6 employees) multiplied by the employment effect (4.7% in the third year), this would lead to an average cost per job of 5,750 euros. This is closer to the lower bound of the interval of effects presented in Criscuolo et al. (2019) (page 80, \$3,541 - \$26,572).

Our third variable is (log) gross value added, defined as output (at basic prices) minus intermediate consumption (at purchaser prices). The results - Figure 5 - are very similar to those of sales. We find very little differences between treated and control firms up to treatment (as under the common trends assumption) and a significant gap emerging and growing precisely from the year when the FIG training grants are made available and training is increased, first at 3% and increasing up to 12% around year seven.

An important component of the total sales of FIG firms (both accepted and rejected applicants) was exports. Moreover, the FIG programme also sought to support firms in their progression along the quality ladder towards increased exports value (Bloom et al. forthcoming). Figures 6 and 7 present our results regarding the impact of the additional training supported by FIG on exports, considering its extensive and intensive margins, respectively. We find that FIG had a positive in both cases, even if typically shorter-lived (for only one or two years), while occurring soon after the training was conducted. While the point estimates are large at least in the case of the intensive margin, they are also subject to larger confidence

[18] Firms may also need to hire workers temporarily to replace their permanent staff while they are undergoing training. This may be particularly important when training is conducted during normal working time, as is the case here (Table 3, columns 1 and 4). Note that the QP data that we use to measure employment in firms includes workers under fixed-term contracts but not workers under temporary work arrangements. The latter are registered in QP with the temporary work agencies that officially employ them but we have no information on the firms in which these workers are placed. Replacement of employees under training is more likely to involve temporary worker than fixed-term contracts. Our results are therefore not likely to be driven by worker replacement.

intervals (2% effect by year three in the case of the the extensive status; and a 15% effect already by year one in the case of exports volume, but subject to a large confidence interval). In contrast to the previous variables, we find evidence of a positive trend in the 'before' period, namely between years -9 and -5, but only in the case of export status.

We also consider the case of (labour) productivity, measured here by the ratio of sales and the number of employees (the same variables used above). As both variables exhibit positive effects, it is unclear if FIG may also have improved firms' productivity. Figure 8 indicates that it did, with statistically significant effects from year 4 onwards, with an effect of about 5% and increasing further over the remaining years. Again, differences between the two types of firms were not significant up to year -1 (as under the common trends assumption).

The results are also very similar when restricting our full sample to narrow bands of the scoring range around the funding threshold, an approach that may ensure greater comparability between treated and control firms. For instance, in Figure 9 we derive our results exclusively from a two-bin band on either side of the threshold (i.e. 0 and 2.5 vs -2.5 and -5 in the centered score, which takes only values that are multiples of 2.5, according to the scoring grid of the FIG agency).[19]

In conclusion, we find that the training grants made available by FIG led both to higher levels of training and higher levels of firm performance, as measured by multiple complementary variables. Besides sales and value added, the additional training also improved exports (along both the intensive and extensive margins), productivity and profitability. The effects along the last two dimensions took longer to emerge while the international trade and, to a lesser extent, employment effects proved to be short-lived. The employer effects last least four years, after which they become less precise from a statistical standpoint. However, the main effects on output and value added appear to be cumulative and largely permanent, at least over the long, ten-year period that we analyse with our data.[20]

[19] See Figure A1 for the full distribution of the scores. We also find similar results when we consider instead a four-bin band (i.e. 0 up to 7.5 vs -2.5 up to -10) - Figure A19. This is also the case when we instead exclude firms at the threshold, namely firms with scores of -2.5 or zero - Figure A20.

[20] The positive effects on value added, productivity and exports may also indicate that the increase in sales effect documented above is driven mostly from market expansion and not market stealing. The latter case would involve reduced sales across FIG-rejected firms or third-party firms operating in the same industries as FIG-supported firms.

6 Additional results

We conduct three types of robustness checks, which we present in the following subsections. First, we examine other potential outcomes, again exploiting the richness of our data set. Second, we examine the robustness of our findings. Specifically, we split our main sample in different ways, including across the five calls that are pooled in our main analysis above. We also compare our results across different subsets of firms.

6.1 Other outcomes

The first additional variable that we examine here is non-salary staff expenditure on a per worker basis. Figure A3 presents the results, which are very similar to those based on total expenditure, with large spikes in the first two years, but now immediately followed by insignificant effects. A second variable we consider is again sales but in its version reported in the SCIE data set (while above we use the version reported in the QP data). Figure A4 indicates very similar effects as before. We also consider the case of gross value added per worker, an alternative measure of productivity. We again find a similar pattern as before - Figure A5 - even if subject to less precision than when considering sales per worker.

Investment in human capital through training may also foster investment in physical capital. Figure A6 considers the investment variable available in our accounting data (SCIE), gross fixed capital formation, which we measure as a share of total sales. The results present suggestive evidence that it may also be positively affected by FIG grants, namely with a large point estimate in the second year. However, all point estimates are insignificant at standard confidence levels.

We also consider the case of profitability, using its accounting version available in the SCIE data and considering both whether the firm has positive profits and the the ratio between profits and sales (Figure A6). This variable exhibit a noisy pattern over the period, including large confidence intervals. There is some suggestive evidence of positive effects from year four onwards in the case of the profit share but the coefficients are again not statistically significant at the 95% level. We also find that no significant differences in revenue taxes paid between the two types of firms over the period examined.

An important result of our main analysis was the positive effects of increased training on employment. Here we investigate this finding further by considering its net job creation rate counterpart (defined as the difference in employment in one year compared to the previous, divided by the mean of the two employment levels). We also decompose it between the hiring and separation rate, by drawing on the individual level information in each firm. (We define the hiring rate as the percentage of workers hired between January and October of each year in terms of the mean of total employment over the two years; and the separation rate as the difference between the hiring rate and the net job creation rate.)

Figure A7 presents the results for these three variables. These indicate that net job creation rates increase by around three percentage points (pp) in year 1, while the hiring rate increases by about one pp and the separation rate drops by two pp. We find evidence on common trends between FIG-supported and FIG-rejected firms up to year -1 in the cases of net job creation and hirings and up to year zero in the case of separations. In the first two cases, the coefficients for most of the 'before' period are significantly different than zero but are statistically equal over the eight years covered. In other words, these results do not suggest that there are different trends across the two groups in the before period while, in contrast, there are significant and large changes (in the opposite direction of trends) as soon as the training grant is made available to successful firms.

Significant changes arise in year 1 and until year 3 in the cases of the net job creation rate and the separation rate, and in year 1 alone in the case of the hiring rate. These results indicate that the increase in employment in FIG-supported firms is driven by a combination of increased hirings and reduced separations, but with a stronger contribution from the latter, both in terms of the magnitude of the effect (more than twice larger) and its duration in time (three years compared to only one). Following the additional training provided, firms appear to become more keen and or able to retain their staff, which contributes to a significant boost to the firms' employment. These results support a causal interpretation of our findings of the effect of FIG on firm performance. The increased hirings may arise from a rightward shift in labour demand following from a firm-wide (and not only worker-specific) increase in productivity. Note that FIG also sought to support the training of (senior) managers. In any case, such increased hirings result may suggest a potential role for training grants as hiring subsidies.

To investigate further our employment findings, we also examine several dimensions of the workforce of FIG supported and rejected firms. Figure A8 presents our findings regarding the female share, age, schooling and tenure. First, we find that in all four cases, there are no significant differences between FIG-supported and FIG-rejected firms up to year when the applications are submitted. While this remains true in the 'after' period in the case of gender, the three remaining variables exhibit changes in their profiles as soon as the FIG-supported training is conducted. Average age and average tenure drops - reflecting the increase in hirings -, while schooling increases - reflecting the typically higher schooling levels of younger workers, that are likely to be overrepresented amongst new hires. Some of the latter effect may also stem from higher-level schooling diplomas awarded to individuals previously hired by these firms, in particular those supported by FIG.

Figure A9 considers the wage dimension (both in terms of base and total wages, the latter including overtime, bonuses and other wage components), as well as the nature of the employment contracts (open-ended, as opposed to fixed-term) and the number of hours of work. We find in all cases insignificant effects, both over the 'before' period but also during the years following FIG-supported training, even if point estimates tend to change in the direction of higher wages and fewer hours. Note that these results do not necessarily imply that the individual returns to training are zero as we have identified above important employment effects which could affect the composition of the workforce of each firm. In particular, such composition effects would bias firm averages towards younger, less experienced and lower paid employees.[21]

Firm survival is an additional relevant dimension of firm performance. We examine this dimension by creating a dummy variable equal to one for the years in which each firm is not present in the data, either because it had not yet entered the market or because it had already exited. We then re-estimate our main model of equation 1 using such dummy variable as our dependent variable. Figure A10 presents the results, which indicate that there are no significant differences between the two group of firms over the three years before the FIG award (or not), but lower non-presence before that - i.e. FIG-awarded firms tend to be older than their non-awarded counterparts over this nine-year time window. More importantly, we find that, over the period following the FIG award, recipient firms exhibit a significantly lower probability of non-presence (or exit), up to -12% after ten years.

Finally, we also analysed the potential role of multiple testing, drawing on Jones et al.

[21] Note also that sectoral collective bargaining is pervasive in Portugal as in several other European countries and may result in compressed wage differentials that limit the scope for wages increases, even in the context of increased productivity and profitability (Martins 2019).

(2019), and computing the Bonferroni-Holm, Sidak-Holm and Westfall-Young (Westfall & Young 1993) adjusted p-values. Specifically, we considered the first four DID coefficients (the interactions between the programme dummy and the first four after years), twelve key outcome variables, while using 30 bootstraps. The twelve outcome variables are: log sales, log number of employees, log sales per worker, export status dummy, log exports, log profits, profits per sales, log profits tax, log non salary staff expenditure, log investment, log sales (2nd variable), and log gross added value per worker. The results are presented in Tables B6 and B7 and indicate that, as expected, the number of coefficients that remain significant drops, in the case of Bonferroni-Holm and Sidak-Holm to half (from 28 to 14), although to only two in the more extreme case of Westfall-Young. Importantly, the variables that remain significant under Bonferroni-Holm and Sidak-Holm are key variables, namely training, employment and sales.

6.2 Different subsamples

Our first analysis in this subsection concerns the potential heterogeneity across the different FIG calls that we pooled together in our main analysis above. Here we consider each one of the five calls separately. Part of our motivation stems from the possible interaction between training and the business cycle and the different GDP growth rates in Portugal over the period examined (including -3.1% in 2009 and -1.7% in 2011 and positive rates in the years of the remaining calls). Our analysis is focused on four main outcome variables: sales, employment, added value, and non-salary staff expenditure. The results are again based on equation 1, except that calendar year dummy variables are excluded: unlike when we pool the different calls in the results of Section 5, now each 'relative year' j also corresponds to a specific calendar year t. This also implies that the time windows considered for each call vary - as we move towards more recent calls, we examine longer 'before' periods and shorter 'after' periods.

The results are presented in Figures A11, A12, A13, A14, A15. As sample sizes drop, the precision of some of our estimates also declines. This is clear in the first call, which is also the one with fewer applicants and successful firms. However, even in this case (Figure A11), we find positive sales and added value effects, even if only materialising later, from years 6 or 7 (2013 or later). While employment effects are not significant in this case, non-salary staff expenditure is, although only in years 2 and 3 (2009 and 2010).[22]

[22]Note that the applications deadline for this call was set in early 2008, implying that funding was conducted

The results for the 2008 call are more precise, indicating significant added value effects from year two (2010) and significant employment and non-salary staff expenditure from year one (2009). In contrast, in the case of the 2009 call, we do not find significant effects in any variable, except in the case of non-salary staff expenditure. Finally, in the cases of the 2010 and 2011 calls (Figures A14 and A15), we find again significant effects in all variables from year one (and insignificant differences in all years in the 'before' period).

In conclusion, we find a remarkable degree of similarity in the results across the five calls, with the exception of 2009 - although even in this case non-salary staff expenditure also increases as in the other calls. The 2009 call funded training that was conducted in a year of economic growth (2010), while all other calls, except 2007, funded training conducted in years of economic contraction. While only suggestive, this relationship may indicate that training delivers higher returns for firms when conducted in times of economic downturn. This could be driven by lower opportunity costs from lost production and sales while workers are participating in training session. This result would mirror similar findings in the case of the training of jobseekers (Lechner & Wunsch 2009). Other explanations for our results involve the diminished opportunities for trained workers in terms of employment in other firms during recessions, particularly at higher wages, and the additional financial market restrictions that applied during both downturns (making it very unlikely that these firms would have invested in training in the absence of the grants). The latter point highlights some potential overlap between training grants and short-time work schemes (Cahuc et al. 2018). In any case, these results highlight a novel type of 'lock-in effect', here in the context of employed individuals. This is in contrast to the training lock-in observed for unemployed jobseekers, as spending time in training can have a negative effect on the time spent searching for jobs and on transitions to employment, at least over the short run.

As discussed before, there is a modest degree of firm exit in our sample. We investigate the role of this in our findings by comparing results for firms that are present in all years (2002-2017) - Figure A16 - and firms that enter the market after 2002 or leave it before 2017 - Figure A17. We find in both cases the same patterns that we observed in our main results, namely positive effects from FIG on sales, employees, added value and non-salary staff expenditure from year one onwards (or soon after year one), without any statistically

from mid 2008, which will explain that the effects on non-salary staff expenditure, our proxy for training expenditure, and, to a lesser extent, sales and value added also emerge later.

significant differences up to year zero.

An important additional robustness check follows from redefining our control group to include exclusively the (423) firms that received a positive score (at or above the funding threshold) but declined to accept the funding. Their decision may have been influenced by changes in their training projects or business priorities. These firms may be regarded as a more comparable control group than our original one in the sense that their applications were regarded to be of a higher quality than those of rejected applicants. (Leuven & Oosterbeek (2008) follow a similar approach in their study of the wage returns to training amongst a sample of Dutch workers.) Indeed, our description of the resulting samples in Tables B8 and B9 indicate fewer observable differences between the two groups of firms. Our results - Figure A18 - are again very similar to the benchmark case, with positive effects in the four key variables starting again at the timing of FIG support and no statistical differences up to that point.

Our final robustness check in this subsection concerns the role of the firms that apply (unsuccessfully) more than once to FIG calls. In our benchmark sample criteria, we keep these firms in the control group of each call in which they apply. Here we conduct our analysis excluding these firms, i.e. restricting our control group to firms that apply (unsuccessfully) only once. Figure A21 presents the results, which are again very similar to our benchmark findings.

6.3 Heterogeneity analysis

In our last subsection, we examine the effects of FIG-induced training upon different types of our firms. First, we consider the role of the sector, comparing the cases of manufacturing and services - Figure A22. While we find that our main results apply equally in the two sectors, they are stronger in manufacturing, both in terms of their size and of the speed at which they emerge. This result may indicate that training in manufacturing tends to be more effective, perhaps because of its possibly stronger load in cognitive elements when compared to training in services.

Next we compare firms of different size, considering their size in the year when they submit their applications and dividing our sample at the median of 28 employees. Firm size may also be regarded as a proxy for financial constraints, as larger firms typically have more means to fund their activities, including training. Figure A23 indicates that, consistent with the role of financial constraints, the effects of FIG funding were larger in raising non-salary staff expenditure in smaller firms. The effects on firm performance are also larger in smaller firms.

Another potential driver of our results is the different level of quality of the submissions by interested firms. We examine this by comparing the results in our key variables for firms that applied to calls that had a threshold higher than the minimum one (50) and the level immediately above (52.5). We find - see Figure A24 - that both the non-salary staff expenditure and firm performance effects are stronger amongst firms that were subject to a higher acceptance threshold.[23]

Second, we consider the role of worker attributes aggregated at the firm level. We consider different dimensions and consider their average per firm in the year when they submit their FIG application. We then split firms in terms of the resulting median value of the resulting distribution or an alternative threshold. Figure A26 considers the nine years of schooling threshold that corresponds to basic and compulsory schooling since the early 1990s until recently (several firms still happen to employ a large share of their workforce with lower levels of schooling, in particular those with an older workforce). We find again the same range of qualitative effects in the two types of firms but stronger effects amongst low-schooling workforce firms, including in terms of employment. This result may suggest that training can add more value when delivered to individuals with lower schooling levels.

When considering the case of age, splitting the data at the median age of 38.25, we find similar positive findings across all variables for both types of firms, but stronger effects for firms with older workforces (typically also firms with lower schooling). Finally, Figure A28 presents the case of gender, comparing firms with a relatively high share of women (above 33% in our data) and those with a lower share. Again we obtain very similar results, for both types of firms, as in our benchmark findings based on the full sample.

7 Concluding remarks

This paper estimated the effects of employee training on firm performance using a quasi-experimental approach. We draw on variation in training hours and expenditure across firms

[23] We also consider the case of exports, comparing firms that export in the year when they apply to FIG and those that do not export at that time (and again using the full data set). The results - Figure A25 - again indicate that FIG effects emerge in both types of firms, without large differences between the two groups of firms.

driven by a large training grants programme supported by the European Social Fund, FIG, and rich longitudinal data sets comparing successful and unsuccessful applicants. First, we find that deadweight losses are limited, at no more and possibly much less than 24%. Second, several dimensions of firm performance are impacted positively by the increase in training driven by the programme: sales, value added, employment, productivity, and exports all increase following the additional training conducted by firms.

Moreover, the magnitude of the firm performance effects is typically economically large, at around 10%, as in the cases of sales, gross value added, and sales per worker. In the cases of other variables, the effects are smaller but still sizable, at around 5% (employment and firm survival), at least in some periods. Exports are also positively affected but these effects are less precise and typically significant only over a small number of years. Firm survival is also positively affected by training.

We also conducted a number of checks that we found to further support the robustness of our findings - while also raising a number of questions for further research. We highlight three examples. First, we decomposed our novel employment effects of training presented here and found that they are driven both by increased hirings and reduced separations, with a stronger contribution from the latter. This result suggests that training grants can also play a role of an active/passive labour market policy, similar to that of short-time work schemes, in increasing the resilience of existing jobs. This interpretation is further supported by the fact that the many positive effects of FIG, including on employment, are stronger in periods of recession. This finding highlights a novel type of 'lock-in effect', here in the context of employed individuals, in contrast to the training lock-in observed for unemployed jobseekers (Lechner & Wunsch 2009). (A related but different question, which we do not examine here, concerns the potential for spillovers to other firms (Criscuolo et al. 2019): these could however be negative, involving some form of market stealing, or positive, namely through mobility of trained workers.)

Second, we did not find significant differences between treated and control firms in the 'before' period in almost all of the large number of potential outcome variables considered. In some cases, we also did not find significant differences in the 'after' period, namely for firm-level wages, despite the positive effects on multiple dimensions of firm performance, including productivity. As mentioned above, this result of no effects on wages does not necessarily imply that the worker-level returns to training are zero since we also found that training has a positive effect both on employment and on hirings. These latter two effects may create composition biases as new hires will typically be paid lower wages, depressing the average wage in the firm. This may also explain at least part of the gaps between productivity and wage premiums of training that were presented in previous research (Konings & Vanormelingen 2015), in which productivity premiums tend to be much larger than the corresponding wage premiums. We plan to investigate this in more detail in future research, drawing on the individual-level dimension of our data.

Finally, we found that training does not have a weaker effect for firms with less educated workforces. In some cases, including employment, the effects of training are even stronger for such firms. While further research here is required, this finding suggests that training may not only have a positive contribution on efficiency - it may also contribute towards the employability of the less educated, with positive effects on equity. This possibility - and the resulting implications regarding the economic and social contributions of training - may be particularly important as the world of work is undergoing major transformations driven by new technologies and the pandemic crisis.

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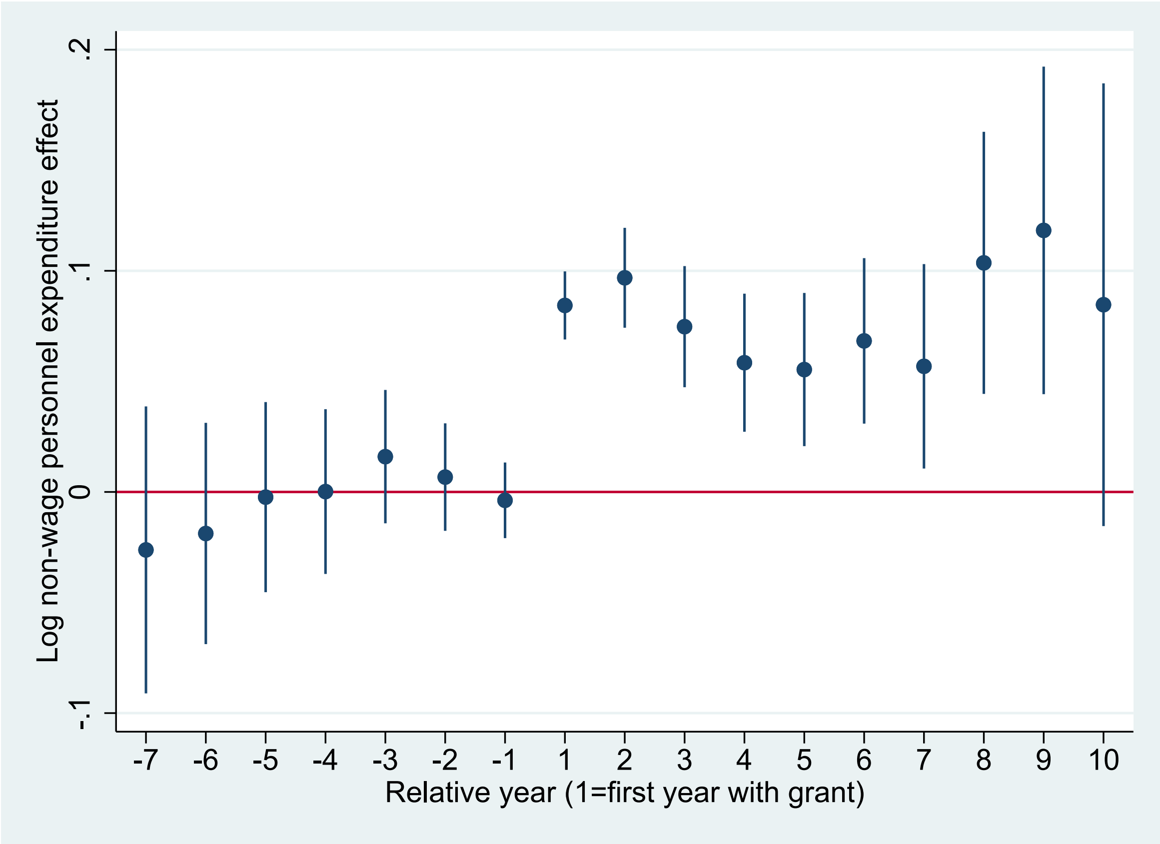
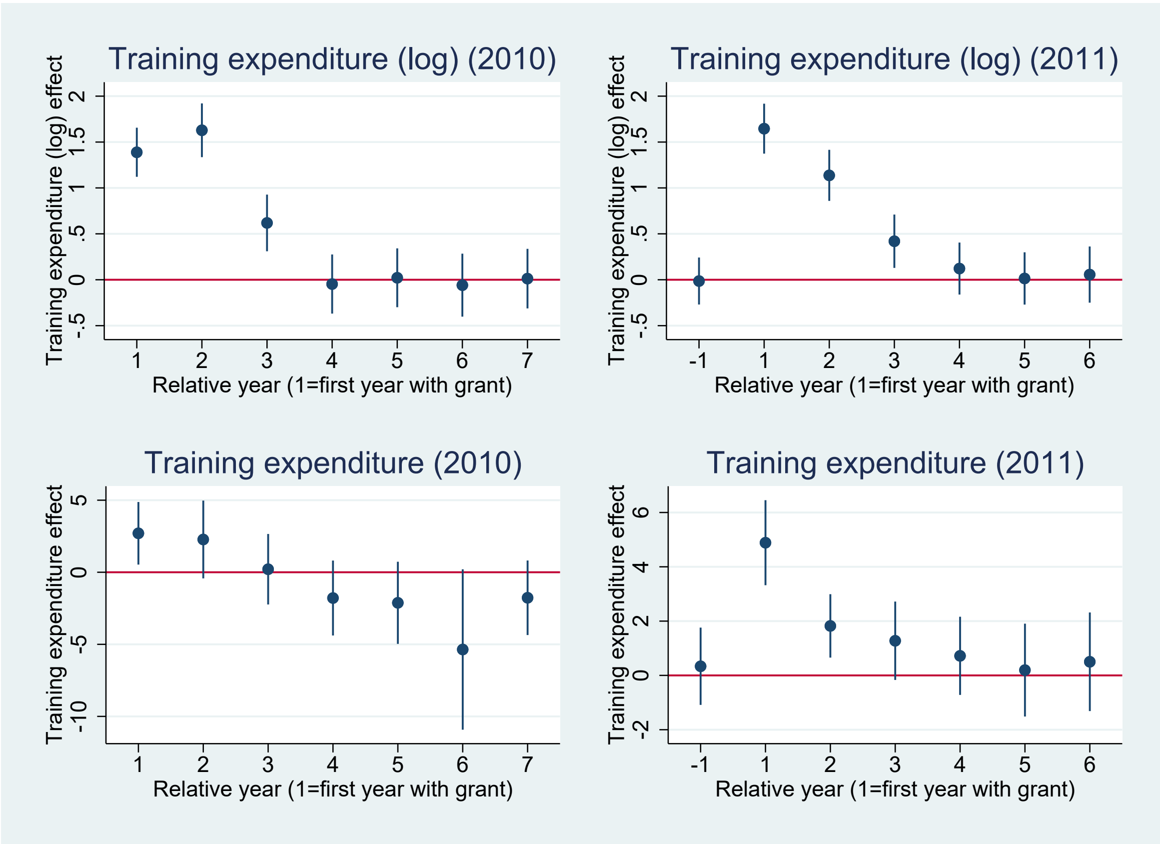
Figure 1: **DID effects: Log non-salary staff expenditure**



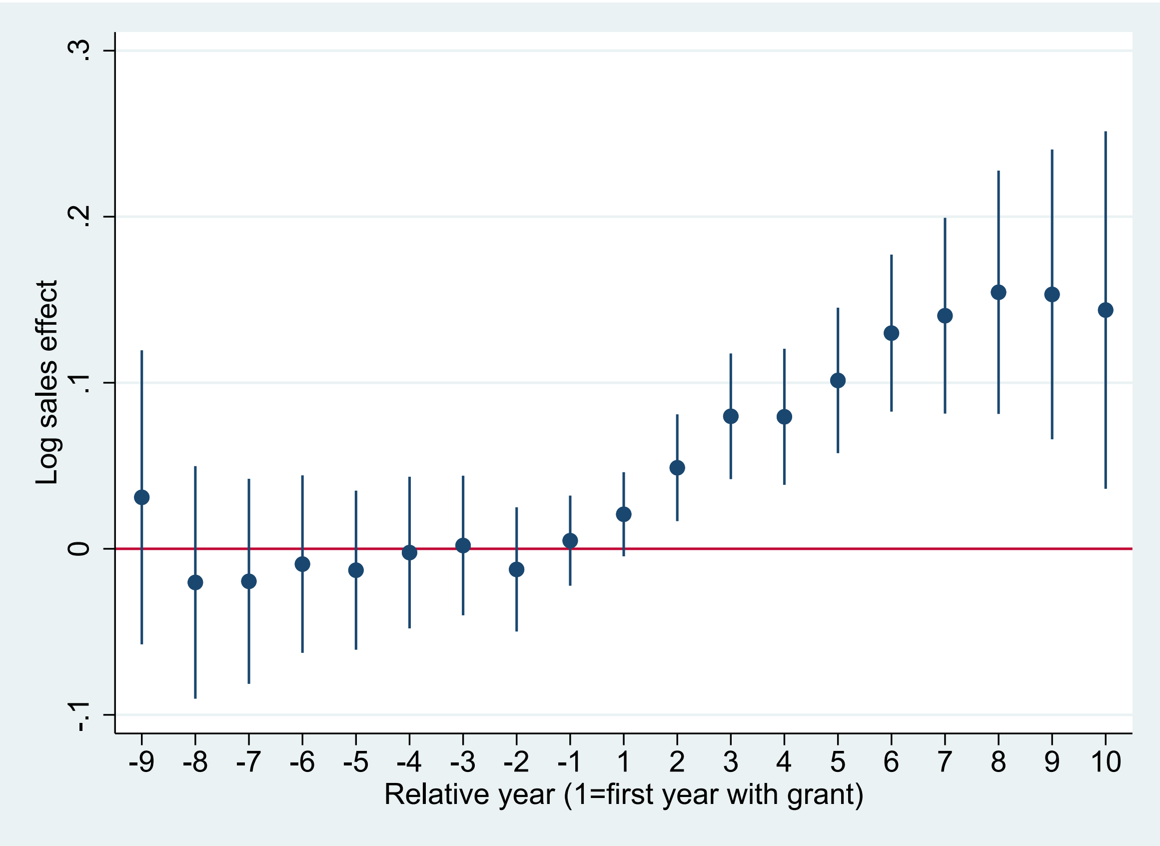
Notes: The dependent variable is the log of each firm's annual expenditure on staff except salaries. Difference-in-differences model, including firm and year fixed effects. The full results including number of observations can be found in Tables B4 and B5. The control group is composed of firms that submitted an application but were rejected (or dropped out). Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call): 1 denotes the first year when the funding is made available, 2 the year after that and so on while -1 denotes the year before the application for funding is submitted, -2 denotes the year before that and so on. In the case of QP or CI variables, X ranges between -9 and 10, covering the period 2002-2017; in the case of SCIE (accounting) variables, X ranges between -7 and 10, covering the period 2004-2017. Standard errors clustered at the firm level.

Figure 2: **DID effects - Training expenditure, 2010 and 2011 calls, 2010-2017**



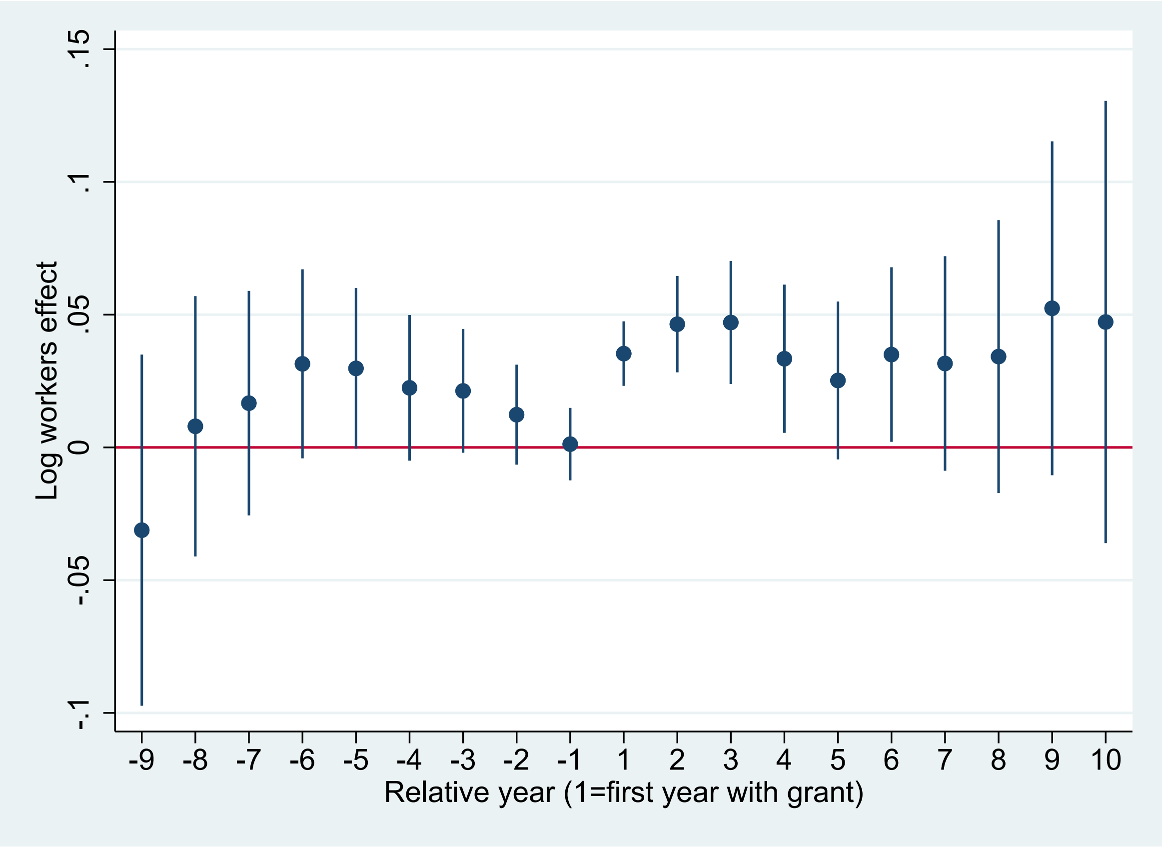
Notes: The dependent variable is the log or level of each firm's annual expenditure on training. This variable is available only from 2010. Difference-in-differences model, including firm and year fixed effects. The control group is composed of firms that submitted an application but were rejected (or dropped out). Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call): 1 denotes the first year when the funding is made available, 2 the year after that and so on while -1 denotes the year before the application for funding is submitted, -2 denotes the year before that and so on. Standard errors clustered at the firm level.

Figure 3: **DID effects: Log sales**



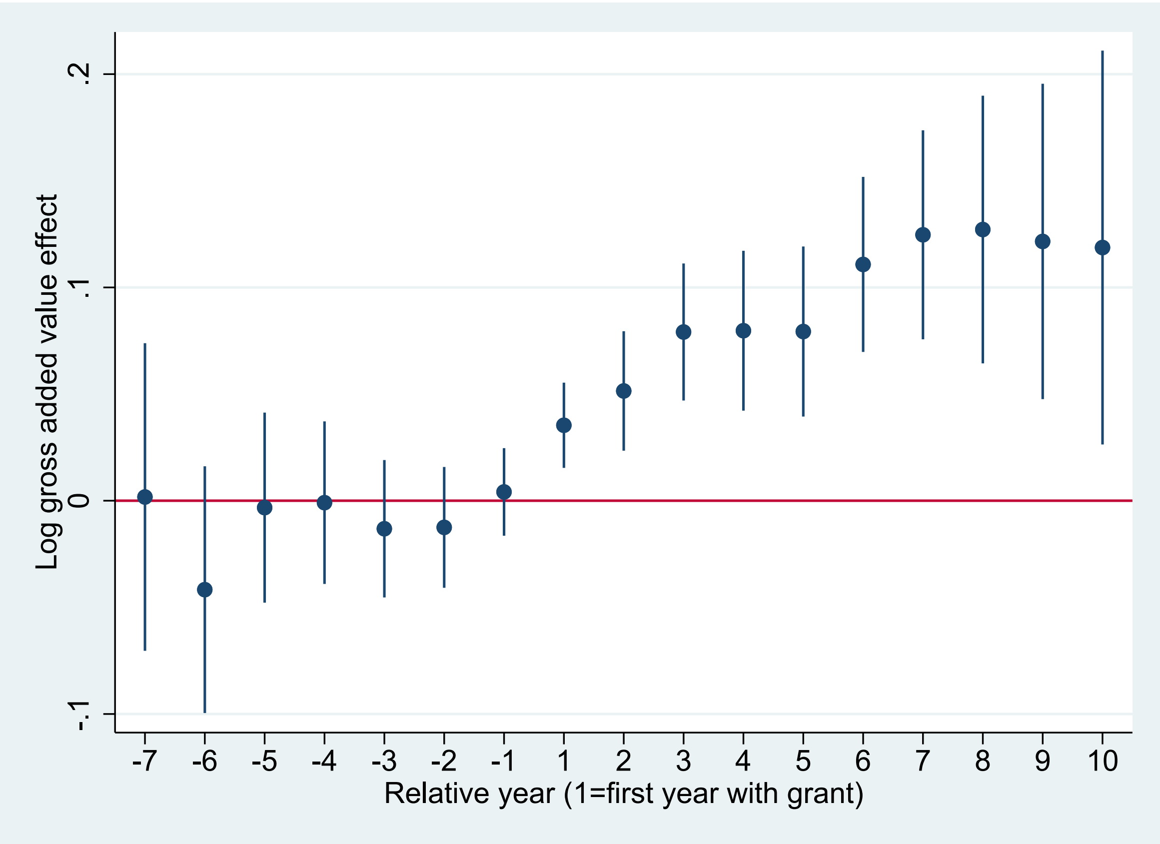
Notes: The dependent variable is the log of each firm's annual sales. Source: QP data set. See notes to Figure 1. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure 4: **DID effects: Log number of employees**



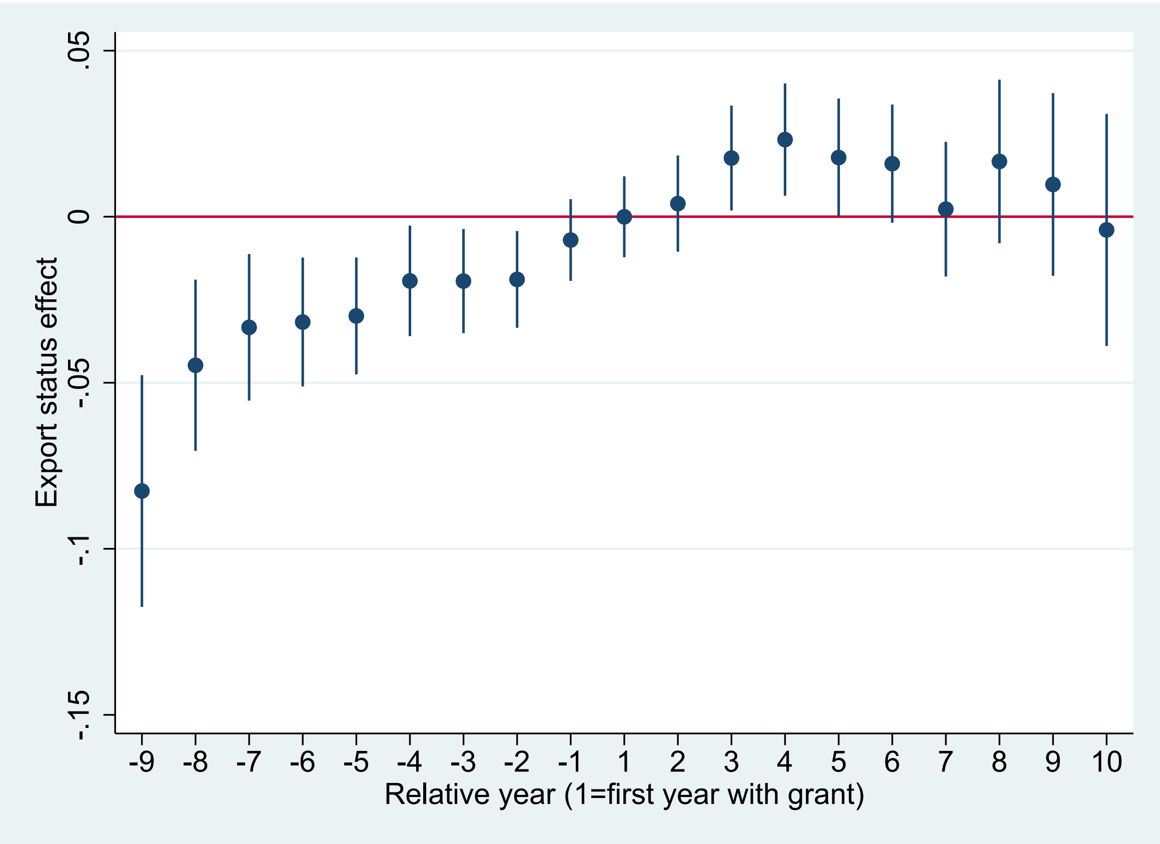
Notes: The dependent variable is the log of each firm's total employment as of October of each year. Source: QP data set. See notes to Figure 1. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure 5: **DID effects: Log gross value added**



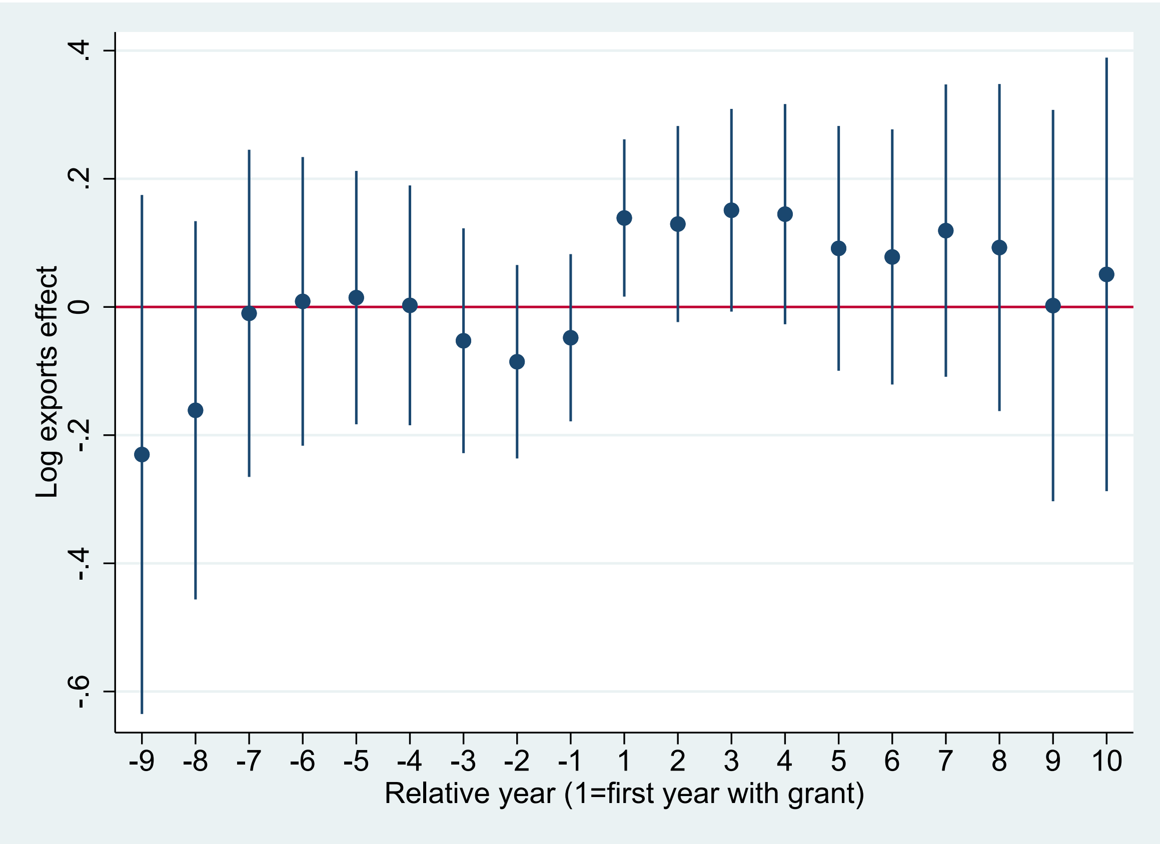
Notes: The dependent variable is the log of each firm's gross value added. Source: SCIE data set. See notes to Figure 1. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure 6: **DID effects: Export status**



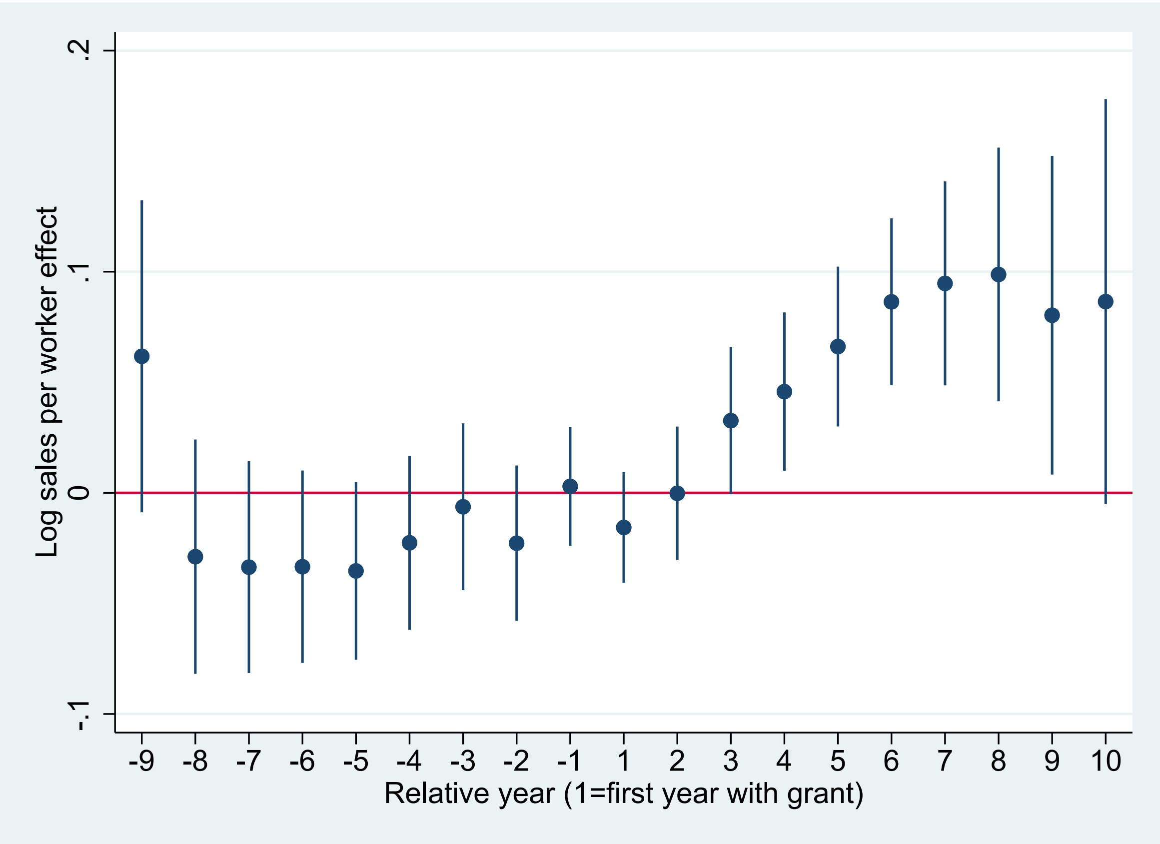
Notes: The dependent variable is a dummy variable equal to one if the firm exports at least one euro in the year. Source: CI data set. See notes to Figure 1. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure 7: **DID effects: Log exports volume**



Notes: The dependent variable is the log of the firm's exports. The sample is restricted to firm-years in which exports are greater than zero. Source: CI data set. See notes to Figure 1. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure 8: **DID effects: Log sales per worker**



Notes: The dependent variable is the log of the ratio of total sales (QP) by total employment (QP). See notes to Figure 1. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure 9: **DID effects - Firms within 2.5 points of funding threshold**

Notes: The figures are based on a subset of firms with application scores within 2.5 points of funding threshold. The number of observations used in the estimations is 16,269. The dependent variables are (clockwise, from top left corner): Net job creation rate (the ratio between the employment change between year t and year $t-1$ and the average employment of both years), the hiring rate (the ratio between the number of workers hired in year t by the average employment of years t and $t-1$) and the separation rate (the ratio between the number of workers that left the firm in year t the average employment of years t and $t-1$). All variables computed using the QP data. Each figure corresponds to a separate estimation of a difference-in-differences model. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Table 1: Descriptive statistics, All applicants, Application year (1/2)

	(1)		(2)		(3)	
	Approved		Rejected		Difference	
	Mean	SD	Mean	SD	b	t
Total sales	19.49	138.94	14.64	183.38	-4.86	(-1.45)
Number of employees	111.66	480.61	109.44	603.76	-2.21	(-0.20)
Capital equity	4.01	40.99	3.49	67.48	-0.52	(-0.47)
Domestic private share	89.49	29.79	82.13	37.72	-7.35***	(-10.47)
Foreign share	6.57	23.83	4.89	20.81	-1.68***	(-3.48)
Firm age	21.35	22.77	21.58	42.65	0.23	(0.34)
Gross added value	5.37	41.36	3.30	19.72	-2.07**	(-2.75)
Total sales (2)	19.76	112.57	15.22	157.01	-4.54	(-1.55)
Investment	1.44	21.80	0.61	23.05	-0.83	(-1.69)
Profits	0.88	13.68	0.43	11.36	-0.46	(-1.62)
Income taxes paid	0.28	3.73	0.11	1.57	-0.17*	(-2.50)
Non-salary staff expenditure	0.66	4.74	0.46	2.20	-0.20*	(-2.32)
Training expenditure	4.98	30.49	4.03	29.01	-0.96	(-1.02)
Food	0.05		0.03		-0.02***	(-4.49)
Clothing	0.04		0.02		-0.01***	(-3.74)
Ceramics	0.04		0.02		-0.02***	(-5.78)
Molds	0.07		0.04		-0.03***	(-5.86)
Construction	0.04		0.05		0.00	(0.92)
Electric appliances	0.04		0.04		0.00	(0.41)
Wholesale	0.11		0.09		-0.02***	(-3.67)
Retail	0.06		0.07		0.01**	(2.83)
Transport	0.03		0.03		-0.01	(-1.70)
North region	0.46		0.42		-0.04***	(-3.81)
Centre region	0.33		0.34		0.01	(1.39)
Lisbon region	0.13		0.16		0.03***	(3.66)
Exports	9.90	54.07	8.42	93.14	-1.47	(-0.52)
N. of products exported	23.43	50.31	24.04	68.97	0.61	(0.27)
N. of countries exported to	8.17	10.82	6.20	9.08	-1.97***	(-5.34)
Observations	3581		5805		9386	

Notes: All statistics refer to the firms observed in the year before the funding starts in the call of the application (2007 to 2011). All monetary variables are measured in millions of 2017 euros, except training funding (thousands of 2017 euros) and salaries (2017 euros). Sales (exports) denotes the total sales (total sales abroad) over the year. Number of employees refers to the employment of the firm in October of the year (including fixed term contracts but not temporary work). Domestic private equity share is the percentage of total equity that is held by private domestic investors. Foreign share is the percentage of total equity that is held by foreign investors. N. of products (countries) exported is the number of products (countries) the firm exports (to) over the year. The first group of variables are obtained from the QP data set, the second from the SCIE data set, and the third from the CI data set.

Table 2: Descriptive statistics, All applicants, Application year (2/2)

	(1)		(2)		(3)	
	Approved		Rejected		Difference	
	Mean	SD	Mean	SD	b	t
Employees' female share	0.36	0.28	0.44	0.31	0.08***	(12.92)
Employees' age	38.35	4.73	38.17	5.05	-0.18	(-1.75)
Employees' tenure	7.58	5.15	6.79	6.10	-0.79***	(-6.72)
Employees' open-ended contract	0.69	0.26	0.68	0.27	-0.00	(-0.79)
Employees' schooling	9.04	2.29	9.76	2.75	0.72***	(13.72)
Employees' base wage	810.85	421.55	817.77	695.53	6.92	(0.60)
Employees' total wage	952.32	473.77	946.30	733.92	-6.01	(-0.48)
Training funding requested	96.80	278.35	78.23	182.06	-18.57***	(-3.55)
Training funding approved	27.79	35.77	1.69	8.35	-26.10***	(-42.95)
Subsidy (wagebill) rate	1.25	5.48	0.11	0.75	-1.14***	(-12.41)
Workers to train request	130.57	189.92	159.39	275.83	28.82***	(5.99)
Workers to train approved	111.81	140.05	0.00	0.00	-111.81***	(-47.77)
Training hours request	3955.13	6690.82	4941.57	10781.12	986.44***	(5.47)
Training hours approved	3371.67	4173.90	0.00	0.00	-3371.67***	(-48.34)
Duration of training (months)	11.39	6.79	10.74	5.19	-0.66***	(-4.96)
Training hours (2011 & 2011)	1149.19	5589.43	1831.11	16018.37	681.92*	(2.09)
Non-catalogue training	441.58	4941.42	947.88	12337.69	506.30	(1.95)
Externals-provided training	674.97	2290.85	838.73	4910.47	163.76	(1.52)
Working-time training	965.94	5497.24	1606.61	15728.52	640.67*	(2.00)
Workers under training	22.64	132.05	51.83	669.94	29.19**	(3.22)
Observations	3581		5805		9386	

Notes: See notes to Table 1. Tenure is measured in years with the firm. Schooling is measured in years. Wages are monthly. The first and third groups of variables are obtained from the QP data set, the second from FIG administrative data. The third group of variables refers to 2010 and 2011 only. Subsidy (wagebill) rate indicates the ratio between the total grant and the wagebill of the firm.

Table 3: Training effects, 2010 and 2011, 2010 call, Different types (1/2)

	(1)	(2)	(3)	(4)
	All training	Non-catalogue training	Externals-provided training	Working-time training
Panel A - Duration in total hours (per firm)				
Treated-After	2491.5	1934.5	1455.1	2041.8
	(859.7)***	(863.9)**	(178.8)***	(832.7)**
After	-823.9	-907.5	-332.7	-739.5
	(725.2)	(751.3)	(129.1)***	(714.2)
Const.	2018.6	1249.8	1004.2	1760.0
	(241.4)***	(246.7)***	(46.4)***	(236.0)***
Obs.	3733	3733	3733	3733
R^2	.68	.61	.86	.68
Panel B - Duration in average hours per person (per firm)				
Treated-After	49.9	21.9	50.0	39.8
	(12.1)***	(7.5)***	(12.0)***	(12.0)***
After	-2.1	-.8	-2.4	-1.1
	(1.3)*	(.8)	(1.1)**	(1.0)
Const.	16.3	4.3	12.4	11.1
	(2.3)***	(1.4)***	(2.3)***	(2.3)***
Obs.	3733	3733	3733	3733
R^2	.51	.51	.51	.51
Panel C - Duration in log total hours (per firm)				
Treated-After	.806	.357	1.098	.743
	(.072)***	(.154)**	(.081)***	(.085)***
After	-.215	-.212	-.389	-.168
	(.053)***	(.118)*	(.061)***	(.064)***
Const.	6.750	6.786	6.468	6.527
	(.025)***	(.051)***	(.028)***	(.029)***
Obs.	3683	1510	3491	3188
R^2	.858	.892	.826	.87

Notes: Calculations based on training data from the QP data set referring to all months of the years of 2010 and 2011. All data aggregated from the worker level to the firm level. The variables in columns 2, 3 and 4 are not necessarily mutually exclusive. The sample is restricted to the years of 2010 and 2011 and to firms that applied to the 2010 FIG call. Difference-in-differences model, including firm fixed effects. The control group is composed of firms that submitted an application but were rejected (or dropped out).

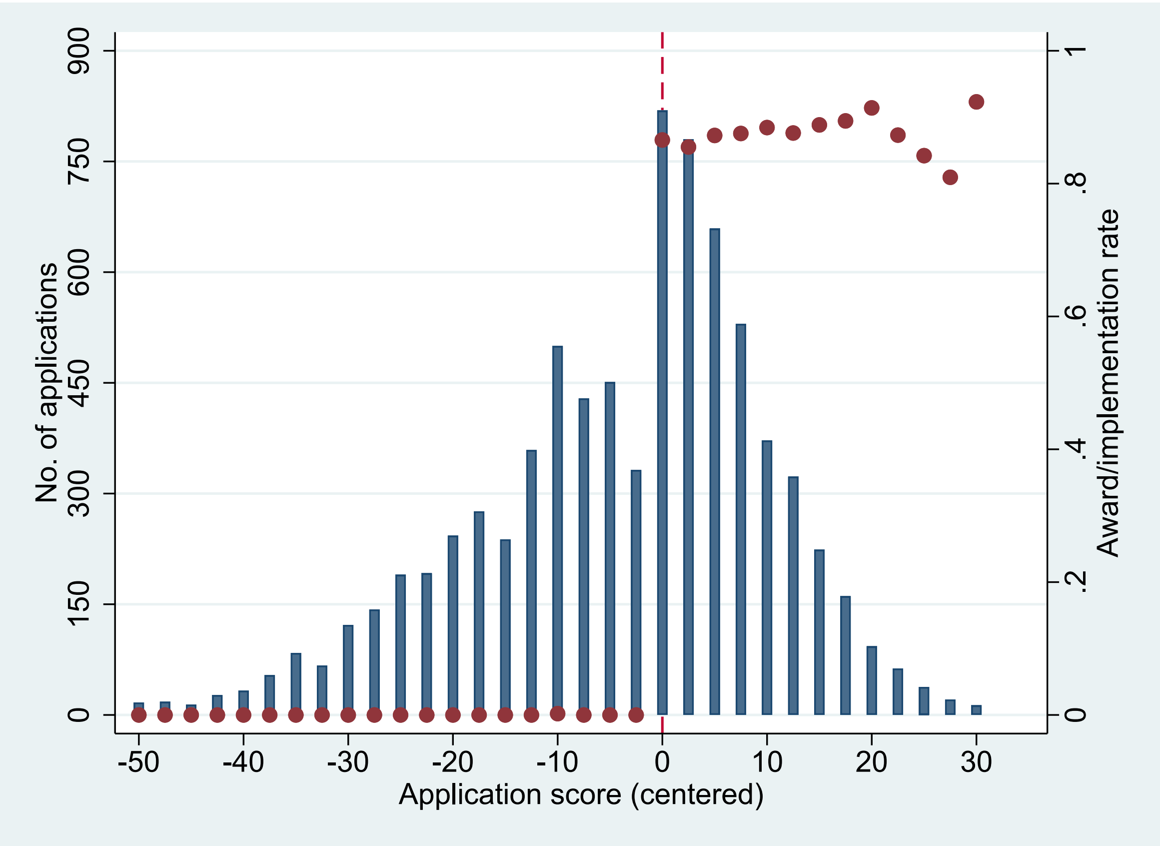
Table 4: Training effects, 2010 and 2011, 2010 call, Workers and Expenditure (2/2)

	(1)	(2)	(3)	(4)
	Level	Per worker	Log	Log per worker
Panel D - Employees under training				
Treated-After	-7.027	.200	.265	.248
	(14.401)	(.117)*	(.061)***	(.062)***
After	17.553	.094	.404	.414
	(14.248)	(.026)***	(.038)***	(.038)***
Const.	70.380	.722	2.681	-.689
	(4.643)***	(.022)***	(.015)***	(.015)***
Obs.	4356	4356	3733	3733
R^2	.948	.52	.839	.64
Panel E - Non-salary staff expenditure				
Treated-After	.040	.0006	.093	.068
	(.021)*	(.0006)	(.014)***	(.017)***
After	-.028	.0003	-.006	.014
	(.020)	(.0003)	(.010)	(.011)
Const.	.440	.004	-2.389	-5.657
	(.006)***	(.0001)***	(.004)***	(.004)***
Obs.	4000	4000	3976	3976
R^2	.995	.57	.988	.891
Panel F - Training expenditure				
Treated-After	2.769	.128	1.288	1.234
	(1.118)**	(.029)***	(.143)***	(.144)***
After	-.226	-.009	-.043	-.004
	(.341)	(.007)	(.092)	(.093)
Const.	4.832	.068	.944	-3.039
	(.228)***	(.006)***	(.035)***	(.036)***
Obs.	4000	4000	1000	1000
R^2	.875	.695	.834	.792

Notes: See notes to Table 3. Panel D uses QP data as in Panels A to C of Table 4. Panels E and F uses SCIE data. Difference-in-differences model, including firm fixed effects. The control group is composed of firms that submitted an application but were rejected (or dropped out).

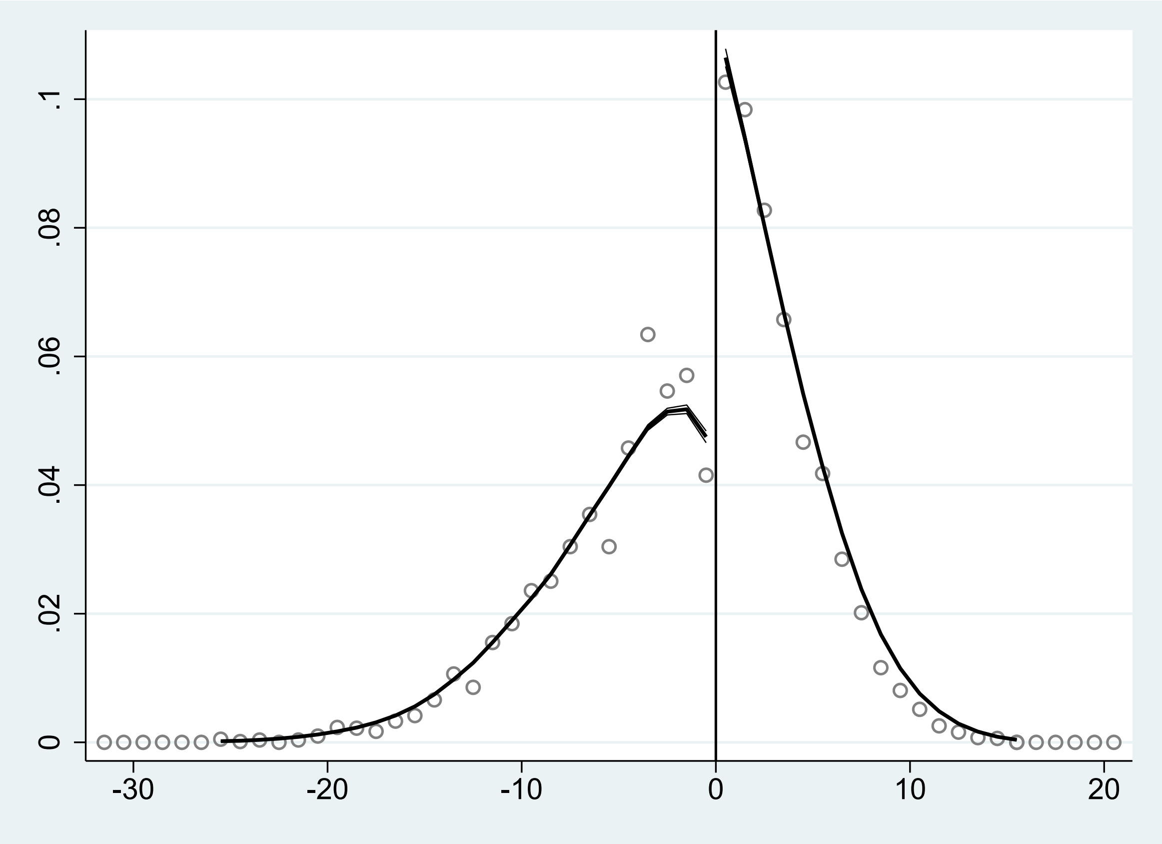
A Appendix: Supplementary Figures and Tables

Figure A1: **Probability of treatment and number of observations by (centered) application score**



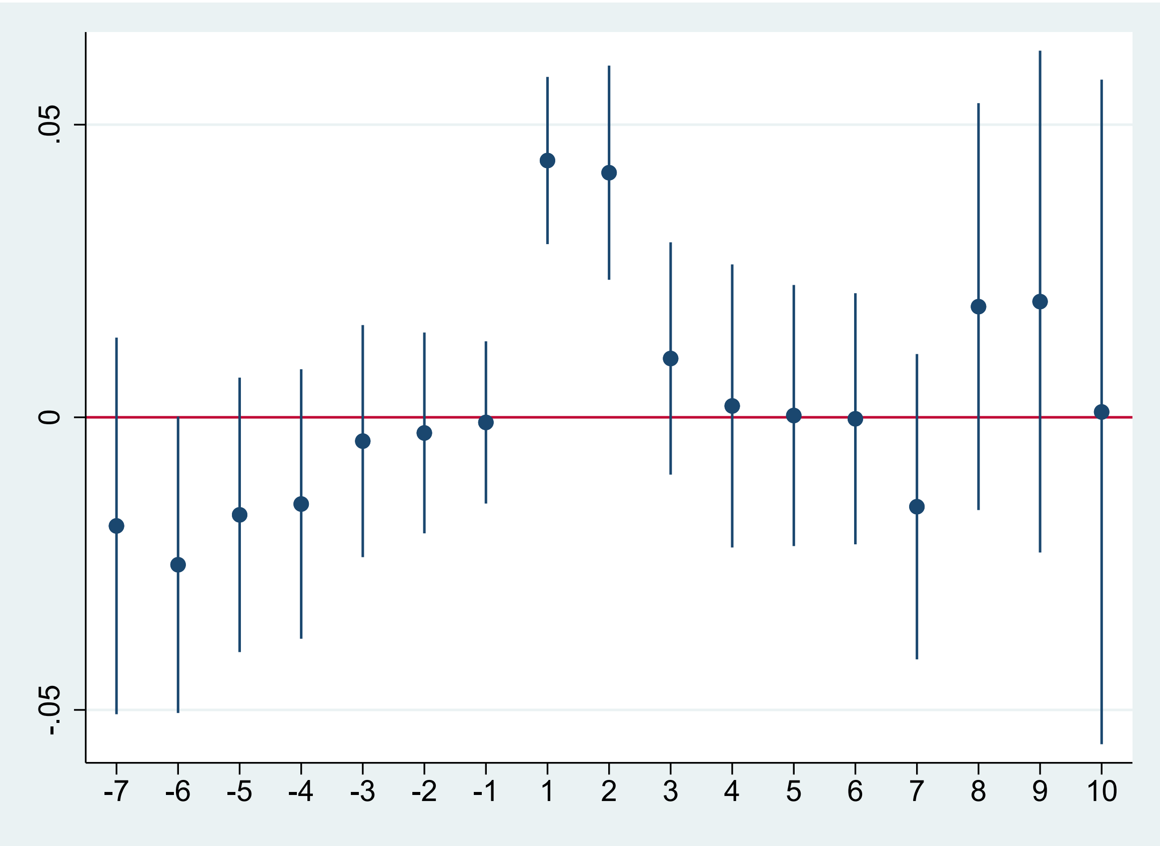
Notes: The horizontal axis indicates the (centered) values of the application score. The left vertical axis (and the bars) indicate the number of firms at each application score. The right vertical axis (and the dots) indicate the percentage of firms with each application score that were accepted and implemented their training project.

Figure A2: **McCrary density analysis**



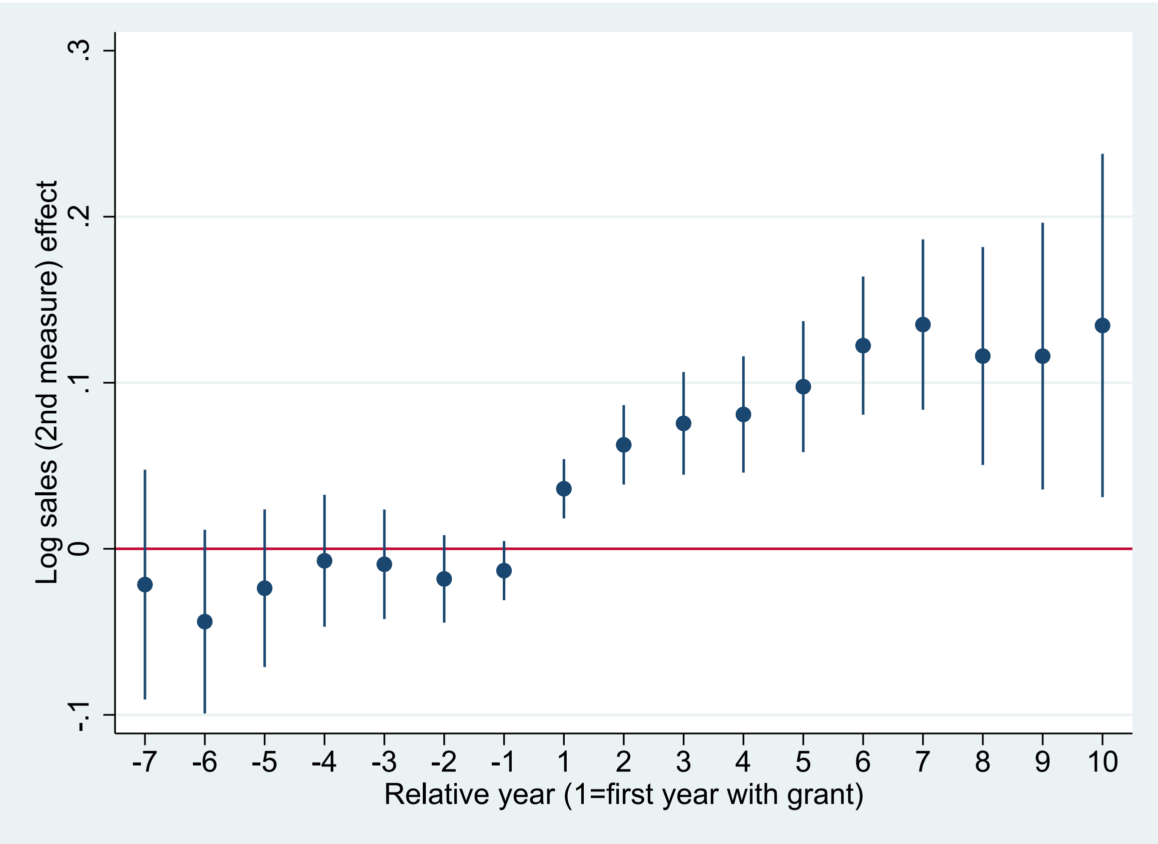
Notes: The figure is based on the data underpinning Figure A1 and the method in McCrary (2008). The scores were divided by 2.5 (the unit used in the original scoring).

Figure A3: **DID effects: Log non-salary staff expenditure per worker**



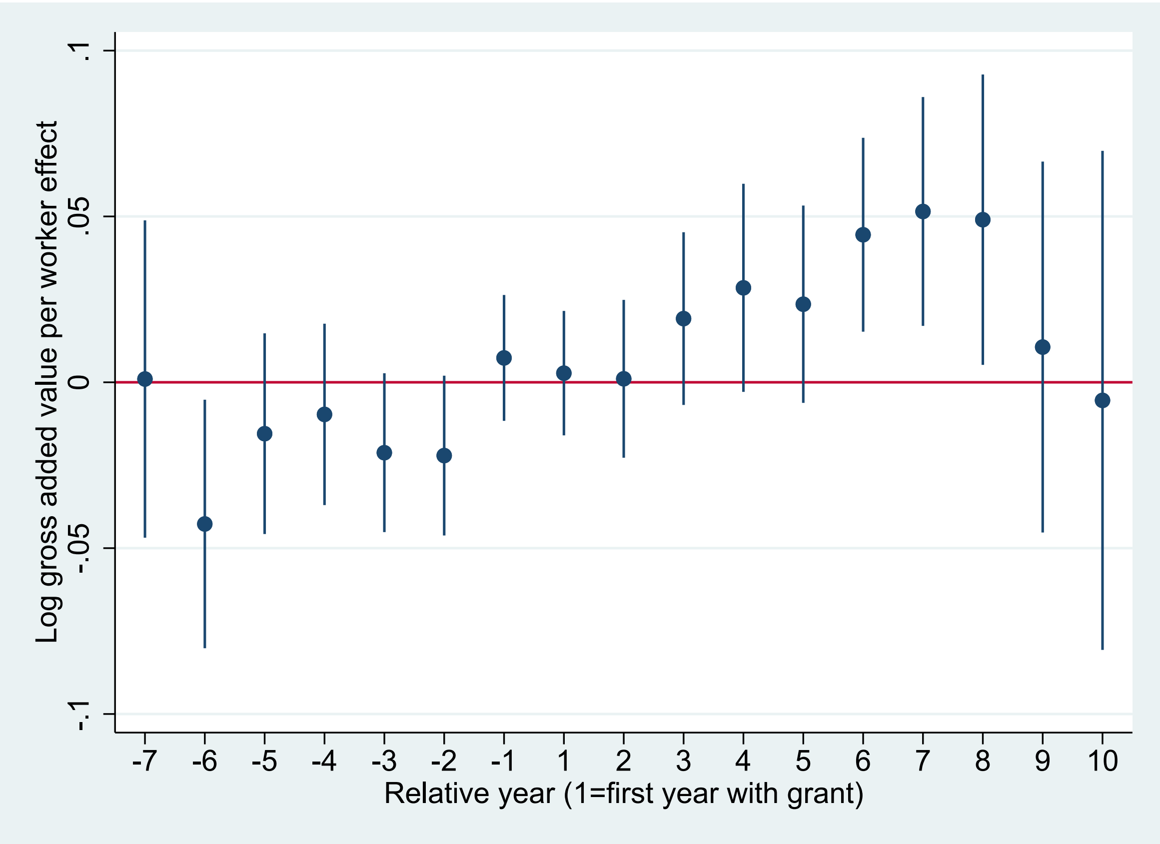
Notes: The dependent variable is the log of the ratio between non-salary staff expenditure (SCIE data set) and the total number of workers (QP data set). See notes to Figure 1. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure A4: **DID effects: Log sales (alternative measure)**



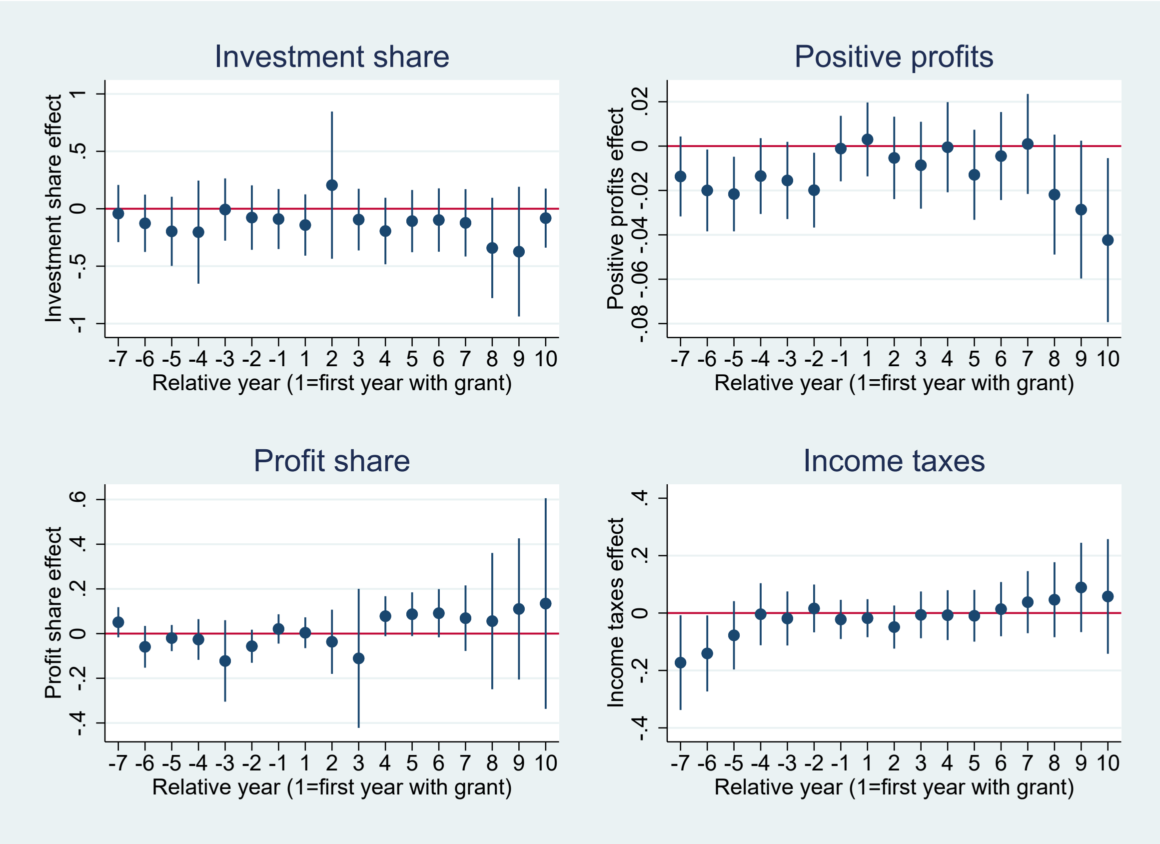
Notes: The dependent variable is the log of total sales of each firm (SCIE data set). The number of observations is 106,692. See notes to Figure 1. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure A5: **DID effects: Log gross value added per worker**



Notes: The dependent variable is the log of the ratio between gross value added (SCIE data set) and the total number of workers (QP data set). The number of observations is 103,699. See notes to Figure 1. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure A6: **DID effects: Investment, profits and taxes**

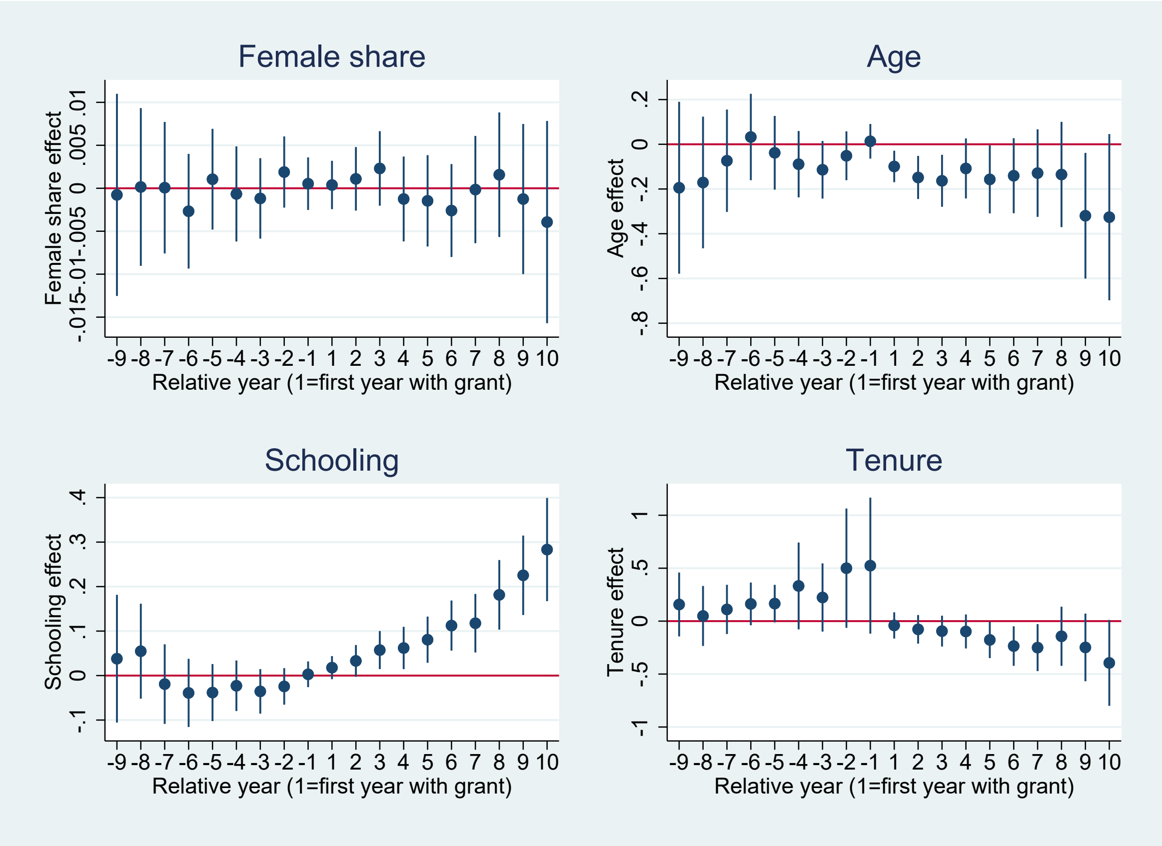


Notes: The dependent variables are (clockwise, from top left corner): the ratio between investment (SCIE) and sales (QP), a dummy variable equal to one if accounting profits (SCIE) are positive, the ratio between profits and sales (QP) and income taxes paid by the firm (SCIE). The number of observations are 103,708, 133,221, 103,708, and 93,812, respectively. See notes to Figure 1. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure A7: **DID effects: Job and worker flows**

Notes: The dependent variables are (clockwise, from top left corner): Net job creation rate (the ratio between the employment change between year t and year $t-1$ and the average employment of both years), the hiring rate (the ratio between the number of workers hired in year t by the average employment of years t and $t-1$) and the separation rate (the ratio between the number of workers that left the firm in year t the average employment of years t and $t-1$). All variables computed using the QP data. Number of observations: 130,415. Each figure corresponds to a separate estimation of a difference-in-differences model. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated*(YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure A8: **DID effects: Worker characteristics**

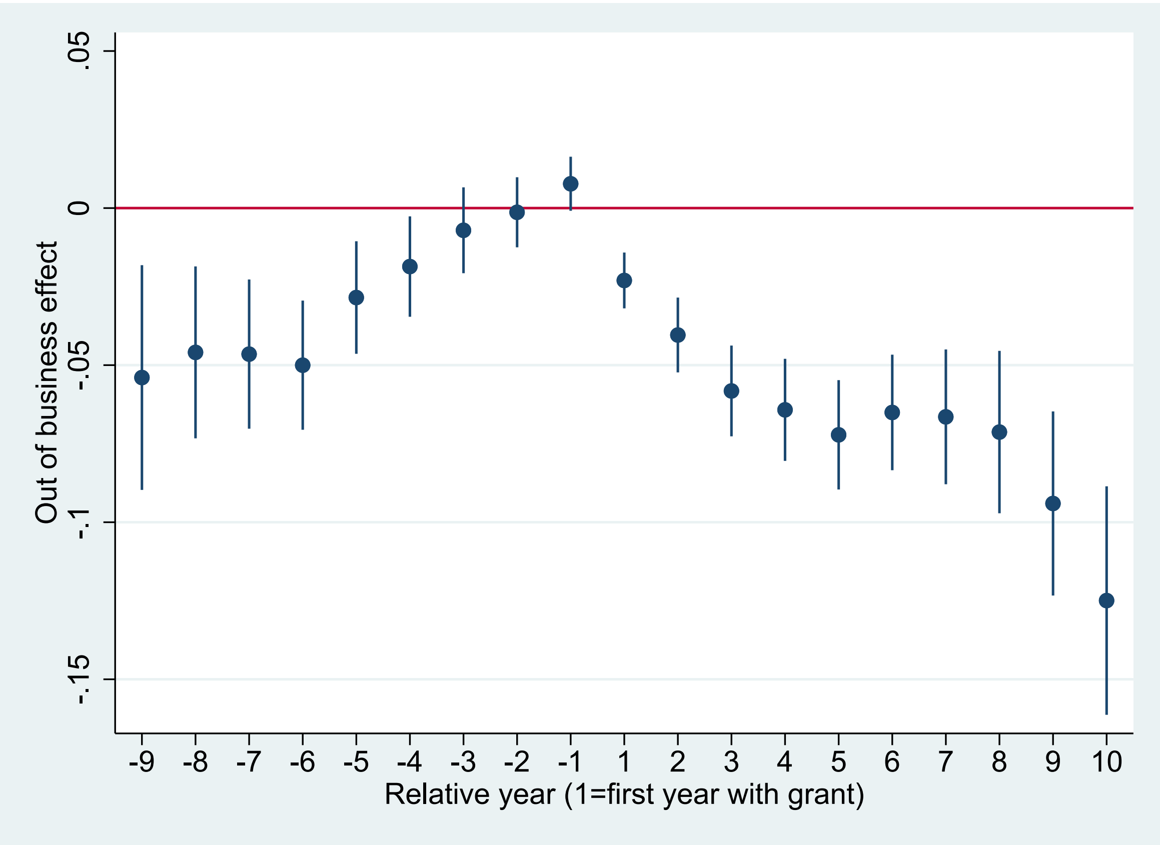


Notes: The dependent variables are (clockwise, from top left corner): Percentage of female workers, the average age, the average tenure (years with the firm) and the average schooling years. All variables refer to all employees of each firm in each year. All variables computed using the QP data. See notes to Figure A7. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure A9: **DID effects: Wages, contracts and hours**

Notes: The dependent variables are (clockwise, from top left corner): Average base wage, average total wage, average hours of worker, percentage of open-ended (permanent) employment contrcts. All variables refer to all employees of each firm in each year. Number of observations: 132,093. All variables computed using the QP data. See notes to Figure A7. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure A10: **DID effects: Firm's entry and exit**



Notes: The dependent variable is a dummy equal to one if the firm is not present in a given year (either because it has not entered the market yet - years -1 to -9) or has already left - years 1 to 10). Source: QP data. Number of observations: 155,760. See notes to Figure 1. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure A11: **DID effects: 2007 call**

Notes: The figures only consider firms that applied to the 2007 call. Year 1 corresponds to 2008, year -1 corresponds to 2006, and so on. See notes to Figure A7. Number of observations: 24,446. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure A12: **DID effects: 2008 call**

Notes: The figures only consider firms that applied to the 2008 call. Year 1 corresponds to 2009, year -1 corresponds to 2007, and so on. See notes to Figure A7. Number of observations: 20,627. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure A13: **DID effects: 2009 call**

Notes: The figures only consider firms that applied to the 2009 call. Year 1 corresponds to 2010, year -1 corresponds to 2008, and so on. See notes to Figure A7. Number of observations: 16,570. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure A14: **DID effects: 2010 call**

Notes: The figures only consider firms that applied to the 2010 call. Year 1 corresponds to 2011, year -1 corresponds to 2009, and so on. See notes to Figure A7. Number of observations: 32,538. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure A15: **DID effects: 2011 call**

Notes: The figures only consider firms that applied to the 2011 call. Year 1 corresponds to 2012, year -1 corresponds to 2010, and so on. See notes to Figure A7. Number of observations: 39,000. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure A16: **DID effects: Firms present in all years**

Notes: The figures only consider firms that are present in QP in all years between 2002 and 2017. See notes to Figure 1. Number of observations: 58,764. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure A17: **DID effects: Firms not present in all years**

Notes: The figures only consider firms that are not present in QP in at least one year between 2002 and 2017. See notes to Figure 1. Number of observations: 47,684. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure A18: **DID effects: Control group of firms that declined funding**

Notes: The figures are based on the main sample except that the control group only includes firms that were approved for funding but then declined it. See notes to Figure A7. Number of observations: 49,407. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure A19: **DID effects - Firms within 5 points of funding threshold**

Notes: The figures are based on a subset of firms with application scores within 5 points of funding threshold. The number of observations used in the estimations is 33,905. See notes to Figure A7. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

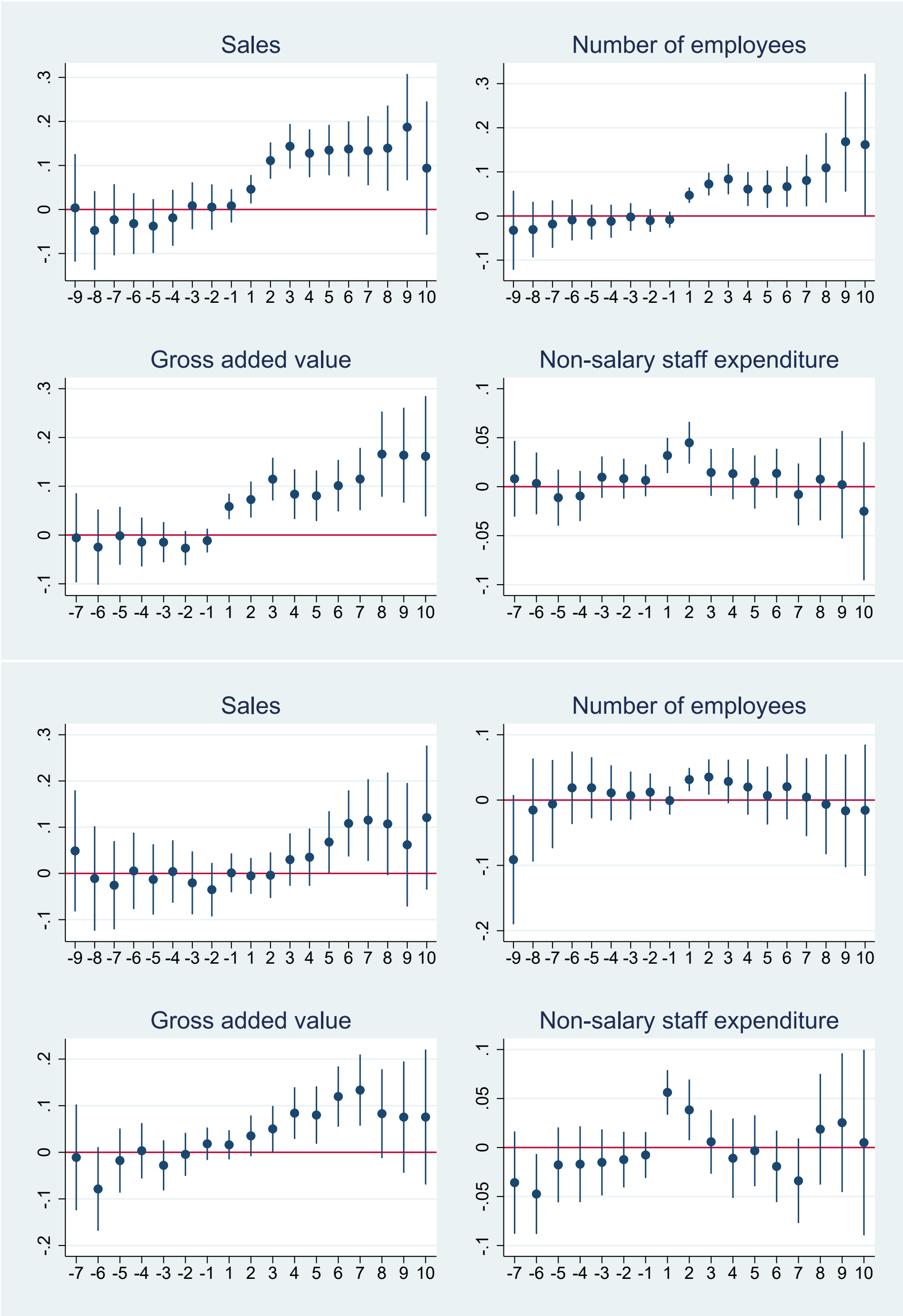
Figure A20: **DID effects - Firms outside 2.5 points of funding threshold**

Notes: The figures are based on all firms except those with application scores within 2.5 points of funding threshold. The number of observations used in the estimations is 116,914. See notes to Figure A7. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure A21: **DID effects - Excluding firms that are rejected more than once**

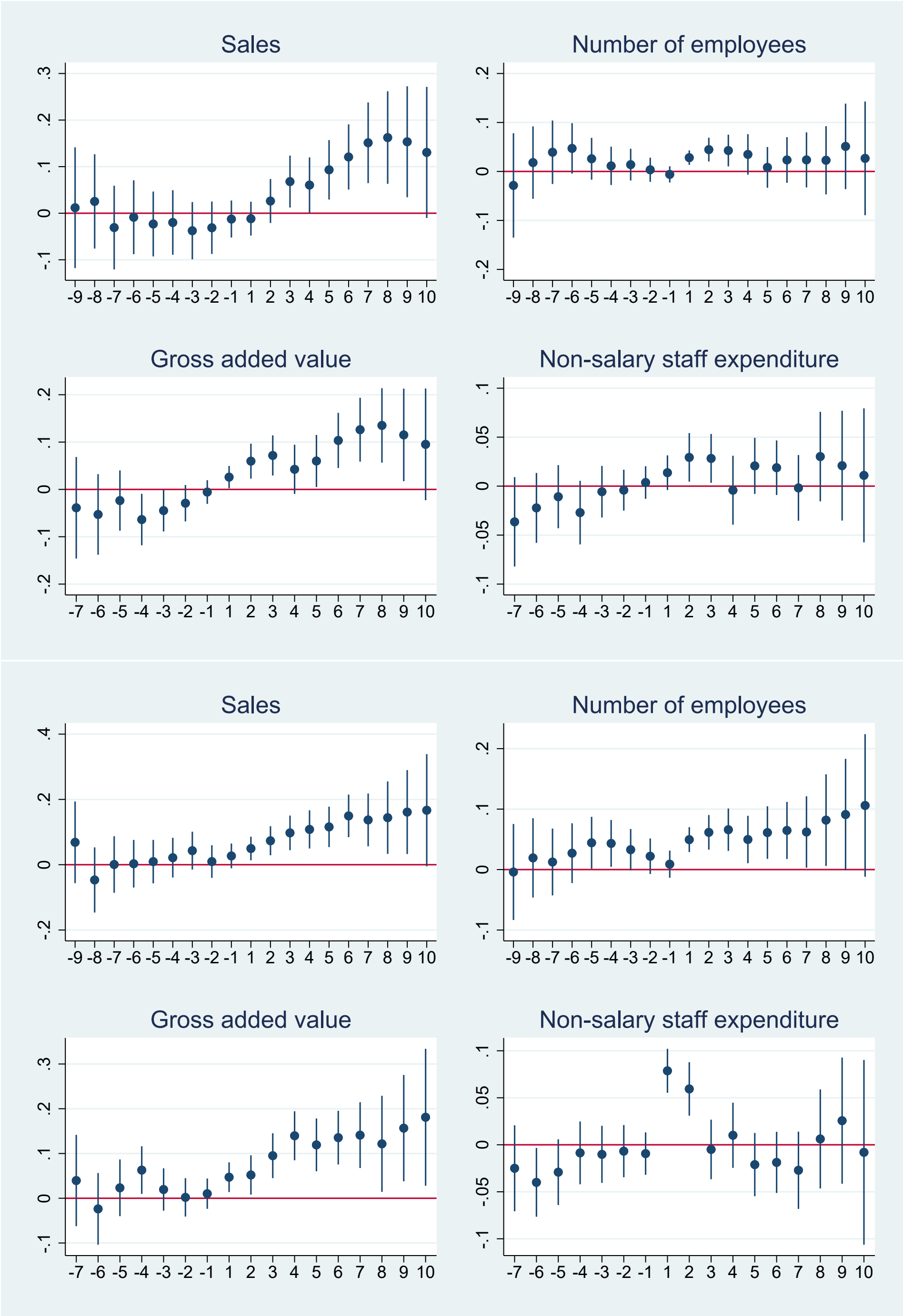
Notes: The figures exclude firms that submit multiple applications and are rejected in all occasions. The number of observations used in the estimations is 67,197. See notes to Figure A7. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure A22: **DID effects - Heterogeneity: Manufacturing (top) and services (bottom) firms only**



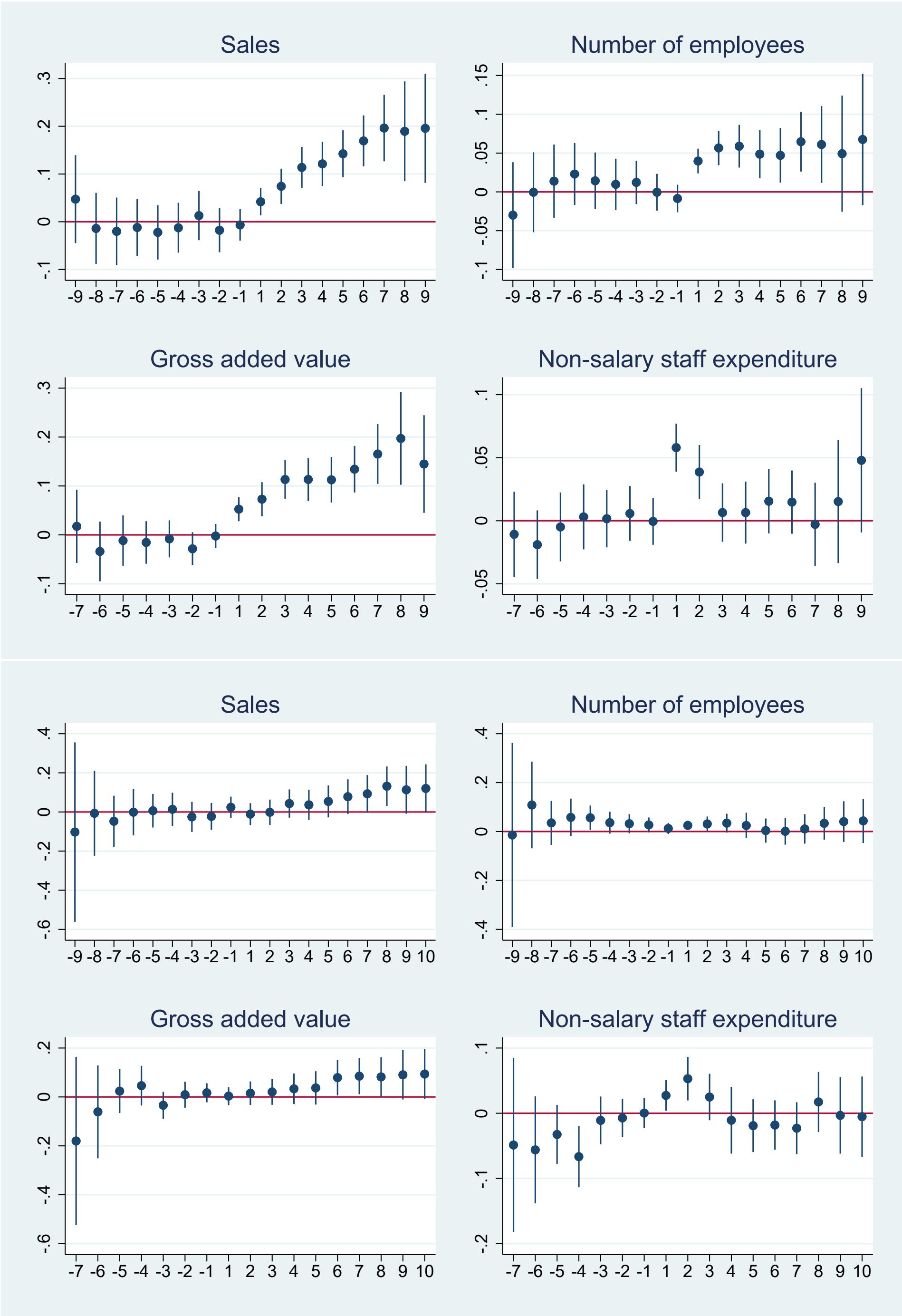
Notes: Analysis conducted separately for manufacturing and services sectors. Number of observations: 64,011 and 69,174, respectively. See notes to Figure A7. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure A23: **DID effects - Heterogeneity: Large firms (top) and smaller firms (bottom) firms only**



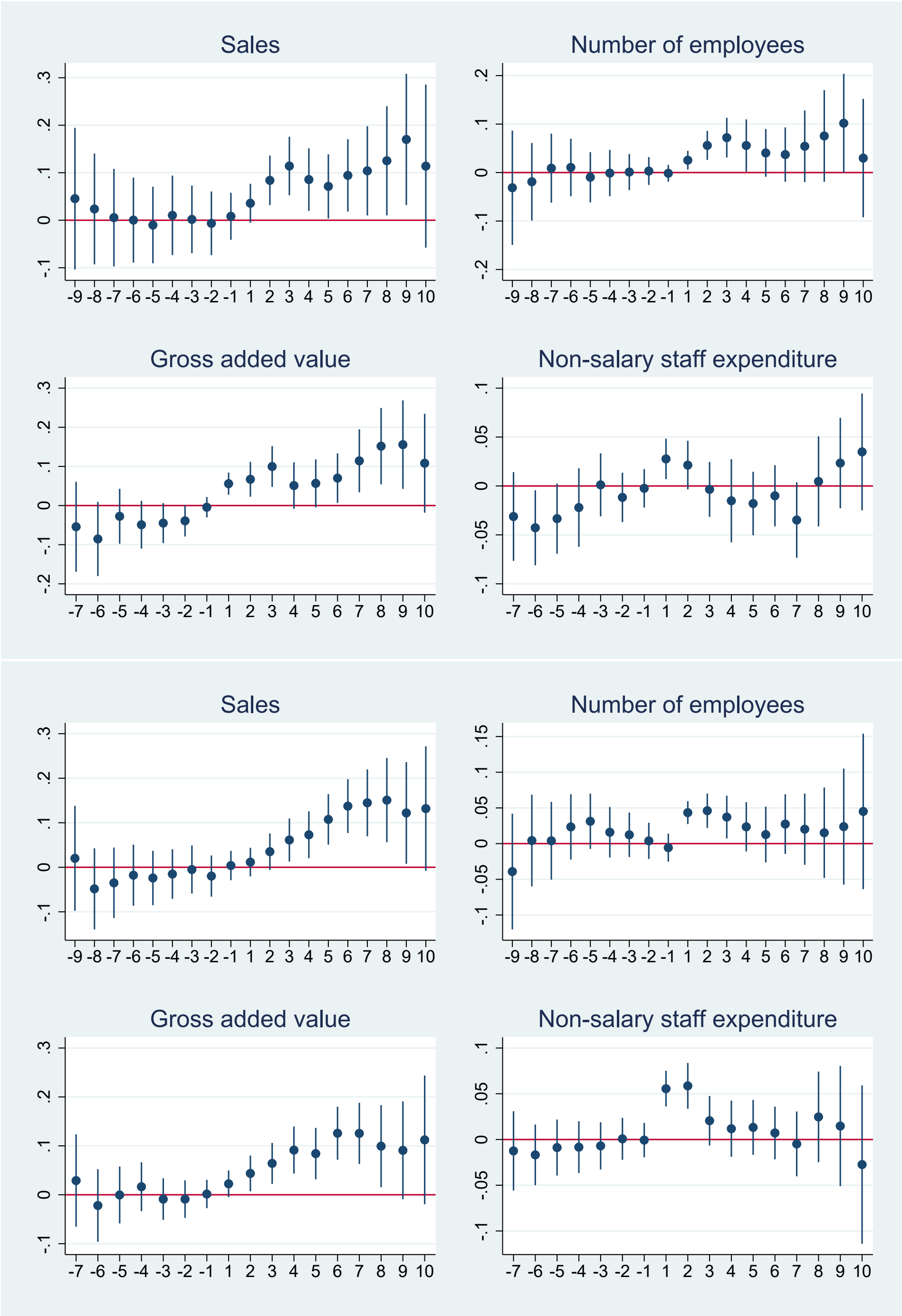
Notes: Analysis conducted separately for large and small firms. See notes to Figure A7. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure A24: **DID effects - Heterogeneity: High scoring threshold (top) and low scoring threshold (bottom) firms only**



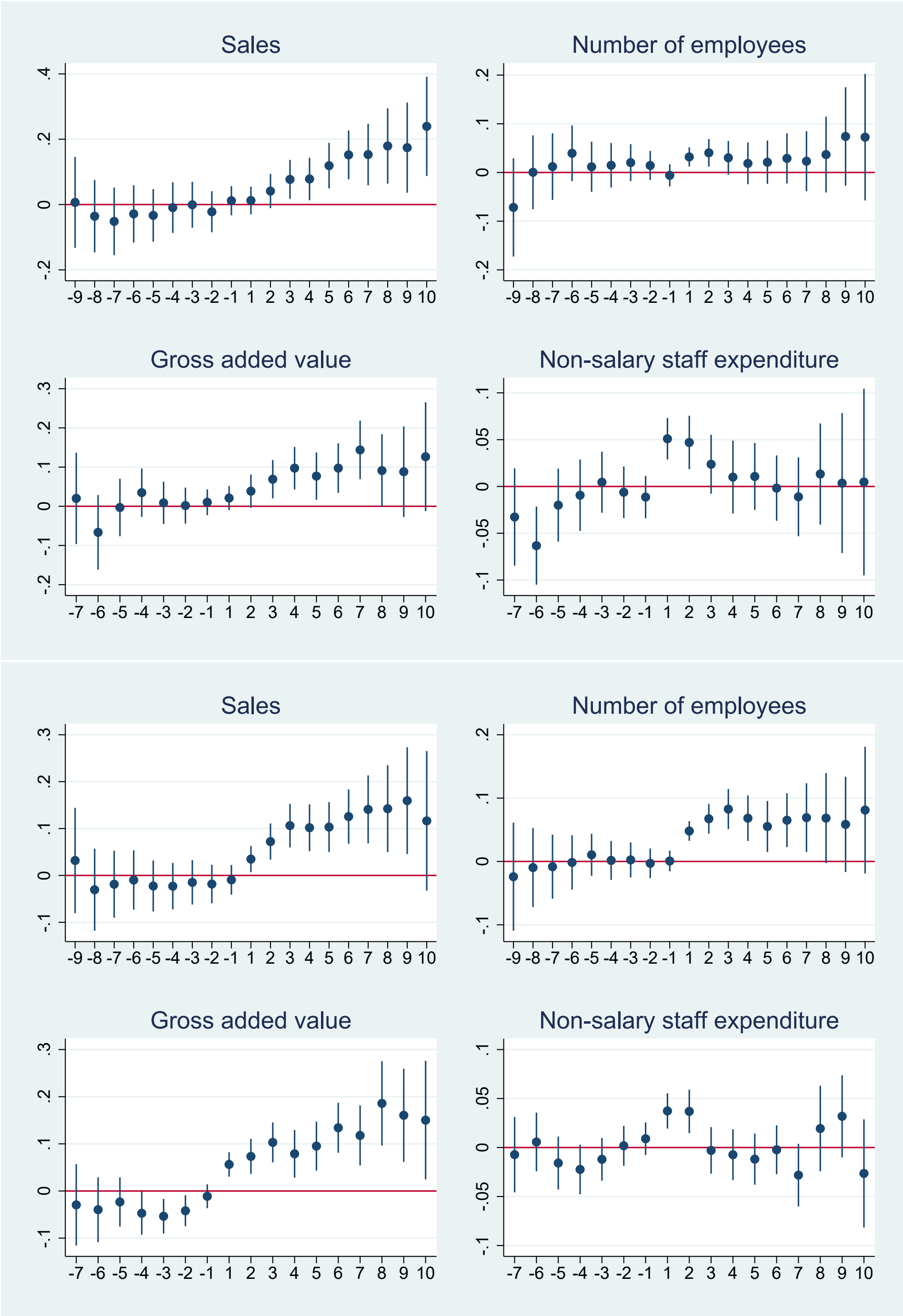
Notes: Analysis conducted separately for firms that applied to calls that were then subject to either high (55 or higher) or low scoring thresholds (52.5 or lower). See notes to Figure A7. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure A25: **DID effects - Heterogeneity: Exporters (top) and non-exporters (bottom) firms only**



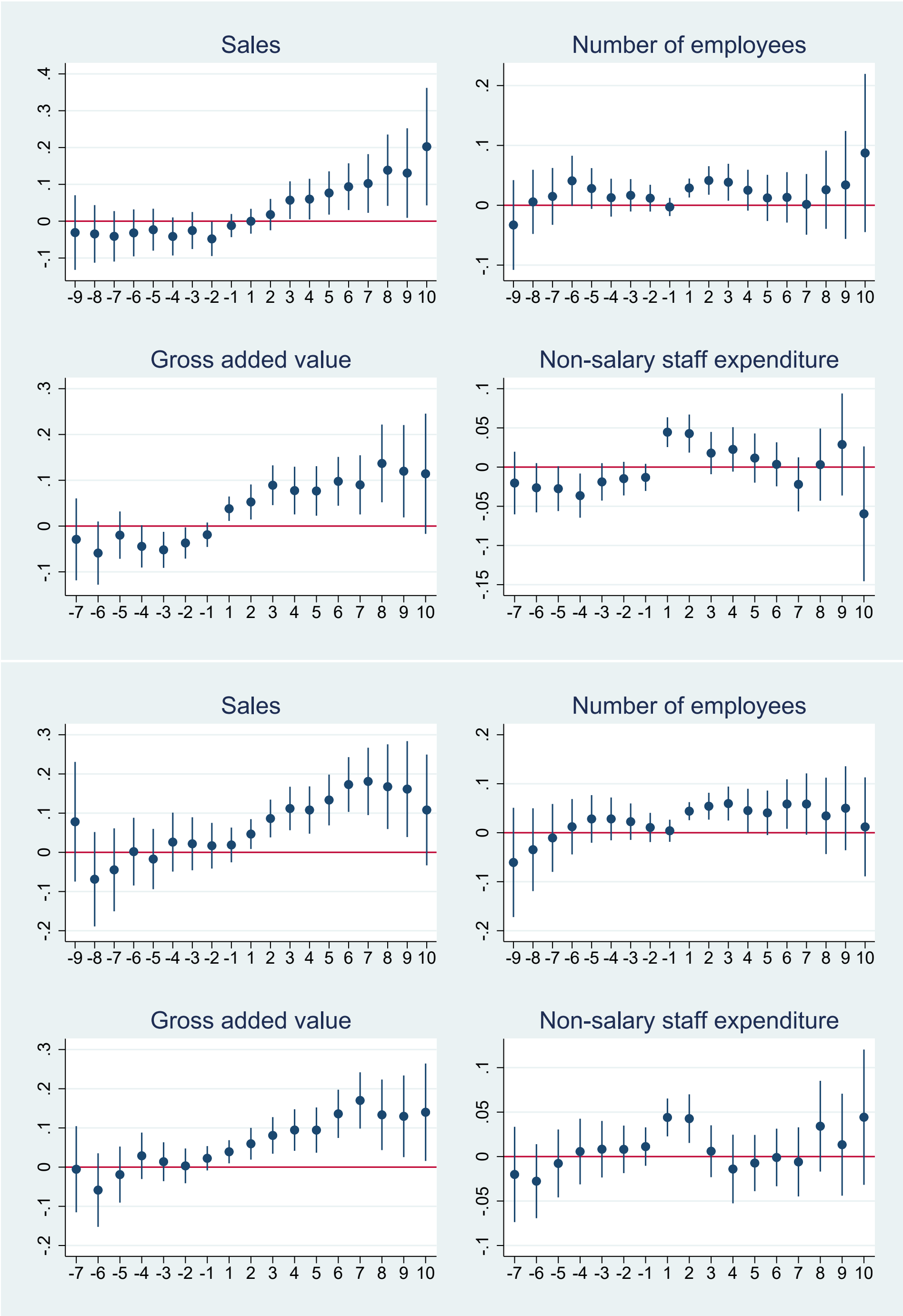
Notes: Analysis conducted separately for firms that exported or not at the time when they apply. See notes to Figure A7. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated*(YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure A26: **DID effects - Heterogeneity: High-schooling (top) and low-schooling firms only**



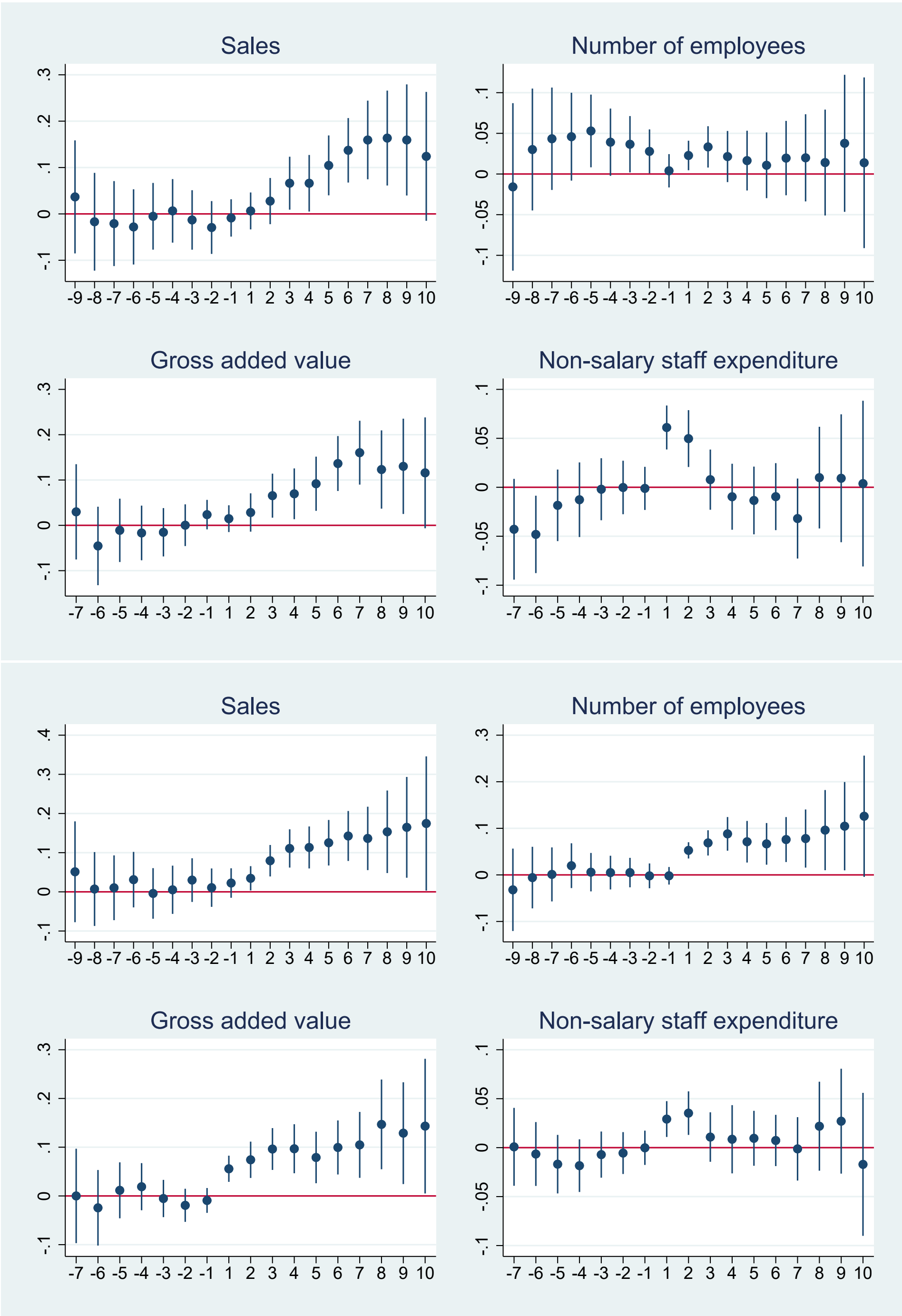
Notes: Analysis conducted separately for firms with high- or low-schooling workforces (at the time when they apply). Number of observations: 65,539 and 67,646, respectively. See notes to Figure A7. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure A27: **DID effects - Heterogeneity: Older workforce (top) and younger workforce (bottom) firms only**



Notes: Analysis conducted separately for firms with older or younger workforces (at the time when they apply). See notes to Figure A7. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Figure A28: **DID effects - Heterogeneity: High female share (top) and low female share (bottom) firms only**



Notes: Analysis conducted separately for firms with high- or low-female workforces (at the time when they apply). See notes to Figure A7. Each dot (line) indicates the point estimate (95% confidence interval) for the $Treated * (YearX)$ coefficient concerning a particular relative year X (with respect to the benchmark year 0 when firms apply to the funding call).

Table B1: Funding thresholds (marks out of 100), years, applicants and amounts

		Regions		Funding starts	Number of Applicants	Public Funding
Call	North & Centre & Alentejo	Algarve	Lisbon			
2007	50	50	50	2008	1,788	22.9
2008	60	50	60	2009	2,203	39.0
2009	62.5	52.5	55	2010	1,736	36.7
2010	65	60	50	2011	2,812	38.7
2011	52.5	50	50	2012	3,852	34.8

Notes: The first three columns indicate the threshold applicable in each call in each region (a 'quality' minimum of 50 or higher if demand exceeded the budget available). Funding to accepted applications began in the year following that of the call, as indicated in the fourth column. Columns five and six indicate the number of firms that applied to each call and the amount of public funding (European Social Fund and national funds) disbursed in each call.

Table B2: Descriptive statistics, application year, 2010 call only

	(1) Approved		(2) Rejected		(3) Difference	
	Mean	SD	Mean	SD	b	t
Total sales	10.05	42.96	23.95	336.93	13.90	(1.56)
Number of employees	65.13	176.46	89.68	485.58	24.55	(1.74)
Capital equity	1.87	14.23	1.88	21.28	0.02	(0.02)
Firm age	19.79	14.49	20.25	33.83	0.46	(0.45)
Gross added value	2.37	8.74	3.56	24.75	1.19	(1.58)
Investment	0.24	4.16	1.91	33.66	1.67	(1.78)
Profits	0.27	4.36	0.64	8.72	0.38	(1.31)
Non-salary staff expenditure	0.34	1.24	0.47	3.12	0.13	(1.33)
Training expenditure	6.02	39.36	3.80	24.95	-2.22	(-1.41)
North region	0.39		0.42		0.02	(1.04)
Centre region	0.34		0.40		0.07**	(3.21)
Employees' female share	0.34	0.26	0.43	0.32	0.09***	(7.24)
Employees' age	38.84	4.71	38.29	4.99	-0.55**	(-2.60)
Employees' tenure	7.32	4.77	6.60	4.74	-0.72***	(-3.43)
Employees' schooling	9.08	2.20	9.60	2.69	0.52***	(4.97)
Employees' total wage	949.84	647.32	885.42	436.92	-64.42*	(-2.50)
Training funding requested	101.47	127.86	87.66	153.23	-13.81*	(-2.28)
Training funding approved	36.55	30.46	1.83	9.99	-34.71***	(-31.00)
Workers to train request	120.70	125.97	135.74	206.79	15.04*	(2.15)
Workers to train approved	109.30	99.12	0.00	0.00	-109.30***	(-30.84)
Training hours request	3720.15	4055.64	4165.69	5559.63	445.54*	(2.18)
Training hours approved	3359.16	3124.01	0.00	0.00	-3359.16***	(-30.07)
Duration of training (months)	13.45	6.59	10.56	4.86	-2.89***	(-10.81)
Training hours	1019.40	3164.10	1937.47	17416.74	918.07*	(1.97)
Non-catalogue training	336.07	1883.36	1292.47	16863.50	956.40*	(2.16)
Externals-provided training	661.08	2386.87	933.39	5350.56	272.32	(1.67)
Working-time training	837.90	2963.10	1691.90	17026.29	854.00	(1.88)
Workers under training	48.26	130.12	75.95	620.28	27.69	(1.65)
Observations	782		1484		2266	

Notes: All statistics refer to 2010, the year before the funding starts in the 2010 call considered here. See the footnotes to Tables 1 and 2 for more information on the variables.

Table B3: Descriptive statistics, full sample

	(1)		(2)		(3)	
	Approved		Rejected		Difference	
	Mean	SD	Mean	SD	b	t
Total sales	19.55	139.00	14.06	170.03	-5.49***	(-6.43)
Number of employees	111.77	493.81	111.16	644.90	-0.61	(-0.19)
Capital equity	4.25	52.01	4.01	75.29	-0.24	(-0.69)
Domestic private share	88.84	30.56	81.19	38.48	-7.65***	(-40.17)
Foreign share	7.26	24.97	5.20	21.51	-2.06***	(-15.50)
Firm age	23.50	46.94	23.85	59.53	0.34	(1.17)
Gross added value	5.19	40.82	3.34	20.21	-1.85***	(-8.83)
Total sales (2)	20.17	124.67	15.80	181.34	-4.37***	(-4.66)
Investment	1.17	15.47	0.62	11.94	-0.55***	(-6.31)
Profits	0.91	34.71	0.40	11.67	-0.51**	(-3.02)
Income taxes paid	0.27	4.08	0.14	2.06	-0.13***	(-6.29)
Non-salary staff expenditure	0.64	3.94	0.49	2.46	-0.16***	(-7.43)
Food	0.05		0.03		-0.02***	(-16.47)
Clothing	0.04		0.02		-0.01***	(-14.34)
Ceramics	0.04		0.02		-0.02***	(-23.04)
Molds	0.07		0.04		-0.03***	(-21.69)
Construction	0.04		0.04		0.00**	(2.81)
Electric appliances	0.04		0.04		-0.00	(-1.63)
Wholesale	0.11		0.09		-0.02***	(-13.33)
Retail	0.05		0.07		0.02***	(11.39)
Transport	0.03		0.03		-0.01***	(-7.26)
North region	0.47		0.42		-0.05***	(-19.01)
Centre region	0.33		0.35		0.02***	(7.78)
Lisbon region	0.13		0.16		0.03***	(16.03)
Exports	10.82	66.86	9.09	109.32	-1.74	(-1.92)
N. of products exported	25.97	57.27	23.56	64.59	-2.41***	(-4.00)
N. of countries exported to	8.89	11.62	6.80	9.96	-2.09***	(-19.81)
Employees' female share	0.36	0.28	0.44	0.32	0.09***	(52.52)
Employees' age	38.77	5.19	38.55	5.56	-0.22***	(-7.34)
Employees' tenure	9.47	34.74	9.10	41.20	-0.37	(-1.75)
Employees' open-ended contract	0.69	0.25	0.67	0.28	-0.02***	(-13.71)
Employees' schooling	9.08	2.37	9.71	2.85	0.63***	(43.50)
Employees' base wage	792.81	389.15	796.41	794.20	3.61	(1.10)
Employees' total wage	930.33	450.06	919.80	826.42	-10.53**	(-3.00)
Observations	51958		81093		133051	

Notes: Full data set, covering all firms observed in all years (2002-2017). See the footnotes to Tables 1 and 2 for more information on the variables..

Table B4: Regression results (1/2)

	(1)	(2)	(3)	(4)
	Log sales	Log employees	Log gross added value	Log non-salary staff expenditure
Year -9*Aprov	.031	-.031		
	(.045)	(.034)		
Year -8*Aprov	-.021	.007		
	(.036)	(.025)		
Year -7*Aprov	-.020	.016	.002	-.019
	(.031)	(.022)	(.037)	(.016)
Year -6*Aprov	-.009	.032	-.042	-.025
	(.027)	(.018)*	(.029)	(.013)*
Year -5*Aprov	-.013	.030	-.003	-.017
	(.024)	(.015)*	(.023)	(.012)
Year -4*Aprov	-.002	.023	-.001	-.015
	(.023)	(.014)	(.019)	(.012)
Year -3*Aprov	.002	.021	-.013	-.004
	(.021)	(.012)*	(.016)	(.010)
Year -2*Aprov	-.012	.012	-.012	-.003
	(.019)	(.010)	(.014)	(.009)
Year -1*Aprov	.005	.001	.004	-.0009
	(.014)	(.007)	(.010)	(.007)
Year +1*Aprov	.021	.035	.035	.044
	(.013)	(.006)***	(.010)***	(.007)***
Year +2*Aprov	.049	.046	.051	.042
	(.016)***	(.009)***	(.014)***	(.009)***
Year +3*Aprov	.080	.047	.079	.010
	(.019)***	(.012)***	(.016)***	(.010)
Year +4*Aprov	.079	.033	.080	.002
	(.021)***	(.014)**	(.019)***	(.012)
Year +5*Aprov	.101	.025	.079	.0003
	(.022)***	(.015)*	(.020)***	(.011)
Year +6*Aprov	.130	.035	.111	-.0002
	(.024)***	(.017)**	(.021)***	(.011)
Year +7*Aprov	.140	.032	.125	-.015
	(.030)***	(.021)	(.025)***	(.013)
Year +8*Aprov	.154	.034	.127	.019
	(.037)***	(.026)	(.032)***	(.018)
Year +9*Aprov	.153	.052	.121	.020
	(.045)***	(.032)	(.038)***	(.022)
Year +10*Aprov	.144	.047	.119	.0009
	(.055)***	(.042)	(.047)**	(.029)
Const.	.781	3.503	-.185	-5.621
	(.012)***	(.008)***	(.008)***	(.005)***
Obs.	125868	133185	103723	106470
R^2	.888	.898	.9	.713

Notes: See notes to Figure 1.

Table B5: Regression results (2/2)

	(1)	(2)	(3)	(4)
	Export status	Log profits	Log sales per worker	Log investment
Year -9*Aprov	-.083 (.018)***		.062 (.036)*	
Year -8*Aprov	-.045 (.013)***		-.029 (.027)	
Year -7*Aprov	-.033 (.011)***	-.183 (.079)**	-.033 (.024)	-.350 (.085)***
Year -6*Aprov	-.032 (.010)***	-.178 (.062)***	-.033 (.022)	-.239 (.068)***
Year -5*Aprov	-.030 (.009)***	-.183 (.053)***	-.035 (.020)*	-.162 (.059)***
Year -4*Aprov	-.019 (.008)**	-.109 (.048)**	-.023 (.020)	-.152 (.054)***
Year -3*Aprov	-.019 (.008)**	-.095 (.043)**	-.006 (.019)	-.068 (.049)
Year -2*Aprov	-.019 (.007)**	-.071 (.041)*	-.023 (.018)	-.123 (.047)***
Year -1*Aprov	-.007 (.006)	-.073 (.033)**	.003 (.014)	-.059 (.041)
Year +1*Aprov	-.00003 (.006)	-.008 (.035)	-.016 (.013)	.071 (.043)*
Year +2*Aprov	.004 (.007)	.040 (.042)	-.0002 (.015)	.085 (.049)*
Year +3*Aprov	.018 (.008)**	.078 (.045)*	.033 (.017)*	.009 (.052)
Year +4*Aprov	.023 (.009)***	.087 (.049)*	.046 (.018)**	.043 (.055)
Year +5*Aprov	.018 (.009)**	.160 (.050)***	.066 (.018)***	.137 (.057)**
Year +6*Aprov	.016 (.009)*	.177 (.051)***	.086 (.019)***	.163 (.057)***
Year +7*Aprov	.002 (.010)	.231 (.059)***	.095 (.024)***	.135 (.066)**
Year +8*Aprov	.017 (.013)	.267 (.069)***	.099 (.029)***	.218 (.078)***
Year +9*Aprov	.010 (.014)	.254 (.078)***	.080 (.037)**	.176 (.089)**
Year +10*Aprov	-.004 (.018)	.434 (.102)***	.086 (.047)*	.376 (.111)***
Const.	.322 (.004)***	-2.943 (.020)***	-2.729 (.009)***	-2.588 (.021)***
Obs.	133221	84424	125838	87984
R^2	.728	.755	.808	.644

Notes: See notes to Figure 1.

Table B6: Multiple testing analysis 1/2

Outcome	Family	Coef	Std Err	p-value	pwyoung	pbonf	psidak
Log sales	1	0.021	0.013	0.107	0.933	1.000	0.895
Log employment	1	0.035	0.006	0.000	0.133	0.000	0.000
Log sales per worker	1	-0.016	0.013	0.221	1.000	1.000	0.982
Export status	1	0.000	0.006	0.996	1.000	1.000	1.000
Log exports	1	0.139	0.063	0.027	0.733	0.825	0.567
Log profits	1	-0.008	0.035	0.809	1.000	1.000	1.000
Profit ratio	1	0.004	0.035	0.913	1.000	1.000	1.000
Log taxes	1	-0.018	0.034	0.595	1.000	1.000	1.000
Log non wage staff expenditure	1	0.084	0.008	0.000	0.000	0.000	0.000
Log investment	1	0.070	0.043	0.101	0.933	1.000	0.895
Log sales (2nd measure)	1	0.036	0.009	0.000	0.267	0.003	0.003
Log added value per worker	1	0.003	0.010	0.773	1.000	1.000	1.000
Log sales	2	0.049	0.016	0.003	0.400	0.103	0.098
Log employment	2	0.046	0.009	0.000	0.200	0.000	0.000
Log sales per worker	2	0.000	0.015	0.990	1.000	1.000	1.000
Export status	2	0.004	0.007	0.593	1.000	1.000	1.000
Log exports	2	0.129	0.078	0.097	0.933	1.000	0.895
Log profits	2	0.040	0.042	0.340	1.000	1.000	0.998
Profit ratio	2	-0.037	0.073	0.618	1.000	1.000	1.000
Log taxes	2	-0.049	0.038	0.203	1.000	1.000	0.979
Log non wage staff expenditure	2	0.097	0.012	0.000	0.000	0.000	0.000
Log investment	2	0.084	0.049	0.085	0.900	1.000	0.891
Log sales (2nd measure)	2	0.063	0.012	0.000	0.200	0.000	0.000
Log added value per worker	2	0.001	0.012	0.931	1.000	1.000	1.000

Notes: The table presents the main results and multiple-test-adjusted p-values using different methodologies using the algorithm of Jones et al. (2019). The first column indicates the outcome variable; the second indicates the year of the applicable difference-in-difference coefficient (e.g. '1' denotes the first year after the FIG subsidy is attributed); the third, fourth and fifth columns indicate the coefficient, standard error and p-values from the main analysis; and the last three columns indicate the p-values computed under different approaches towards multiple testing: Westfall & Young (1993), Bonferroni-Holm and Sidak-Holm adjusted p-values.

Table B7: Multiple testing analysis 1/2

Outcome	Family	Coef	Std Err	p-value	pwyoung	pbonf	psidak
Log sales	3	0.080	0.019	0.000	0.233	0.001	0.001
Log employment	3	0.047	0.012	0.000	0.233	0.003	0.003
Log sales per worker	3	0.033	0.017	0.054	0.900	1.000	0.803
Export status	3	0.018	0.008	0.028	0.767	0.851	0.578
Log exports	3	0.151	0.081	0.061	0.900	1.000	0.831
Log profits	3	0.078	0.045	0.087	0.933	1.000	0.891
Profit ratio	3	-0.111	0.159	0.485	1.000	1.000	1.000
Log taxes	3	-0.006	0.042	0.878	1.000	1.000	1.000
Log non wage staff expenditure	3	0.075	0.014	0.000	0.167	0.000	0.000
Log investment	3	0.008	0.052	0.877	1.000	1.000	1.000
Log sales (2nd measure)	3	0.076	0.016	0.000	0.233	0.000	0.000
Log added value per worker	3	0.019	0.013	0.148	0.967	1.000	0.944
Log sales	4	0.080	0.021	0.000	0.267	0.005	0.005
Log employment	4	0.033	0.014	0.019	0.700	0.609	0.459
Log sales per worker	4	0.046	0.018	0.012	0.600	0.404	0.334
Export status	4	0.023	0.009	0.007	0.500	0.243	0.216
Log exports	4	0.145	0.088	0.098	0.933	1.000	0.895
Log profits	4	0.086	0.049	0.079	0.900	1.000	0.883
Profit ratio	4	0.078	0.046	0.088	0.933	1.000	0.891
Log taxes	4	-0.007	0.044	0.869	1.000	1.000	1.000
Log non wage staff expenditure	4	0.058	0.016	0.000	0.267	0.009	0.009
Log investment	4	0.042	0.055	0.447	1.000	1.000	1.000
Log sales (2nd measure)	4	0.081	0.018	0.000	0.233	0.000	0.000
Log added value per worker	4	0.028	0.016	0.075	0.900	1.000	0.879

Notes: The table presents the main results and multiple-test-adjusted p-values using different methodologies using the algorithm of Jones et al. (2019). The first column indicates the outcome variable; the second indicates the year of the applicable difference-in-difference coefficient (e.g. '3' denotes the third year after the FIG subsidy is attributed); the third, fourth and fifth columns indicate the coefficient, standard error and p-values from the main analysis; and the last three columns indicate the p-values computed under different approaches towards multiple testing: Westfall & Young (1993), Bonferroni-Holm and Sidak-Holm adjusted p-values.

Table B8: Descriptive statistics, All successful applicants, Application year (1/2)

	(1)		(2)		(3)	
	Approved		Rejected		Difference	
	Mean	SD	Mean	SD	b	t
Total sales	19.49	138.94	11.65	71.09	-7.84	(-1.88)
Number of employees	111.66	480.61	62.52	222.63	-49.13***	(-3.65)
Capital equity	4.01	40.99	6.43	107.96	2.42	(0.46)
Domestic private share	89.49	29.79	90.14	28.85	0.65	(0.44)
Foreign share	6.57	23.83	6.76	23.99	0.19	(0.16)
Firm age	21.35	22.77	17.36	12.27	-3.99***	(-5.64)
Gross added value	5.37	41.36	3.14	31.92	-2.23	(-1.29)
Total sales (2)	19.76	112.57	10.89	74.75	-8.87*	(-2.13)
Investment	1.44	21.80	1.11	16.71	-0.33	(-0.36)
Profits	0.88	13.68	0.56	11.28	-0.32	(-0.53)
Income taxes paid	0.28	3.73	0.30	4.40	0.02	(0.09)
Non-salary staff expenditure	0.66	4.74	0.30	1.53	-0.36**	(-3.24)
Training expenditure	4.98	30.49	6.11	65.36	1.13	(0.22)
Food	0.05		0.04		-0.01	(-0.86)
Clothing	0.04		0.05		0.02	(1.40)
Ceramics	0.04		0.03		-0.01	(-1.07)
Molds	0.07		0.06		-0.01	(-0.41)
Construction	0.04		0.07		0.02	(1.91)
Electric appliances	0.04		0.05		0.01	(0.60)
Wholesale	0.11		0.09		-0.03	(-1.76)
Retail	0.06		0.09		0.03*	(2.07)
Transport	0.03		0.03		-0.00	(-0.37)
North region	0.46		0.52		0.06*	(2.41)
Centre region	0.33		0.19		-0.14***	(-6.59)
Lisbon region	0.13		0.15		0.02	(1.08)
Exports	9.90	54.07	3.65	8.68	-6.24***	(-4.02)
N. of products exported	23.43	50.31	14.07	26.58	-9.36***	(-3.75)
N. of countries exported to	8.17	10.82	5.74	6.80	-2.44***	(-3.98)
Observations	3581		423		4004	

Notes: See notes to Table 1. All firms were approved in their applications. Rejected are firms that decided not to accept the offer.

Table B9: Descriptive statistics, All successful applicants, Application year (2/2)

	(1) Accepted by firm		(2) Rejected by firm		(3) Difference	
	Mean	SD	Mean	SD	b	t
Employees' female share	0.36	0.28	0.36	0.28	0.00	(0.06)
Employees' age	38.35	4.73	38.16	4.76	-0.20	(-0.80)
Employees' tenure	7.58	5.15	6.81	4.58	-0.76**	(-3.20)
Employees' open-ended contract	0.69	0.26	0.68	0.27	-0.01	(-0.67)
Employees' schooling	9.04	2.29	9.19	2.47	0.15	(1.19)
Employees' base wage	810.85	421.55	801.11	453.12	-9.74	(-0.42)
Employees' total wage	952.32	473.77	933.16	501.48	-19.15	(-0.75)
Training funding requested	96.80	278.35	68.55	82.81	-28.26***	(-4.59)
Training funding approved	27.79	35.77	23.15	21.46	-4.65***	(-3.86)
Subsidy (wagebill) rate	1.25	5.48	1.48	2.37	0.22	(1.52)
Workers to train request	130.57	189.92	156.40	216.18	25.83*	(2.35)
Workers to train approved	111.81	140.05	0.00	0.00	-111.81***	(-47.77)
Training hours request	3955.13	6690.82	4514.11	5483.69	558.98	(1.93)
Training hours approved	3371.67	4173.90	0.00	0.00	-3371.67***	(-48.34)
Duration of training (months)	11.39	6.79	8.58	3.83	-2.82***	(-12.90)
Training hours	1149.19	5589.43	825.90	3662.64	-323.29	(-0.98)
Non-catalogue training	441.58	4941.42	122.78	732.22	-318.80*	(-2.20)
Externals-provided training	674.97	2290.85	633.14	2973.78	-41.83	(-0.17)
Working-time training	965.94	5497.24	636.55	3460.37	-329.39	(-1.04)
Workers under training	22.64	132.05	14.63	79.34	-8.01	(-1.80)
Observations	3581		423		4004	

Notes: See notes to Table 2. All firms were approved in their applications. Rejected are firms that decided not to accept the offer.