Effects of the Award of Public Service Contracts on the Performance and Payroll of Winning Firms

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Abstract

In this study, we investigate the effects of an exogenous demand shock arising from the award of public service contracts by Italian public administrations in 2015 on a sample of 1,782 winning small and medium firms that were not awarded any contract during the previous three years.

Using a difference-in-differences model with continuous treatments estimated on a propensity score matched sample, our results reveal that higher awarded values enhance various performance dimensions of the winning firms as well as their average payroll per employee. Nonetheless, higher winning rebates moderate the positive effects of the award on payroll by inducing the winning firms to downward manage both salaries and social security contributions per employee to maintain their desired level of performance. The effects are mostly significant for smaller micro enterprises. In addition, winning rebates negatively affect the performance of firms in the construction industry by leading these firms to downward manage the payroll of their employees more aggressively than firms in other industries.

Our findings provide novel insights for the implementation of industrial policies aimed at achieving sustainable macroeconomic and social goals, within the business fabric, through the effective management of public service procurement.

Keywords: demand shock; firm performance; public procurement; public service contracts; social security contributions.

Abbreviations in the paper: DID (difference-in-differences); NN (nearest neighbour); PP (public procurement); PSCs (public service contracts); PSM (propensity score matching); SMEs (small and medium enterprises); SSCs (social security contributions).

1 Introduction

The economic significance of public procurement (PP) within EU countries is supported by the fact that in recent years, publicly procured services, works, and supplies have represented about 14% of the EU's GDP (European Commission, 2019) and 29% of government spending (OECD, 2016). Therefore, PP efficiency and the pursuit of 'value for money' have become strategic objectives for many European governments to reduce public spending under the heavy pressure of fiscal austerity (Onur et al., 2012; OECD, 2016; Jaehrling et al., 2018). This pressure has led to the outsourcing of public services due to a common belief among national policymakers that the private sector can provide higher-quality services at a lower price than public administrations (Wollmann, 2018; Jaehrling et al., 2018).

However, in some circumstances, the efficiency objective may not be compatible with the consideration of PP as an industrial policy instrument to pursue broader social objectives as recognised by recent EU Directives (2014/24/EU, 2014/25/EU, and 2014/23/EU). These objectives include economic growth, employment creation, the support of small and medium enterprises (SMEs), the inclusion of minority-owned businesses, and the fostering of sustainable practices within firms (Flynn, 2017; Crespi and Guarascio, 2019; Divella and Sterlacchini, 2020).

In particular, supporting the growth of SMEs by facilitating their access to PP markets is one of policymakers' main concerns because of the significant role SMEs play in generating employment in developed and developing countries (Cravo and Piza, 2019). Nonetheless, the challenge is not only to create new jobs, but also to create 'good jobs' with decent working conditions. In this line, recent studies stress the state's role in indirectly shaping the working conditions of subcontracted staff through the socially responsible PP of services from the private sector. Indeed, in the private sector, the risk of precarious work may be significant due

to the pressure to reduce costs (Jaehrling et al., 2018; Brennan et al., 2012; Vrangbæk et al., 2015).

Several scholars examine governments' attempts to uphold minimum labour standards for workers providing contracted services in PP circumstances (Holley et al., 2015; Holley, 2014). More specifically, the inclusion of 'labour clauses' in awarded public service contracts (PSCs), aimed at establishing minimum working conditions and protecting the employees of winning firms from labour exploitation, could ensure socially responsible PP (Keulemans and Van de Walle, 2017). Nonetheless, recent studies question the effectiveness of these labour clauses as, in some cases, they may be merely 'rhetoric' and cannot replace stronger collective action and legal protective mechanisms (Holley et al., 2015).

That said, to empirically assess the adequacy of PP for the implementation of the aforementioned public policies, in this study we analyse the effects of the award of PSCs by Italian public administrations in 2015 on a sample of 1,782 winning SMEs that were not awarded PSCs during the previous three years. The award of PSCs can be considered as a temporary and exogenous demand shock for the winning firms, the intensity of which depends on the size of PSCs relative to the size of the firm. More specifically, we examine the impact on the performance of the winning firms and the ways in which such firms manage salaries and social security contributions (SSCs) included in the payroll of their employees to achieve that performance.

The aspects of the award examined are the awarded value of PSCs and the corresponding winning rebate (discount over the starting tender price) deflated by the turnover of the winning firms in the pre-contract period to normalise the size of the shock (Lee, 2021). Indeed, we expect these aspects of awards to be significantly associated with the performance, employment decisions, and payroll management of the winning firms. Ultimately, our main purpose is to determine whether higher winning rebates, which are economically beneficial for public

administrations, moderate the effects of the award on the firms' performance and are achieved at the expense of worse economic conditions for the employees of the winning firms and lower payments of SSCs. SSCs can be considered the labour taxes, which are needed to finance public goods and pensions, that each employer is legally required to withhold from personnel salaries and pay to tax authorities.

More specifically, we seek to identify whether higher PSC awarding values and rebates lead winning firms to aggressively downward manage SSCs in a manner that, following previous studies (Ravenda et al., 2020, 2021), may provide evidence of labour tax avoidance. It is worth noting that labour tax avoidance is not necessarily illegal. Indeed, similar to the concept of income tax avoidance, we include within labour tax avoidance a 'continuum of labour tax planning strategies, spanning from relatively benign strategies, envisioned by tax policies, on the left to extremely aggressive or illegal strategies on the right' (Ravenda et al., 2021). We indirectly infer labour tax avoidance by assessing the change in SSCs per employee, following the award of PSCs, conditional on salaries per employee, firm resources, and turnover, among others. We consider this effect relevant in itself and therefore do not specifically address the practices adopted by the winning firms to avoid SSCs.

To perform our analysis, we use a quasi-experimental design that consists of estimating a difference-in-differences (DID) regression model after matching, based on the propensity score in the pre-contract period (2014), 1,782 firms with awarded PSCs in 2015 to a control group of firms without awarded PSCs over the period 2012–2017. The awarded PSCs generate an exogenous demand shock for the winning firms.

Our estimations, using firm fixed effects, show that higher awarded contract values enhance the performance of the winning firms in terms of profitability (ROA)[1], labour productivity,

[1]We use profitability, measured by the return on assets (ROA) ratio, as our main proxy for firms' financial performance.

employment growth, and sales growth. Their improved performance is also reflected in a positive effect on the average payroll (salaries and SSCs) per employee. Importantly, higher winning rebates moderate the positive effects of the award on payroll by inducing the winning firms to downward manage both salaries and SSCs per employee to maintain certain levels of performance. These effects are mostly significant for smaller micro enterprises. Furthermore, winning rebates have a negative impact on the performance of firms in the construction industry by inducing these firms to downward manage the payroll of their employees more aggressively than firms in other industries. Our results are robust to tests supporting the parallel trend assumption, which is a necessary condition for the validity of the DID model.

In summary, our findings support our prediction regarding the tendency of winning firms to pass higher awarding rebates onto their employees by reducing their salaries and onto the social security system by reducing their payment of SSCs. Furthermore, the award of PSCs alone, which could enhance the financial performance of the winning firms, may not push these firms to a significant increase in their permanent workforce or its remuneration given that they might make the most of their current labour capacity or use precarious forms of work to avoid SSCs.

Several studies examine the effects of the demand shocks caused by PP on the performance of winning firms in different legal and institutional contexts (Fadic, 2020; Ferraz et al., 2015; Hoekman and Sanfilippo, 2020; Lee, 2021). To the best of our knowledge, however, our study is the first to apply a DID model with continuous treatments on a propensity score matched sample to draw causal inferences on the impact of awarded PSC values and related winning rebates on various dimensions of performance and the payroll management practices of the winning firms.

Therefore, our study contributes to the literature on the effects of exogenous demand shocks, triggered by public authorities, on firms' dynamics (Fadic, 2020; Ferraz et al., 2015; Hoekman and Sanfilippo, 2020) by showing that PP can be an effective industrial policy to foster growth

and financial performance of supplying service firms, especially if they are micro enterprises facing demand constraints.

In this vein, our research also responds to previous studies that examine public policies and included interventions to support the performance of SMEs and, in particular, micro enterprises (Cravo and Piza, 2019; Grimm and Paffhausen, 2015). However, as suggested by Cravo and Piza (2019), the identification strategies these prior studies adopt to isolate the causal impact of the interventions as well as their intensity are weak. Furthermore, they do not specifically address the role of PP. Hence, our study aims to fill these gaps.

However, the magnitude, duration, and quality of the demand shocks in terms of awarding conditions should be considered to assess the sustainability and other social implications of the positive influence on growth and financial performance of the supplying firms, which may even be reverted once the effects of the shocks are exhausted. In this regard, as a further contribution, our empirical findings provide quasi-experimental evidence that the awarding of PSCs mostly based on the lowest price, leading to higher rebates, implies that efficiency gains for public contracting authorities could be achieved at the expense of the conditions of the employees within the winning firms and of a reduction of paid SSCs needed to finance national social security systems. This issue could be more common in sectors that are characterised by higher insecurity and employment vulnerability, such as construction.

These results can be extended to many other countries that, like Italy, have weak labour law enforcement, ineffective labour inspection mechanisms, and therefore, high levels of irregular employment. For example, recent studies confirm that undeclared work in the EU remains a concern, especially in new member states as well as in three older members: Greece, Spain, and Italy (Williams et al., 2018; Horodnic and Williams, 2019). In addition, in several European countries, the construction industry is among the most affected by irregular

employment involving undeclared work and SSC evasion (Ravenda et al., 2021; Williams, 2013; Williams et al., 2011).

Finally, our study also contributes to the literature that analyses how service firms manage their labour capacity and expenses to meet temporary demand shocks and achieve their desired levels of financial performance (Hart, 2017).

The remainder of the paper proceeds as follows: section 2 presents some related research and develops the hypotheses; section 3 describes the data and identification strategy; section 4 presents and discusses empirical results; and section 5 comprises concluding remarks.

2 Related Research and Hypotheses

Firms, especially SMEs, may be interested in PSC awarding because of related perceived benefits in terms of the certainty of payments, opportunities for growth, security and continuity of the business relationships, easier access to borrowing, reputation enhancement, and contacts in the public sector (Flynn et al., 2015; Loader, 2013; Duggan et al., 2016). In particular, PSC-winning firms may find additional opportunities to increase their sales to public administrations (Fadic, 2020).

In this regard, previous studies examine the effects of demand shocks on firm dynamics, including growth and financial performance. In particular, Fadic (2019) finds that demand shocks arising from the award of public contracts have a positive and significant effect on the growth of a sample of 1,179 SMEs in Ecuador over the period 2009-2012, compared to the runners-up of the contests. Growth is measured in terms of increases in sales, wage expenses, and fixed assets. The effects of demand shocks are only detected in the year of the contract award, probably due to the low monetary value of the public contracts awarded to SMEs.

Using a quasi-experimental design, Ferraz et al. (2015) find that in Brazil, firms winning public contracts grow significantly more in terms of the number of their employees than losing

firms competing for the same contracts. In addition, these effects extend beyond the term of the contracts, given that the winning firms can learn about the demand of their products. Hence, they are more likely to participate in future higher value auctions and enter new markets.

Hoekman and Sanfilippo (2020) provide evidence that participation in PP, measured as the share of total sales to the government, enhances the performance of roughly 6,700 companies based in 19 countries in sub-Saharan Africa. The positive effects of PP are stronger for smaller and domestically owned firms. The authors use labour productivity, based on the ratio of sales to number of employees, as the main measure of performance. The main limitation of the study lies in the usage of cross-sectional data on winning firms and public contract awards, rather than longitudinal data, that precludes both addressing selection issues and any inference on causality.

Finally, Lee (2021) finds that temporary and exogenous demand shocks, represented by Korean PP, foster firm growth (revenue, value-added, and employment) beyond the contract term, especially among small, young, and financially constrained firms. Specifically, sustainable firm growth arises from the development of private-sector business rather than merely from the execution of public contracts. This persistent development is empirically supported by two mechanisms boosted by PP—the enhanced reputation with private customers and the relaxation of financial constraints.

That said, our first hypothesis arises from the findings of prior research that PP can support the growth and financial performance of winning firms by generating additional demand. Therefore, we formulate the following general hypothesis:

Hypothesis 1. *Ceteris paribus*, awarded PSCs enhance the performance of the winning firms.

In recent decades, the market of PSCs has significantly grown because of the tendency of many governments to outsource a wide range of public services, the production of which has

been gradually transferred from the public to the private sector (Vrangbæk et al., 2015). This transfer has mostly been driven by efficiency concerns and the contraction of public spending, especially in wages, in labour-intensive sectors (Peters, 2012). Therefore, the award of PSCs typically takes place through public tender auctions in which the lowest price is often the main criterion to determine the winning firm.

In this regard, previous studies support public tender auctions that may lead to the selection of the most efficient contractor by fostering competition and enhancing incentives for bidders to reveal their private information regarding productions costs (Chever et al., 2017; Albano et al., 2017). However, competitive tenders may lead participants to bid abnormally low prices (aggressive bidding) to increase their chances to be awarded PSCs (Coviello et al., 2018a).

Importantly, aggressive bidding may increase bidders' chances of being awarded a contract even when the winner is determined by assessing a range of qualitative parameters (criterion of 'most economically advantageous offer'), specified in the call for tender, as well as the lowest price (Decarolis and Giorgiantonio, 2015). Indeed, Dekel and Schurr (2014) show through controlled experiments that PP tender evaluators, assessing qualitative indicators of competing bids while being exposed to the bid prices, are systematically biased by giving an unjust advantage to the lower bidder.

Aggressive bidding may arise from the adverse selection of the bidder that uses private information on its production costs, and it may be allowed by inadequate mechanisms to assess the reliability of abnormally low bids in public tenders (Baldi et al., 2016).

Prior research shows that aggressive bidding, which leads to abnormally high winning rebates, is associated with a higher probability of lower quality, ex-post contract price renegotiations, and therefore, cost overruns for the public contracting authorities (Decarolis, 2014; Coviello et al., 2018b). However, as well as determining lower delivery standards, aggressive bidding may lead winning firms to downward manage their costs to maintain the

desired level of financial performance. In particular, in labour-intensive service sectors, labour costs represent most of the total costs and their reduction is considered to be an effective way for private-sector firms to obtain a competitive advantage in public tenders (Vrangbæk et al., 2015). This reduction may be carried out through precarious work, lower salaries, longer working hours, and other forms of labour exploitation.

In this vein, Vrangbæk et al. (2015) review twenty-six empirical studies published over the period 2000-2012 on the consequences for employees arising from contracting out services from public administrations to private-sector companies. The authors mostly find negative effects for employees, including a reduction in the workforce, increase in temporary and precarious work, higher work intensity, worse economic conditions, fewer benefits, and reduced job satisfaction (Flecker and Hermann, 2011; Dube and Kaplan, 2010).

Ravenswood and Kaine (2015) highlight the low work conditions, especially in terms of salaries, of predominantly female workers employed in residential aged care in Australia and New Zealand, whose services are publicly procured. The authors support the view of other scholars regarding the positive role of governments, as indirect employers, to enhance and protect labour standards in contracted services by making the award of PSCs conditional on the supplier complying with minimum labour standard laws and voluntary industry codes (Jaehrling, 2015). Nonetheless, public tender processes are mostly driven by the pursuit of efficiency at the expense of the labour standards of the employees of subcontracted companies (Holley, 2014).

Holley et al. (2015) examine the case of school cleaners who were employed under New South Wales (Australia) government contracts between 2010 and 2011 to show that the contracting-out of government services through PP can have a negative impact on the working conditions of the subcontracted workers. Furthermore, the inclusion of clauses in PSCs requiring contractors to comply with minimum labour standards for their employees is

ineffective in the Australian context due to the inadequate monitoring and enforcement by the contracting public authorities.

In Italy, the main labour protection established by PP regulations[2] consists of the application of the collective agreements in force for the sector and the area in which the work is performed. These collective agreements define minimum working conditions, including wages, for the employees of the winning firms. Nonetheless, there is no indication of the adequacy of the monitoring and enforcement of collective agreements in Italy to make this protection effective (Jaehrling et al., 2018). These monitoring activities are assigned to specific labour inspection bodies other than public buyers. In this regard, several studies find that irregular employment is widespread in Italy, especially in certain sectors like construction, agriculture, and specific services (Ravenda et al., 2021; Williams et al., 2018; Kelmanson et al., 2019). This is an indication of the ineffectiveness of labour inspection activities in Italy.

Importantly, although the award of PSCs may enhance winning firms' opportunities for growth, the temporary nature of PSCs, especially in competitive public tender markets with low entry barriers and in the absence of consolidated contractual relationships, may lead firms to perceive the demand shock as unsustainable and they may prudently avoid hiring additional permanent staff (Fadic, 2020). The reduced staffing model that firms may adopt to increase efficiency can be effective when workloads are stable. However, in the case of temporary peaks of demand (demand shock), it may lead to excessive pressure and workloads for the current employees (Zuberi, 2011) or the resort to temporary and precarious workers that are paid less, especially when they belong to weaker and less unionised categories (Dube and Kaplan, 2010; Vrangbæk et al., 2015). This scenario may be reflected in our study design given that the winning firms in our sample have not been awarded any PSC over the previous three years, and therefore, they cannot count on a stable contractual relationship with public authorities.

[2]Legislative Decree 12 April 2006 N. 163 is the PP law that was in force over the period of our study.

However, capacity constraints may lead winning firms to give up additional private contracts and hold back on their potential growth (Fadic, 2020). Nonetheless, this scenario seems less plausible within labour-intensive service sectors in which firms benefit from greater leeway to quickly respond to demand shocks due to more flexible—especially if less qualified—labour capacity relative to capital capacity.

Following previous considerations, our second general hypothesis is the following:

Hypothesis 2. *Ceteris paribus*, higher rebates in awarded PSCs induce winning firms to downward manage the payroll (salaries and SSCs) of their employees.

3 Data and Empirical Strategy

3.1 Data and Sample Selection

Our sample consists of 1,782 unlisted SMEs[3] with awarded PSCs in 2015 that have not won any PSC over the previous period from 2012 to 2014. The information on the firms and related PSCs is obtained from the national database of public contracts managed by the National Anti-Corruption Authority (ANAC). This database includes all public contracts awarded in Italy since 2007 and the characteristics of the related public tenders. The object of public contracts can be works, services, or supplies. ANAC granted us access to the database for PSCs with a value above € 40,000[4] that had been published over the period 2012–2017. In 2015, 13,874 different companies, excluding consortia and temporary joint ventures[5], were awarded PSCs.

[3]Following the definition of Eurostat (European Commission 2003), the firms are classified as SMEs because they have fewer than 250 employees.

[4]Based on the Italian PP law (Legislative Decree 12 April 2006 N. 163) in force in 2015, public authorities can directly award public service contracts for an amount lower than €40,000 to a designated contractor (direct assignment) without consulting with two or more competing economic operators.

[5]We exclude firms in consortia or temporary joint ventures, as the effects of the award of PSCs on each firm cannot be specifically identified.

Of these 13,874 companies, we identify 6,499 companies with no PSC awarded over the prior period 2012–2014. This restriction aims at isolating the effects of the awards in 2015 from prior PSCs that may confound our inferences.

Subsequently, using their tax code, we search for these companies in the AIDA database[6] and find 2,420 companies with all accounting information and other master data needed for our study. However, we further restrict our sample by only including in our study those companies whose total PSC awarded value represents at least 5% of their sales revenues in 2014. Therefore, we have a final sample of 1,782 SMEs winning PSCs in 2015. Table 1 shows the distribution of the 1,782 winning firms by two-digit NACE[7] industry. In addition, for the winning firms in each industry, the table displays the total PSC awarded value, the average awarded value to sales in 2014, the average winning rebate to the reserve price, and the average winning rebate to sales in 2014. The winning rebate is the difference between the reserve price, the maximum value that the contracting authority is willing to pay at the time of tender publication, and the awarding price that the contracting authority will eventually pay to the winning firm for the contracted service.

(Insert Table 1 here)

Notably, the industries with the greatest number of winning firms are NACE 43 (specialised construction activities), with 185 firms representing 10.38% of the total, followed by NACE 71 (architectural and engineering activities; technical testing and analysis), with 153 firms representing 8.59% of the total.

The industries with the highest medians of awarded value to sales are NACE 91 (libraries, archives, museums, and other cultural activities) (0.432), NACE 52 (warehousing and support

[6]AIDA is the database managed by Italian Bureau van Dijk, which includes the financial statements, other master data, and details for 1 million Italian companies.

[7]NACE is the statistical classification of economic activities used in the European Union. The current version is revision 2 and was established by Regulation (EC) No 1893/2006.

activities for transportation) (0.382), and NACE 87 (residential care activities) (0.364). This means that, within our sample, in these latter industries, the winning firms may have capitalised more on the award of PSCs for their growth.

Finally, among the most represented industries, NACE 71 (architectural and engineering activities; technical testing and analysis) has the highest medians of rebate to reserve price and rebate to sales. Higher rebates may indicate stronger competition in the public tenders (Coviello and Mariniello, 2014).

To build a control sample for the winning firms, which is needed to estimate the DID model presented later, we first download all available needed data for unlisted firms in the same three-digit NACE industries as those of the winning firms, for the period 2012-2017, from the AIDA database. After removing observations with missing variable data and 16,655 firms with awarded public contracts over the period 2012–2017, according to the ANAC database, we are left with a sample of 199,868 firms that have not won any public contract over the period. Thus, we select the control sample for our estimations by applying the propensity score matching (PSM) method based on firm observations in 2014, the year before the award of PSCs. The purpose of PSM is to reduce the covariate imbalance between the treated and control groups. It involves using a logit model to estimate the propensity score (Rosenbaum and Rubin, 1985), defined as the probability of receiving the treatment that, in our study, is the award of PSCs.

We perform the PSM for each of the 15 subsamples of the treated and control firms based on their belonging to the same NACE level 1 industry[8]. Hence, we impose an exact matching on NACE 1 level to strengthen the weight of the industry variable (King and Nielsen, 2019), and therefore achieve a greater sectoral homogeneity between treated and control firms in our final matched sample. This homogeneity may be needed, as the industry could significantly

[8]NACE level 1 is the first hierarchical level of NACE and includes 21 sections identified by alphabetical letters A to U.

affect the type of competition within the PP market and the consequent behaviour of participant firms (Hoekman and Sanfilippo, 2020; Ferraz et al., 2015).

We test several PSM procedures including 1-nearest neighbour (NN), 2-NN, 3-NN, 4-NN, 5-NN, radius matching, kernel matching, and local linear regression (Stuart, 2010; Caliendo and Kopeinig, 2008). Finally, we select the 5-NN with replacement that best balances the distribution of PSM variables in both the control and treatment groups. Indeed, after the matching, this procedure yields the lowest mean and median Standardised Bias[9] and the smallest Standardised Bias across the largest number of PSM variables (Caliendo and Kopeinig, 2008). In addition, using more than one NN, as in 5-NN, may lead to more precise estimates when the number of observations in the control group is much higher than that in the treated group as in our study[10] (Caliendo and Kopeinig, 2008; Stuart, 2010).

Using the 5-NN PSM method with replacement, we match each winning firm with the five AIDA control firms scoring the closest logit of the propensity score[11] (Austin, 2011). Through the selection of only 5-nearest neighbours, we discard a large portion of the original AIDA sample. However, studies show that this significant sample restriction is unlikely to lead to reduced power (Stuart, 2010).

To address the PSM common support condition requiring an overlapping in the propensity score distributions between treated and control observations, we follow Austin (2011) by setting a caliper of 0.2 times the standard deviation of the logit of the propensity score, which in our case is equal to 0.346. Therefore, only observations within the caliper are included in the final matched sample by discarding those outside the common support area.

[9]The Standardised Bias is computed as difference of means in the treated and control subsamples as a percentage of the square root of the average of sample variances in both groups (Rosenbaum and Rubin, 1985).

[10]In our study, there are about 112 times as many control firms as treated firms.

[11]We use the STATA command psmatch2 (Leuven and Sianesi, 2018) to run the PSM method.

An important assumption for the validity of PSM is the strongly ignorable treatment assignment (SITA) (Rosenbaum and Rubin, 1985). This states that the treatment assignment (the award of PSCs) should be independent of the potential outcomes (firm performance and payroll decisions) conditional on observable control variables unaffected by the treatment (Stuart, 2010). The first SITA implication, also known as unconfoundedness (Caliendo and Kopeinig, 2008), is that there should not be unobservable variables, excluded from the model, associated with both the potential outcomes and the treatment (Caliendo and Kopeinig, 2008).

To address this strong assumption, we include in our PSM logit estimation all the control variables included in the baseline regression model (see Appendix A) that previous studies indicate are likely to affect our outcome variables and the probability of winning PSCs. In addition, we include some time-invariant firm variables[12] that, although dropped by the firm fixed effect estimations of the baseline DID regression, may influence both the treatment and the outcomes. These latter variables are dummies for two-digit NACE industries (*NACE2_IND*), dummies for regional locations (*REGIONS*)[13], dummies for corporate legal forms (*LEGAL_FORMS)*, number of companies in the group (*NUMCO*), number of subsidiaries (*NUMSUB*), and the Bureau van Dijk (BvD) independence indicator (*INDIP*) that measures the degree of a company's independence from its shareholders[14].

To address the SITA requirement that observable covariates should not be affected by the treatment, we estimate the PSM logit model by only including variable observations in 2014

[12]Although these variables measure firm characteristics that are relatively stable over time, they may occasionally change. Nonetheless, AIDA database only provides the last available data with no historical information.

[13]Italy is divided into 20 regions, representing the first-level administrative entities of the Italian Republic defined in the Italian Constitution. Each region is divided into provinces and each province into municipalities.

[14]The BvD indicator takes 10 possible categorical qualifications that we have converted in a discrete variable, ranging from 0 to 10, in increasing order of independence.

that, because they were either predetermined to the tender publication and award of PSCs in 2015 or fixed, cannot be affected by the treatment. Furthermore, for the same reasons, in the DID baseline regression estimations, we include control variables lagged by one year.

Finally, although we seek to exclude from the control sample any firm with awarded public contracts over the period 2012–2017, there may be a low probability that some firms in the matched control group are winners of public contracts. However, this measurement error is unlikely to be problematic for our identification strategy given that it could only bias the treatment effects towards zero.

3.2 Baseline DID Model and Variables

To test our hypotheses, we estimate a baseline DID regression model by including treated and matched firm observations in 2014 (pre-treatment period) and average observations for the same firms in 2015 and 2016 that are, therefore, collapsed into a single post-treatment period. Indeed, although PSCs are published and awarded in 2015, only about 40% are finalised within 2015 and about 90% are finalised within 2016. Furthermore, some firms may have won various PSCs with different execution terms. Hence, the effects of contract awards and particularly their accounting effects are likely to span at least two years.

The dependent variables related to the hypothesis 1 are sales growth (***SALGROW***), employment growth (***EMPGROW***), return on assets (***ROA***) profitability ratio, and labour productivity (***SALEMP***). These variables are widely used in previous studies as measures for different firm performance dimensions (Fadic, 2020; Ferraz et al., 2015; Barbosa and Faria, 2020; Pompei et al., 2019; Hoekman and Sanfilippo, 2020; Flammer, 2015). Specifically, *SALGROW* is the natural logarithm of sales in year *t* to sales in *t-1*; *EMPGROW* is the natural logarithm of average number of employees in year *t* to average number of employees in year *t-*

1; *ROA* is net income in year *t* divided by book value of total assets in year *t*; and *SALEMP* is the ratio of sales revenue to average number of employees per year.

The dependent variables related to hypothesis 2 are salaries per employee (***PAYEMP***) and SSCs per employee (***SSCEMP***), both of which are included in the payroll. In Italy, expenses for salaries and SSCs incurred by the employer[15] are separately reported in the income statement that all private companies must file with the public Register of Companies, kept by the Chambers of Commerce, as part of full financial statements[16].

Our DID model specification relies on the assumption that the expected outcomes of the treated and control groups would exhibit parallel trends over the period leading up to the treatment, conditional on the observable covariates, in the unverifiable scenario of the absence of treatment. Failing this assumption, DID would produce biased estimates of the treatment effects because of confounding changes unrelated to the treatment with the effects of the treatment (Lindner and McConnell, 2019). Our strategy of matching treated firms that won PSCs in 2015 with non-treated firms based on observables in 2014, the closest pre-treatment year, may reduce concerns regarding bias for non-parallel trends of the tested outcomes. We further address these concerns by including firm fixed effects to eliminate unobserved time-invariant heterogeneity at the firm level, as well as a wide set of time-varying controls in the DID regression. Furthermore, to avoid changes in sample composition affecting our inferences, we use balanced firm panels and correct standard errors to allow for serial correlation at the firm level in DID regressions (Anders and De, 2019). Finally, we perform additional tests to lend support to the parallel trend assumption (see the section on robustness checks).

[15]A flat rate ranging from 29% to 32% of each employee's gross salary is charged to the employer as SSCs.

[16]Italian accounting regulation for private companies is based on the Italian Civil Code (articles from 2423 to 2429), compliant with 2013/34/UE Directive, and accounting standards issued by the OIC (Italian Accounting Standard Setter).

Another assumption of the DID specification is the stable unit treatment value assumption (SUTVA) implying that the outcomes of one individual are unaffected by the treatment assignment of any other individuals (Lindner and McConnell, 2019). Therefore, there must not be spill over effects among the treated and non-treated groups. In our research design, this assumption may be more plausible than other studies comparing losers and winners in the same public tenders that may more closely compete and interact (Fadic, 2020; Ferraz et al., 2015).

Another DID assumption is that the treatment has no effects on the outcome variables in the pre-treatment period, and therefore, there are no anticipation effects (Lechner 2010). This assumption is supported by the fact that the publication of public tenders in 2015 is hardly predictable one year in advance. Moreover, the award of PSCs is even more unpredictable given that the treated firms have no ongoing PSCs that might, for example, generate renewal expectations.

Finally, the DID exogeneity assumption implies that the covariates are not influenced by the treatment (Lechner 2010). This requirement is ensured by the usage of lagged controlled variables measured in the pre-treatment period (2014), and by the unlikeliness of anticipation effects in 2014 due to the aforementioned reasons. In contrast, time-invariant variables such as the industry dummies can be considered exogenous by construction.

That said, following a similar structure to the DID models in the paper by Acemoglu et al. (2004), in our DID specification, we measure the intensity of the treatment (the award of PSCs) by interacting two continuous variables with the ***POST*** binary variable, indicating the post-treatment period. Specifically, the first variable ***AWARD*** is the ratio of total awarded value to sales in 2014, at the winning firm level. The second variable ***REBATE*** is the ratio of total winning rebates to sales in 2014, at the winning firm level. Obviously, the variables *AWARD* and *REBATE* take a value of 0 for the control firms. Similar to Lee (2021), we normalise the shock of the awarded value and the winning rebate to sales in 2014, rather than sales in 2015,

to establish a common base of reference. Indeed, we cannot clearly distinguish the sales arising from PSCs recorded in 2015 from those recorded in the following years. Furthermore, sales from PSCs might affect other sales of the same firm that would not be independent from the exogenous shock.

Finally, our DID baseline regression model is the following equation:

$$Y_{it} = \beta_0 + \beta_1 POST_t + \beta_2 POST_t \times AWARD_{it} + \beta_3 POST_t \times REBATE_{it} + \sum_k \beta_k CONTROLS^k_{it-1} + u_i + v_{it} \quad (1)$$

Where, for firm i in period t (pre-treatment or post-treatment), Y_{it} is one of the aforementioned dependent variables, measuring firm performance or payroll expenses per employee; $POST_t$ is a dummy for the post-treatment period; $POST_t \times AWARD_{it}$ is the interaction between *POST* and *AWARD*[17], denoting the continuous DID effect related to the awarded value of PSCs; $POST_t \times REBATE_{it}$ is the interaction between *POST* and *REBATE*, denoting the continuous DID effect related to the winning rebates; $CONTROLS^k_{it-1}$ is a set of k lagged control variables, presented in the Appendix A and including industry-year fixed effects, that previous studies find to be associated with firm performance, payroll expenses (e.g. Ding et al., 2018; Ravenda et al., 2019b, 2019a), and the likelihood of participating in public tenders and winning them (Lee, 2021; Hoekman and Sanfilippo, 2020; Ferraz et al., 2015; Fadic, 2020); u_i denotes unobserved time-invariant firm fixed effects; and v_{it} is the error term.

Regarding control variables, previous studies find a relationship between participation in PP and different firm characteristics and dimensions of firm performance. For example, the size of firms may affect firms' propensity to participate in public tenders, the likelihood of winning them, and the effects of public contract awards on firm performance (Hoekman and Sanfilippo,

[17]Variables *AWARD* and *REBATE* cannot be included uninteracted in the DID model, given that they do not vary over the two periods at the firm level, and therefore, they would be absorbed by firm fixed effects u_i in the estimations.

2020; Albano et al., 2015; Flynn et al., 2015; Divella and Sterlacchini, 2020). We account for firm size by including control variables related to the number of employees (*EMPL*) and book value of total assets (*ASSETS*). Prior financial constraints and performance can also affect firms' participation in PP and the related effects (Lee, 2021; Fadic, 2020). Therefore, we include control variables related to firm indebtedness (*INDEBT*) and liquidity (*CASH*) to account for financial constraints. In addition, we include other variables to control for firms' performance in terms of profitability (*ROA* and *LOSS*) and efficiency (*SALEMP* and *SERVEMP*). Finally, studies find heterogeneous effects of PP on firm performance across different industries (Hoekman and Sanfilippo, 2020; Ferraz et al., 2015). Hence, we also include dummy variables for two-digit NACE industries (*NACE2_IND*) interacted with the years.

4 Empirical Results and Analysis

4.1 Matching Results

We test whether the 5-NN PSM effectively reduces the covariate imbalance between the two subsamples by achieving good matching, which may lend support to the assumption regarding common trends in the outcomes in the absence of the treatment. Table 2 shows the variable means[18] for the treated and control subsamples, the Standardised Bias (%bias) with its percentage reduction, and the t-tests for differences in means after the matching. All continuous variables are winsorised at the 2.5th and 97.5th percentiles of their annual distributions to mitigate the influence of outliers.

(Insert Table 2 here)

[18]Due to their large number, we do not show the dummy variables for regional locations (*REGIONS*), firm legal forms (*LEGAL_FORMS*), and two-digit NACE industries (*NACE2_IND*). However, the quality of the matching for these variables is equivalent to that of the presented variables.

It is noteworthy that the PSM significantly reduces the absolute value of the Standardised Bias for all variables except for *INDEBT*. More importantly, after the matching, the absolute value of the Standardised Bias for all variables is far below the commonly accepted maximum threshold of 5% that defines a good matching (Caliendo and Kopeinig, 2008) and the mean and median are both 1.1%. Furthermore, the t-tests show insignificant mean differences for all the variables between the two subsamples.

Finally, after re-estimating the PSM on the matched sample, relative to the first PSM logit, the pseudo-R^2 decreases from 0.063 to < 0.001, and the likelihood ratio χ^2 test on the joint significance of the regressors in the logit decreases from 1,292.73 (p-value < 0.001) to 2.22 (p-value ≈ 1.000). Hence, all our analyses show that the 5-NN PSM succeeds in significantly decreasing the covariate imbalance between treated and control subsamples.

In Appendix A.2, we present the univariate DID analysis on the outcome variables providing preliminary evidence of the effects of the award of PSCs on the winning firms. Finally, the variance inflation factor (VIF) and Pearson pairwise correlations for all the variables, examined in Appendix A.3, do not raise any multicollinearity concerns.

4.2 Baseline Regression Results

Table 3 presents the estimations of Eq. (1) baseline DID model for each firm performance measure. We present two specifications for each dependent variable. In the first, we only include the DID variable of interest *POST*×*AWARD*, whereas in the second, we also add the DID variable of interest *POST*×*REBATE*.

(Insert Table 3 here)

Notably, the coefficient on the DID interaction variable *POST×AWARD* is positive and significant[19] in all regression specifications. This suggests that higher PSC awarded values enhance firms' performance in terms of profitability (*ROA*), labour productivity (*SALEMP*), employment growth (*EMPGROW*), and sales growth (*SALGROW*). Overall, these results provide support for hypothesis 1.

The coefficient on the DID interaction variable *POST×REBATE* is statistically insignificant in all specifications 2, except for the *EMPGROW* regression, where it is positive and significant. This indicates that, given the awarded values, higher winning rebates do not negatively affect firm performance. Therefore, the winning firms somehow manage their activities and related expenses to prevent the pressure on their financial margins, due to high rebates, from affecting their performance improvement arising from the award of PSCs.

Our results confirm the evidence of previous studies that, in different institutional contexts, there are positive effects of exogenous demand shocks caused by PP on various dimensions of firm performance (Fadic, 2020; Ferraz et al., 2015; Hoekman and Sanfilippo, 2020; Lee, 2021). Nonetheless, relative to these prior studies, we show that, at least for specific performance dimensions, the magnitude of these positive effects varies with the intensity of the demand shocks. In addition, these effects can occur regardless of the awarding conditions (e.g. rebates).

Table 4 shows the estimations of Eq. (1) baseline DID model for the payroll expense proxies. We estimate the same two specifications as those for the performance proxy regressions. Moreover, for the SSCs per employee variable (*SSCEMP*), we estimate a third specification (3) that includes a control for the contemporary salaries per employee (*PAYEMP*). Specification 3 aims at assessing whether the winning firms manage SSCs relative to the salaries on which they are computed, therefore engaging in labour tax avoidance practices (Ravenda et al., 2021).

(Insert Table 4 here)

[19]In this study, we consider any two-tailed p-value lower than 0.05 to be significant.

First, in specifications 1 and 2 of the *PAYEMP* regression, the coefficient on the DID variable *POST×AWARD* is positive and significant, indicating that higher PSC awarded values are associated with higher salaries per employee. Conversely, the coefficient is positive and only marginally significant ($p < 0.10$) in specifications 1 and 2 of the *SSCEMP* regression. Overall, these results provide evidence that the award of PSCs alone also benefits the employees of the winning firms. Nonetheless, in specifications 2, the coefficient on the DID variable *POST×REBATE* is negative and significant, suggesting that higher winning rebates have a negative impact on salaries and SSCs per employee, consistent with hypothesis 2. This may imply that winning firms pass the burden of high rebates on their employees by downward managing their economic conditions.

Furthermore, in specification 3, the insignificant coefficient on the DID variable *POST×AWARD* indicates that the positive effects of awarded PSCs on *SSCEMP* are mostly due to the increase in salaries per employee (*PAYEMP*) on which SSCs are computed. More importantly, the negative and significant coefficient on *POST×REBATE*, despite controlling for *PAYEMP*, suggests that the winning firms may avoid SSCs (labour tax avoidance) to soften the negative effects of high rebates on their financial margins.

It should be stressed that there are two main strategies for labour tax avoidance (Ravenda et al., 2021). The first strategy involves rearranging—even fraudulently—some salary concepts, taxable under the legislation in force[20], with other kinds of compensation excluded from the social security tax base such as fringe benefits, travel, and meal allowances. The second strategy consists of illegal undeclared work, namely the underreporting of employee worked hours and the payment of undeclared black wages. Both strategies may be reflected in our results revealing

[20]The social security taxable base is regulated by the Legislative Decree n. 314 of 1997.

lower paid SSCs for higher winning rebates conditional on reported salaries, resources, and turnover.

In summary, the award of PSCs may have positive effects on various dimensions of winning firms' performance. These effects are proportional to the value awarded. Nonetheless, high winning rebates may lead winning firms to downward manage their payroll expenses to fully capitalise on the opportunity to enhance their performance.

4.3 Additional Analyses and Robustness Checks

4.3.1 Parallel Trend Tests

Although the parallel trend is empirically untestable, we perform some standard tests to indirectly support the assumption and make it more plausible. Specifically, we carry out a univariate DID analysis of the outcome variables based on their changes from 2013 to 2014, namely the two years before the treatment year. Therefore, we test whether there are significant differences in the changes between the two groups that may reveal a non-parallel trend. Table 5 presents this analysis.

(Insert Table 5 here)

It is noteworthy that that the average DID (treated minus control) of variable changes over the two years is not significantly different from zero for any of the outcome variables, providing support for the parallel trend.

In addition, we carry out a so-called 'placebo experiment' by pretending that the treatment, namely the award of PSCs, occurs earlier in 2014 rather than in 2015. Then, we re-estimate the DID model by considering 2013 as the pre-treatment period and 2014 as the only post-treatment period. If the DID treatment effects in the placebo regressions are not significant at conventional levels across all the estimations, this supports the parallel trend assumption. Conversely, as we may exclude anticipation effects based on our research design, if we find some significant

effects of this placebo treatment, some doubts may be cast on the validity of the parallel trend assumption (Lechner, 2010). Table 6 shows the placebo regression estimations.

(Insert Table 6 here)

As expected, all the coefficients on the DID variables *POST×AWARD* and *POST×REBATE* are not significant at the conventional level in any of the regression specifications. These results enhance the credibility of the parallel trend assumption.

4.3.2 Heterogeneous Effects

We next examine whether the effects of PSCs are heterogenous across different subsamples of firms built based on characteristics defined by the covariate number of employees (*EMPL*) and the industry. More specifically, we re-estimate the Eq. (1) DID regression for each subsample of firms above and below the median of covariate *EMPL* measured in the pre-contract period. Table 7 presents the results for the firm performance proxies (Panel A) and the payroll expense proxies (Panel B).

(Insert Table 7 here)

Regarding performance proxy regressions (Panel A), the significance of the coefficient on DID variable *POST×AWARD* is confirmed in all regressions with the subsample of firms having a number of employees below the median of eight. In contrast, for the subsample of firms with more than eight employees, the coefficient on *POST×AWARD* only remains significant in the *SALEMP* regression. This scenario suggests that the demand shock of PP has stronger positive effects on the profitability and growth of micro enterprises (0–9 employees), as defined by Eurostat (European Commission, 2003). Indeed, these firms are more demand-constrained and the award of PSCs may be more effective in fostering their employment and sales growth relative to larger firms (Hoekman and Sanfilippo, 2020).

Turning to payroll expense regressions (Panel B), the negative coefficient on the DID variable *POST×REBATE* is significant in all specifications only for firms with *EMPL* below the median. Conversely, the coefficient is insignificant for firms with *EMPL* above the median. In addition, in the *PAYEMP* regression, the coefficient on the variable *POST×AWARD* is positive and significant only for firms with *EMPL* below the median. Overall, these results suggest that, on the one hand, micro enterprises are more sensitive to higher winning rebates that may induce them to downward manage their payroll to remain competitive. On the other hand, the award of PSCs benefits the employees of micro enterprises more than those of larger firms, regarding the positive impact on average salaries.

Studies show that in several European countries, the construction industry, which is characterised by high labour-intensity and low qualified labour force, is among the most affected by precarious or irregular employment involving undeclared work, exploitation of immigrant workers, and consequent evasion of SSCs (Ravenda et al., 2021; Williams, 2013; Williams et al., 2011). To address the peculiarities of the construction industry, which may cause significant heterogeneity within our sample, we re-estimate the Eq. (1) DID regression separately for the construction industry identified by the higher NACE level 1 section F. This section in turn includes two-digit NACE codes 41 (construction of buildings), 42 (civil engineering), and 43 (specialised construction activities). As can be seen in Table 1, the winning firms included in the construction industry NACE codes are 309 and represent 17.34% of our sample. Table 8 shows the regression estimations separately for the construction subsample and the other industries.

(Insert Table 8 here)

Notably, in regressions on firm performance proxies (Panel A), the positive effect of the awarded PSCs on firm performance is only confirmed in terms of sales growth (*SALGROW*) with the construction subsample. In all other regressions, the coefficient on *POST×AWARD* is

not significant at conventional levels. In contrast, in the other industries, the estimations confirm the full sample results. These results are consistent with studies that find sectorial heterogeneity in the effects of PP on firm performance in some countries (Hoekman and Sanfilippo, 2020; Ferraz et al., 2015). These studies suggest some possible reasons for this heterogeneity, which include differential potential for productivity improvements and differences in average contract sizes across sectors, among others.

In addition, the negative and significant coefficient on *POST×REBATE*, in specific performance regressions, suggests that construction firms may be particularly sensitive to high rebates. Indeed, these rebates negatively affect construction firms' performance in terms of profitability (*ROA*), labour productivity (*SALEMP*), and sales growth (*SALGROW*).

Turning to payroll expense regressions (Panel B), the negative and significant coefficient on *POST×REBATE* in the construction subsample and the insignificance of the coefficient in the other industry subsample indicate that higher winning rebates negatively impact the salaries and SSCs of the employees, mostly in the construction industry. Furthermore, the positive coefficient on *POST×AWARD* in *PAYEMP* regression is only significant at the 0.10 level for construction firms. This means that the positive effect of awarded PSCs on salaries is weaker for construction firms. Overall, these results confirm studies (Ravenda et al., 2021; Williams, 2013; Williams et al., 2011) that document higher insecurity and vulnerability of employment in the construction industry.

5 Conclusions and Discussion

We examine the effects of the award of PSCs by Italian public administrations in 2015 on a sample of 1,782 winning SMEs that were not awarded any PSC during the previous three years. Our results show that higher awarded values are positively associated with the performance of the winning firms and their average payroll per employee. Nonetheless, higher winning rebates

moderate the positive effects of the award on payroll by leading the winning firms to downward manage both salaries and SSCs per employee to maintain their desired level of performance. These effects are mostly significant for micro enterprises. In addition, firms in the construction industry show higher sensitivity to winning rebates. Indeed, these rebates have a negative impact on the performance of construction firms, and therefore lead these firms to downward manage the payroll of their employees more aggressively than firms in other industries.

Overall, our findings suggest some industrial policy implications regarding the management of public service procurement to achieve macroeconomic and social goals within the business fabric. Specifically, the award of PSCs could be a valid instrument to foster the sustainable growth of micro enterprises facing demand constraints in a highly competitive environment (Fadic, 2020). These results may be explained by the learning process including management skills and business practices, the efficiency gains, and the enhancement of reputation, networks, and business opportunities with the public and private sectors following the contract awards (Ferraz et al., 2015).

Therefore, these results may support the adoption of all suggested solutions to remove the obstacles that SMEs, and specifically micro enterprises, face when attempting to access PP markets (Albano et al., 2015; Stake, 2017). Indeed, micro enterprises are underrepresented in PP markets due to several constraints, such as limited access to PP information, high participation costs, reduced resources and capabilities for tendering, and delays in payments by public authorities, among others (Flynn et al., 2015; Flynn, 2017).

However, the award mostly based on the lowest price leading to higher rebates, which may in the first instance produce efficiency gains for public administrations, may generate an undesirable pressure on the financial margins of the winning firms. Indeed, to maintain an acceptable level of performance, these firms may tend to downward manage their payroll expenses by causing their employees to bear the final burden of high winning rebates. This may

be more likely in sectors such as construction, which are characterised by high labour intensity, low qualified labour force, and weaker employment protection. In addition, the reduction of SSCs collection from social security systems, even arising from labour tax avoidance practices, may represent a further social cost for the sustainability of national welfare.

In this context, the award of PSCs based on more qualitative criteria (e.g. the most economically advantageous offer), including social, labour, and environmental parameters (Decarolis and Giorgiantonio, 2015), may discourage aggressive bidding practices leading to abnormally high rebates. In addition, it may facilitate the access by SMEs to PP contracts (European Commission, 2008). The apparent efficiency losses for public contracting authorities may be more than offset by better economic conditions for the employees of the winning firms, higher social security revenues, and the provision of higher-quality public services. Indeed, the stricter enforcement of labour protection clauses within PSCs may be more costly even in terms of the negative impact on the growth of SMEs that may arise from forcing them to operate with excessively reduced financial margins.

Future research could explore whether the effects of PSCs are heterogenous across different typologies of PSCs, public tender procedures, and the related workforce qualification required. In addition, the quality of services provided may be another factor, significantly influenced by the awarding criterion, that could be analysed. Indeed, we expect high winning rebates to negatively affect the quality of public services. This may imply additional costs for the community, which could further undermine the efficiency gains for public contracting authorities. Finally, inferences on the macroeconomic effects of PP require an empirical analysis of the spill over effects on firms that are in competition or have business relationships with the winning firms in the same territories.

Appendix A.

A.1 Definition of Variables

Dependent Variables:

ROA = net income in year *t* divided by book value of total assets in year *t*.

EMPGROW = natural logarithm of average number of employees in year *t* to average number of employees in year *t-1*.

SALGROW = natural logarithm of sales in year *t* to sales in *t-1*.

PAYEMP = salary expenses divided by average number of employees per year.

SSCEMP = social security contributions divided by average number of employees per year.

Independent Variables of Interest:

Post = dummy variable indicating the post-treatment period in the DID model.

AWARD = total contract awarded values to sales in 2014 at the winning firm level.

REBATE = total contract winning rebates to sales in 2014 at the winning firm level.

Other Covariates:

SERVEMP = service expenses divided by average number of employees per year.

SALEMP = sales revenue divided by average number of employees per year.

Δ*SALEMP* = annual change in sales revenue divided by average number of employees per year.

EMPL = natural logarithm of average number of employees per year.

ASSETS = natural logarithm of book value of total assets.

Δ*ASSETS* = percentage change in book value of total assets relative to previous year.

INDEBT = indebtedness computed as total debt divided by book value of total assets.

CAPINT = capital intensity computed as net intangible and tangible fixed assets divided by book value of total assets.

LOSS = indicator variable for firms recording a loss for two or more consecutive years including the current year.

CASH = total cash and cash equivalents divided by book value of total assets.

ACCR = discretionary accruals (earnings management proxy) estimated based on the performance-adjusted modified Jones model (Dechow et al., 2010).

INDIP = Bureau van Dijk (BvD) company independence indicator ranging from 0 to 10 in increasing order of independence.

NUMSUB = number of company subsidiaries.

NUMCO = number of companies in the group.

REGIONS = dummy variables for the twenty Italian regions.

LEGAL_FORMS = dummy variables for corporate legal forms.

NACE2_IND = dummy variables for two-digit NACE industries.

A.2 Univariate DID Analysis

Table A1 presents the univariate DID analysis by comparing the changes in the outcome variables from the pre-treatment (Pre) to the post-treatment (Post) period, between the treated group of winning firms and the PSM matched sample.

(Insert Table A1 here)

Regarding the treated group, the variables *ROA* and *EMPGROW* show a significant increase in the post-treatment period. In contrast, the variable *SSCEMP* shows a significant decrease and the variables *SALEMP*, *SALGROW*, and *PAYEMP* do not exhibit any significant variation. Regarding the control group, the performance variables *ROA*, *SALGROW* and *EMPGROW* significantly decrease, whereas labour productivity (*SALEMP*) significantly increases. Finally, the payroll variable *PAYEMP* significantly increases and the variable *SSCEMP* significantly decreases. Notably, the trend of all outcome variables is mostly inconsistent between the treated

and control group, except for variable *SSCEMP*. Therefore, the average univariate DID (treated minus control) of variable changes over the two periods is positive and significant for the performance variables *ROA*, *SALGROW*, and *EMPGROW*, whereas it is negative, although not significant at conventional levels, for the payroll per employee variables.

Overall, the univariate DID analysis provides first evidence of a positive impact of the award of PSCs on the performance of winning firms, consistent with hypothesis 1. Conversely, the negative effects on firm payroll predicted by hypothesis 2 are less clear and need to be confirmed by a multivariate analysis including observable covariates, and more importantly, the continuous treatment effects depending on the awarded values and the winning rebates.

A.3 Multicollinearity Check

Table A2 displays the Pearson pairwise correlations among the covariates included in the Eq. (1) baseline DID model and the related variance inflation factor (VIF).

(Insert Table A2 here)

Notably, the average VIF is 1.85 and the VIF values for the individual covariates oscillate between a minimum of 1.00 for *POST*×*REBATE* to a maximum of 4.07 for *SALEMP*. Therefore, all the values are far below the standard maximum cut-off of 10, which is typically accepted in previous research to rule out multicollinearity issues in regression estimations (Cameron and Trivedi, 2010). These VIF results may relieve some concerns arising from high correlations between *SALEMP* and *SERVEMP* (0.822) and between *ASSETS* and *EMPL* (0.579). In contrast, the absolute values of all the other correlation coefficients are relatively small (always below 0.42). Overall, these results suggest that our regression estimations are unlikely to be influenced by multicollinearity.

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Table 1. Distribution of Winning Firms and PSCs Awarding Values by Firm Industry

		Firm freq.		Awarded value (in thousands)		Awarded/sales		Rebate/reserve price		Rebate/sales	
NACE	**Industry description**	**N**	**%**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**
43	Specialized construction activities	185	10.38	339.20	120.00	0.459	0.151	0.168	0.085	0.072	0.011
71	Architectural and engineering activities; technical testing and analysis	153	8.59	210.46	74.01	0.508	0.186	0.213	0.132	0.110	0.031
81	Services to buildings and landscape activities	114	6.40	462.31	120.58	0.405	0.196	0.159	0.105	0.085	0.020
62	Computer programming, consultancy, and related activities	112	6.29	369.47	105.60	0.397	0.149	0.086	0.005	0.030	0.000
88	Social work activities without accommodation	102	5.72	433.78	162.92	0.661	0.313	0.033	0.000	0.020	0.000
41	Construction of buildings	95	5.33	819.33	162.47	0.977	0.186	0.151	0.043	0.785	0.002
49	Land transport and transport via pipelines	68	3.82	1,800.00	185.70	0.513	0.204	0.098	0.018	0.073	0.004
46	Wholesale trade, except of motor vehicles and motorcycles	63	3.54	665.95	176.85	0.376	0.131	0.091	0.003	0.589	0.000
82	Office administrative, office support and other business support activities	60	3.37	1,000.00	146.35	0.655	0.198	0.073	0.000	0.088	0.000
70	Activities of head offices; management consultancy activities	57	3.20	187.00	104.80	0.521	0.233	0.098	0.000	0.055	0.000
87	Residential care activities	44	2.47	1,300.00	172.12	1.203	0.364	0.058	0.000	0.048	0.000
59	Motion picture, video and television programme production, sound recording and music publishing activities	40	2.24	403.71	124.21	6.659	0.309	0.136	0.081	0.006	0.000
56	Food and beverage service activities	39	2.19	302.24	148.50	0.661	0.233	0.050	0.000	0.025	0.000
45	Wholesale and retail trade and repair of motor vehicles and motorcycles	38	2.13	313.45	116.01	0.299	0.130	0.052	0.000	0.013	0.000
38	Waste collection, treatment, and disposal activities; materials recovery	37	2.08	11,000.00	378.00	0.719	0.259	0.047	0.012	0.018	0.002

Table 1. Distribution of Winning Firms and PSCs Awarding Values by Firm Industry

		Firm freq.		Awarded value (in thousands)		Awarded/sales		Rebate/reserve price		Rebate/sales	
NACE	**Industry description**	**N**	**%**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**
33	Repair and installation of machinery and equipment	35	1.96	910.79	130.00	0.381	0.111	0.133	0.012	0.078	0.004
74	Other professional, scientific, and technical activities	35	1.96	279.38	99.89	0.415	0.227	0.161	0.026	0.132	0.003
52	Warehousing and support activities for transportation	34	1.91	2,800.00	277.33	1.958	0.382	0.107	0.024	0.115	0.002
85	Education	31	1.74	165.64	118.20	0.534	0.208	0.073	0.015	0.034	0.000
42	Civil engineering	29	1.63	578.66	198.09	1.162	0.241	0.115	0.065	0.123	0.019
73	Advertising and market research	28	1.57	1,000.00	103.35	0.329	0.133	0.045	0.000	0.059	0.000
96	Other personal service activities	27	1.52	846.09	98.55	0.572	0.188	0.069	0.005	0.016	0.000
25	Manufacture of fabricated metal products, except machinery and equipment	26	1.46	501.37	188.63	0.302	0.128	0.089	0.000	0.026	0.000
90	Creative, arts and entertainment activities	26	1.46	139.56	86.25	0.301	0.218	0.113	0.026	0.025	0.000
77	Rental and leasing activities	24	1.35	270.18	123.30	0.240	0.149	0.107	0.038	0.049	0.003
72	Scientific research and development	23	1.29	374.60	140.00	0.521	0.301	0.055	0.001	0.035	0.000
26	Manufacture of computer, electronic and optical products	22	1.23	165.78	99.41	0.263	0.116	0.035	0.000	0.008	0.000
28	Manufacture of machinery and equipment n.e.c.	22	1.23	323.80	167.88	0.306	0.093	0.114	0.015	0.035	0.001
93	Sports activities and amusement and recreation activities	22	1.23	390.40	182.96	0.795	0.288	0.366	0.000	1.043	0.000
86	Human health activities	19	1.07	1,000.00	174.00	0.479	0.262	0.016	0.000	0.002	0.000
55	Accommodation	18	1.01	680.37	179.07	1.404	0.314	0.088	0.073	0.288	0.000
80	Security and investigation activities	18	1.01	480.03	216.83	4.126	0.287	0.090	0.000	0.033	0.000
01	Crop and animal production, hunting and related service activities	17	0.95	451.61	79.81	1.737	0.212	0.140	0.083	0.083	0.010
63	Information service activities	16	0.90	320.48	99.97	0.464	0.296	0.147	0.034	0.089	0.015

Table 1. Distribution of Winning Firms and PSCs Awarding Values by Firm Industry

		Firm freq.		Awarded value (in thousands)		Awarded/sales		Rebate/reserve price		Rebate/sales	
NACE	**Industry description**	**N**	**%**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**
91	Libraries, archives, museums, and other cultural activities	15	0.84	240.52	96.29	0.746	0.432	0.078	0.010	0.024	0.000
47	Retail trade, except of motor vehicles and motorcycles	14	0.79	183.41	91.97	0.333	0.155	0.055	0.010	0.009	0.000
68	Real estate activities	14	0.79	344.23	151.25	0.876	0.215	0.025	0.000	0.052	0.000
79	Travel agency, tour operator and other reservation service and related activities	14	0.79	283.65	65.01	0.309	0.096	0.034	0.000	0.022	0.000
18	Printing and reproduction of recorded media	12	0.67	529.76	348.38	0.373	0.174	0.153	0.105	0.071	0.024
37	Sewerage	11	0.62	497.95	132.05	0.189	0.124	0.086	0.020	0.063	0.003
39	Remediation activities and other waste management services	9	0.51	513.13	73.33	0.327	0.153	0.264	0.074	0.072	0.025
27	Manufacture of electrical equipment	8	0.45	302.33	110.88	0.342	0.074	0.233	0.110	0.053	0.014
53	Postal and courier activities	6	0.34	188.97	155.30	0.345	0.253	0.243	0.218	0.173	0.075
Total		1,782	100.00	778.58	129.89	0.757	0.200	0.120	0.018	0.131	0.000

Source: authors' elaborations on data provided by National Anti-Corruption Authority (ANAC) and AIDA database, 2020.

Table 2. Variable Balance after 5-NN PSM with Replacement

Variable	Mean Treated	Mean Control	%bias	%reduction |bias|	t-test p-value
ROA	0.014	0.015	-0.5	93.2	0.882
SERVEMP	73,380	76,121	-2.0	52.0	0.578
SALEMP	157,286	157,184	-2.0	86.6	0.506
ΔSALEMP	-133.33	1,886.30	-1.7	64.3	0.546
EMPL	2.152	2.138	1.3	98.2	0.697
ASSETS	13.544	13.531	0.9	90.6	0.782
ΔASSETS	15.749	15.049	1.3	92.3	0.739
INDEBT	0.633	0.627	1.9	-0.70	0.539
CAPINT	0.210	0.207	1.0	97.5	0.712
LOSS	0.132	0.129	0.7	95.0	0.827
CASH	0.132	0.132	-0.5	95.9	0.874
ACCR	-0.009	-0.011	1.2	65.2	0.717
INDIP	2.948	2.958	-0.3	98.7	0.925
NUMSUB	0.457	0.453	0.4	97.0	0.904
NUMCO	2.834	2.781	0.6	71.6	0.856
REGIONS	Included				
LEGAL_FORMS	Included				
NACE2_IND	Included				
Mean %bias			1.1		
Median %bias			1.1		

Notes: The number of treated firms is 1,782 and the number of control firms before the matching is 199,868. Variable observations refer to the year 2014 (pre-treatment period). %bias indicates the Standardised Bias, which is computed as the difference of sample means in the treated and control samples as a percentage of the square root of the average of sample variances in both groups (Rosenbaum and Rubin, 1985). %reduction |bias| indicates the percentage reduction in the absolute value of %bias due to the matching. 5-NN PSM with replacement is based on the logit of the propensity score with a caliper of 0.346. The p-values of t-test for the differences in means are two-tailed. All variables are defined in Appendix A and continuous variables are winsorized at the 2.5th and 97.5th percentiles of their annual distributions.

Table 3. Baseline DID Regressions on Firm Performance Proxies

	ROA		*SALEMP*		*EMPGROW*		*SALGROW*	
Variables	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**
$POST_t$	-0.0141*	-0.0141*	9,680	9,677	-0.0310	-0.0310	-0.0718*	-0.0718*
	(0.008)	(0.008)	(8,413)	(8,413)	(0.037)	(0.037)	(0.039)	(0.039)
$POST_t \times AWARD_t$	0.0017***	0.0017***	4,376***	4,367***	0.0087***	0.0086***	0.0280***	0.0280***
	(0.001)	(0.001)	(846)	(852)	(0.002)	(0.002)	(0.007)	(0.007)
$POST_t \times REBATE_t$		0.0010		1,083		0.0101**		0.0162
		0.002)		(3,554)		(0.004)		(0.028)
ROA_{t-1}	0.1792***	0.1792***	2,678	2,685	0.0503	0.0504	-0.1240	-0.1239
	(0.039)	(0.039)	(15,184)	(15,181)	(0.053)	(0.053)	(0.096)	(0.096)
$SERVEMP_{t-1}$	0.0000	0.0000	0.1268	0.1268	0.0000	0.0000	0.0000**	0.0000**
	(0.000)	(0.000)	(0.087)	(0.087)	(0.000)	(0.000)	(0.000)	(0.000)
$SALEMP_{t-1}$	0.0000	0.0000	0.0114	0.0114	0.0000***	0.0000***	0.0000***	0.0000***
	(0.000)	(0.000)	(0.052)	(0.052)	(0.000)	(0.000)	(0.000)	(0.000)
$\Delta SALEMP_{t-1}$	0.0000**	0.0000**	0.1208***	0.1206***	0.0000	0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.041)	(0.041)	(0.000)	(0.000)	(0.000)	(0.000)
$EMPL_{t-1}$	0.0157***	0.0157***	-18,527***	-18,502***	-0.6112***	-0.6110***	-0.1741***	-0.1737***
	(0.006)	(0.006)	(6,897)	(6,894)	(0.022)	(0.022)	(0.036)	(0.036)
$ASSETS_{t-1}$	-0.0284***	-0.0284***	25,753***	25,762***	0.0056	0.0057	-0.2847***	-0.2845***
	(0.009)	(0.009)	(7,550)	(7,550)	(0.024)	(0.024)	(0.040)	(0.040)
$\Delta ASSETS_{t-1}$	0.0000	0.0000	12.80	12.90	0.0001	0.0001	0.0007***	0.0007***
	(0.000)	(0.000)	(25.91)	(25.91)	(0.000)	(0.000)	(0.000)	(0.000)
$INDEBT_{t-1}$	0.1061***	0.1061***	-21,337	-21,299	-0.0901*	-0.0898*	-0.2869***	-0.2863***
	(0.037)	(0.037)	(15,208)	(15,205)	(0.052)	(0.052)	(0.090)	(0.090)
$CAPINT_{t-1}$	0.0453*	0.0453*	-626	-641	0.0388	0.0386	0.2167*	0.2165*
	(0.025)	(0.025)	(18,055)	(18,056)	(0.059)	(0.059)	(0.127)	(0.127)
$LOSS_{t-1}$	0.0358***	0.0358***	6,855**	6,853**	-0.0375***	-0.0375***	0.0590***	0.0589***
	(0.005)	(0.005)	(3,137)	(3,137)	(0.014)	(0.014)	(0.021)	(0.021)
$CASH_{t-1}$	-0.0236	-0.0236	-19,454	-19,465	0.0182	0.0181	-0.2929***	-0.2931***
	(0.019)	(0.019)	(17,446)	(17,443)	(0.053)	(0.053)	(0.089)	(0.089)
$ACCR_{t-1}$	0.0019	0.0019	11,195	11,150	-0.0325	-0.0330	-0.0782**	-0.0789**
	(0.009)	(0.009)	(9,212)	(9,212)	(0.024)	(0.024)	(0.038)	(0.038)
IND-YEAR FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FIRM FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	21,384	21,384	21,384	21,384	21,384	21,384	21,384	21,384
R-squared	0.0422	0.0422	0.4411	0.4411	0.3022	0.3024	0.1234	0.1237

Notes: *, ** and *** denote significance levels at 10%, 5% and 1%, respectively, based on two-tailed tests. Standard errors clustered at the firm level are presented in parentheses. *IND-YEAR* denotes two-digit NACE industry-year fixed effects; *FIRM FE* denotes firm fixed effects. The rest of variables are defined in Appendix A.

Table 4. Baseline DID Regressions on Payroll Expense Proxies

	PAYEMP		*SSCEMP*		
Variables	**(1)**	**(2)**	**(1)**	**(2)**	**(3)**
$POST_t$	1,358.28*	1,358.54*	142.65	142.75	-195.57
	(767.97)	(767.50)	(228.13)	(228.14)	(135.47)
$POST_t \times AWARD_t$	199.4***	200.31***	39.30*	39.65*	-10.23
	(63.59)	(63.06)	(21.54)	(21.35)	(8.58)
$POST_t \times REBATE_t$		-115.61***		-43.87***	-15.08***
		(44.56)		(11.40)	(5.32)
ROA_{t-1}	-2,168.49*	-2,169.29*	-1,032.58***	-1,032.89***	-492.66***
	(1116.23)	(1,116.27)	(321.78)	(321.79)	(182.06)
$SERVEMP_{t-1}$	-0.001	-0.001	-0.001	-0.001	0.000
	(0.003)	(0.003)	(0.001)	(0.001)	(0.000)
$SALEMP_{t-1}$	0.001	0.001	0.001	0.001	0.000
	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)
$\Delta SALEMP_{t-1}$	0.003**	0.003**	0.001*	0.001*	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
$EMPL_{t-1}$	2,700.91***	2,698.20***	580.19***	579.17***	-92.77
	(404.04)	(404.10)	(122.24)	(122.26)	(67.60)
$ASSETS_{t-1}$	2,383.03***	2,382.07***	468.84***	468.48***	-124.74*
	(396.80)	(396.82)	(116.62)	(116.63)	(69.02)
$\Delta ASSETS_{t-1}$	-0.675	-0.686	0.027	0.023	0.194
	(1.618)	(1.619)	(0.508)	(0.508)	(0.355)
$INDEBT_{t-1}$	-2,422.59**	-2,426.60**	-829.66***	-831.18***	-226.88
	1,018.25	(1,018.35)	(298.35)	(298.38)	(143.27)
$CAPINT_{t-1}$	316.87	318.42	-90.36	-89.77	-169.07
	(1,331.92)	(1,331.95)	(383.16)	(383.17)	(198.70)
$LOSS_{t-1}$	-129.65	-129.36	28.41	28.52	60.73
	(276.98)	(276.99)	(84.50)	(84.50)	(45.99)
$CASH_{t-1}$	396.79	398.00	-43.34	-42.88	-141.99
	(1,101.52)	(1,101.47)	(323.84)	(323.86)	(191.88)
$ACCR_{t-1}$	21.19	25.96	40.89	42.70	36.24
	(489.78)	(489.86)	(157.98)	(158.02)	(102.10)
$PAYEMP_t$					0.249***
					(0.004)
IND-YEAR FE	Yes	Yes	Yes	Yes	Yes
FIRM FE	Yes	Yes	Yes	Yes	Yes
Number of obs.	21,384	21,384	21,384	21,384	21,384
R-squared	0.2419	0.2420	0.2544	0.2542	0.7620

Notes: *, ** and *** denote significance levels at 10%, 5% and 1%, respectively, based on two-tailed tests. Standard errors clustered at the firm level are presented in parentheses. *IND-YEAR* denotes two-digit NACE industry-year fixed effects; *FIRM FE* denotes firm fixed effects. The rest of variables are defined in Appendix A.

Table 5. DID Univariate Analysis over the Pre-Treatment Period 2013-2014

	Treated firms (T)				Control firms (C)				T - C	
	2013	2014	2014 - 2013		2013	2014	2014 - 2013		DID	
Variables	Mean	Mean	Mean	t-test mean ≠ 0	Mean	Mean	Mean	t-test mean ≠ 0	Mean	t-test mean ≠ 0
ROA	0.009	0.014	0.005	*	0.010	0.015	0.004	**	0.001	
SALEMP	161,681	157,286	-4,395		161,134	154,171	-6,963	***	2,568	
SALGROW	0.153	0.078	-0.076	***	0.082	0.025	-0.056	***	-0.019	
EMPGROW	0.056	0.051	-0.005		0.044	0.053	0.009		-0.015	
PAYEMP	20,241	20,310	68.87		20,055	19,666	-389.4	***	458.2	
SSCEMP	5,852	5,827	-25.13		5,863	5,748	-115.4	***	90.28	

Notes: the number of treated firms is 1,782 and the number of control firms is 8,910. The variables, which are defined in Appendix A, are winsorized at the 2.5th and 97.5th percentiles of their annual distributions. *, ** and *** denote significance levels at 10%, 5% and 1%, respectively, based on two-tailed t-tests for differences of means from zero.

Table 6. DID Placebo Regressions for Parallel Trend Testing

						SSCEMP	
Variables	***ROA***	***SALEMP***	***EMPGROW***	***SALGROW***	***PAYEMP***	**(1)**	**(2)**
$POST_t$	0.0121**	-10,873***	0.0315	-0.0730*	-357.76	-232.96	-143.58
	(0.006)	(3,239)	(0.037)	(0.042)	(643.52)	(205.86)	(117.96)
$POST_t \times AWARD_t$	0.0005	-1,064	-0.0041	-0.0405	29.905	14.398	6.927
	(0.000)	(2,058)	(0.003)	(0.040)	(28.88)	(11.90)	(6.82)
$POST_t \times REBATE_t$	-0.0012	-476.12	-0.0118	-0.1900	-87.389	-23.853	-2.021
	(0.002)	(708.63)	(0.010)	(0.141)	(151.32)	(34.60)	(19.82)
$PAYEMP_t$	No	No	No	No	No	No	Yes
$CONTROLS_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IND-YEAR FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FIRM FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	21,384	21,384	21,384	21,384	21,384	21,384	21,384
R-squared	0.2505	0.3826	0.5336	0.4661	0.1088	0.0992	0.7043

Notes: The sample period is from 2013 to 2014. *, ** and *** denote significance levels at 10%, 5% and 1%, respectively, based on two-tailed tests. Standard errors clustered at the firm level are presented in parentheses. $CONTROLS_{t-1}$ are the same control variables as those included in Table 3 for *ROA*, *SALEMP*, *EMPGROW* and *SALGROW* and Table 4 for *PAYEMP* and *SSCEMP*. *IND-YEAR* denotes two-digit NACE industry-year fixed effects; *FIRM FE* denotes firm fixed effects. The rest of variables are defined in Appendix A.

Table 7. Baseline DID Regressions with Subsamples based on Number of Employees (*EMPL*)

Panel A: Regressions on Firm Peformance Proxies

	ROA		***SALEMP***		***EMPGROW***		***SALGROW***	
Variables	**< 50th pct**	**> 50th pct**	**< 50th pct**	**> 50th pct**	**< 50th pct**	**> 50th pct**	**< 50th pct**	**> 50th pct**
$POST_t \times AWARD_t$	0.0017***	0.0016	4,752***	1,365**	0.0086***	0.0095	0.0279***	0.0420
	(0.001)	(0.002)	(600.5)	(538.6)	(0.003)	(0.006)	(0.007)	(0.035)
$POST_t \times REBATE_t$	0.0014	-0.0017	1,123	827.5	0.0111**	0.0013	0.0171	0.0023
	(0.002)	(0.006)	(3,884)	(1,136)	(0.005)	(0.007)	(0.031)	(0.019)
$CONTROLS_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	10,692	10,692	10,692	10,692	10,692	10,692	10,692	10,692
R-squared	0.0436	0.0446	0.4363	0.449	0.2875	0.3113	0.1162	0.1063

Panel B: Regressions on Payroll Expense Proxies

	PAYEMP		***SSCEMP***		***SSCEMP***	
Variables	**< 50th pct**	**> 50th pct**	**< 50th pct**	**> 50th pct**	**< 50th pct**	**> 50th pct**
$POST_t \times AWARD_t$	224.99***	-4.247	49.25***	-48.07***	-6.633	-47.01***
	(50.64)	(44.86)	(13.31)	(17.44)	(5.72)	(17.91)
$POST_t \times REBATE_t$	-114.46**	-63.28	-45.01***	10.48	-17.58***	26.40
	(49.10)	(69.17)	(12.57)	(18.21)	(5.18)	(18.84)
$PAYEMP_t$	No	No	No	No	Yes	Yes
$CONTROLS_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	10,692	10,692	10,692	10,692	10,692	10,692
R-squared	0.2497	0.2611	0.2582	0.2677	0.7554	0.7654

Notes: $CONTROLS_{t-1}$ include variable *POST* and the same control variables as those included in Table 3. *Fixed effects* include two-digit NACE industry-year fixed effects and firm fixed effects. *, ** and *** denote significance levels at 10%, 5% and 1%, respectively, based on two-tailed tests. Standard errors clustered at the firm level are presented in parentheses. pct denotes the percentile of the classification variable *EMPL*. All variables are defined in Appendix A.

Table 8. Baseline DID Regressions with Subsamples based on Industry

Panel A: Regressions on Firm Peformance Proxies

	ROA		***SALEMP***		***EMPGROW***		***SALGROW***	
Variables	**Construction**	**Others**	**Construction**	**Others**	**Construction**	**Others**	**Construction**	**Others**
$POST_t \times AWARD_t$	0.0016	0.0017***	1,887	4,342***	0.0162	0.0088***	0.1033***	0.0260***
	(0.002)	(0.001)	(1,536)	(903.3)	(0.012)	(0.002)	(0.038)	(0.005)
$POST_t \times REBATE_t$	-0.0006***	0.0055*	-2,781***	8,265*	0.0054***	0.0223***	-0.0127***	0.0813***
	(0.000)	(0.003)	(457.8)	(4,802)	(0.001)	(0.008)	(0.002)	(0.031)
$CONTROLS_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	3,708	17,676	3,708	17,676	3,708	17,676	3,708	17,676
R-squared	0.0178	0.0500	0.1576	0.5158	0.3899	0.2879	0.1761	0.1292

Panel B: Regressions on Payroll Expense Proxies

	PAYEMP		***SSCEMP***		***SSCEMP***	
Variables	**Construction**	**Others**	**Construction**	**Others**	**Construction**	**Others**
$POST_t \times AWARD_t$	292.05*	194.98***	1.434	40.25*	-79.39	-7.351
	(172.89)	(66.66)	(57.50)	(21.20)	(50.48)	(8.34)
$POST_t \times REBATE_t$	-121.31***	-137.12	-48.05***	-41.70	-14.47**	-8.225
	(21.83)	(147.6)	(6.53)	(32.00)	(6.83)	(15.54)
$PAYEMP_t$	No	No	No	No	Yes	Yes
$CONTROLS_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	3,708	17,676	3,708	17,676	3,708	17,676
R-squared	0.2644	0.2415	0.1864	0.2728	0.6499	0.8020

Notes: $CONTROLS_{t-1}$ include variable *POST* and the same control variables as those included in Table 3. *Fixed effects* include two-digit NACE industry-year fixed effects and firm fixed effects. *, ** and *** denote significance levels at 10%, 5% and 1%, respectively, based on two-tailed tests. Standard errors clustered at the firm level are presented in parentheses. Construction is the NACE level 1 industrial sector identified with the letter F. Others are all other NACE level 1 sectors in the full sample. All variables are defined in Appendix A.

Table A1. DID Univariate Analysis

	Treated firms (T)				Control firms (C)				T - C	
	Pre	Post	Post - Pre		Pre	Post	Post - Pre		DID	
Variables	Mean	Mean	Mean	t-test mean ≠ 0	Mean	Mean	Mean	t-test mean ≠ 0	Mean	t-test mean ≠ 0
ROA	0.014	0.021	0.008	***	0.015	0.005	-0.009	***	0.017	***
SALEMP	157,286	159,540	1,437		154,171	159,155	4,983	***	-3,546	
SALGROW	0.078	0.077	-0.004		0.025	-0.020	-0.045	***	0.042	**
EMPGROW	0.051	0.082	0.030	**	0.053	-0.007	-0.061	***	0.090	***
PAYEMP	20,310	20,744	368.1		19,666	20,481	815.3	***	-447.2	
SSCEMP	5,827	5,666	-192.0	***	5,748	5,673	-74.28	**	-117.7	

Notes: the number of treated firms is 1,782 and the number of control firms is 8,910. The variables, which are defined in Appendix A, are winsorized at the 2.5th and 97.5th percentiles of their annual distributions. Pre and Post denote the pre-treatment and post-treatment periods, respectively. *, ** and *** denote significance levels at 10%, 5% and 1%, respectively, based on two-tailed t-tests for differences of means from zero.

Table A2. Pearson Correlations and VIF of DID Model Covariates

Variables	VIF	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*
1.POST×REBATE	1.00	1													
2.POST×AWARD	1.02	***0.021***	1												
3.ROA	1.46	-0.001	-0.001	1											
4.SERVEMP	3.80	0.003	***0.015***	***0.032***	1										
5.SALEMP	4.07	0.003	-0.009	***0.087***	***0.822***	1									
6.∆SALEMP	1.13	0.008	***-0.030***	***0.099***	***0.113***	***0.188***	1								
7.EMPL	2.90	-0.006	***-0.013***	-0.001	***-0.235***	***-0.202***	***0.012***	1							
8.ASSETS	2.94	-0.001	-0.003	***0.063***	***0.202***	***0.292***	***0.015***	***0.579***	1						
9.∆ASSETS	1.11	0.000	***0.057***	***0.126***	***0.025***	0.011	***0.219***	***0.013***	***-0.041***	1					
10.INDEBT	1.40	-0.003	***0.012***	***-0.374***	***0.085***	***0.053***	***0.022***	***-0.014***	***-0.034***	***0.098***	1				
11.CAPINT	1.31	-0.004	0.000	***-0.107***	***-0.094***	***-0.078***	-0.006	***-0.019***	***0.118***	***-0.051***	***0.018***	1			
12.LOSS	1.24	-0.005	0.006	***-0.417***	***-0.054***	***-0.080***	***-0.058***	***-0.037***	***-0.033***	***-0.066***	***0.158***	***0.123***	1		
13.CASH	1.39	0.004	0.003	***0.174***	***0.031***	***0.017***	***0.017***	***-0.138***	***-0.244***	0.010	***-0.317***	***-0.244***	***-0.099***	1	
14.ACCR	1.08	0.000	***-0.022***	***-0.032***	***-0.034***	***-0.027***	***0.036***	0.009	0.003	-0.011	***-0.044***	***0.076***	***0.028***	***-0.213***	1
Mean VIF	1.85														

Notes: coefficients in bold italics are significantly different from zero at the 0.10 level or lower, based on two-tailed tests. All variables are defined in Appendix A.