THE ECONOMIC IMPACT OF CERN PROCUREMENT: EVIDENCE FROM THE LARGE HADRON COLLIDER

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The economic impact of CERN procurement: evidence from the Large Hadron Collider

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Abstract: Building the Large Hadron Collider (1995-2008) required frontier technologies. We wanted to discover whether there has been a long-term "learning by doing" effect on CERN suppliers' profitability, beyond the initial order. The evidence on this effect was until now fragmentary, mainly based on interviews or case histories. CERN granted us access to their LHC procurement database, including 1360 suppliers from 35 countries for a total of 11969 orders. We collected 23-year long time series of financial data (1991-2013) for a large sample of companies. After controlling for time fixed-effects and trends, firm-level and country-level possible confounding factors, we observe a statistically significant ($p<0.01$) 'CERN effect' on long-run profit margin of high-tech suppliers, while the effect on non-high-tech suppliers is not statistically significant.

JEL: O30, O33, Q55

Keywords: CERN, Large Hadron Collider, technological spillovers, supply chain.

Big Science projects are expensive, while the ultimate impact of discovery on society is unpredictable, particularly for basic research. It may take decades to understand how the knowledge of fundamental features of nature may be of any practical use. In the meantime governments are expected to support investment in science against uncertain social returns. There are, however, benefits that can be observed even during the construction phase of a large research infrastructure. Some of these arise from unprecedented technological challenges (*1*). To achieve the exacting standards of experimental devices at the frontier of science close collaboration is needed between laboratories and firms in the supply chain of discovery machines. Such collaboration generates learning effects, which directly spill over as an externality from basic research to firms through procurement contracts. Technological learning can lead firms to product and process innovation and ultimately to increased growth opportunities. Can we measure these economic effects?

Several approaches have been tried (*2*). Case histories may offer interesting qualitative insights into the learning effects of technological procurement by research infrastructures, and subsequent commercial developments by firms (*3, 4*). Failures to translate R&D in marketable innovation are rarely reported, and this creates a selection bias. Surveys of stakeholders may be more informative. Some years ago a survey (*5*) of CERN suppliers found that product innovation was developed by more than one third of the firms; around 15% started either new R&D or a new business unit, or opened a new market; more than 40% of the respondents stated that after the contract the firm was more internationalized and benefited from technological learning. The average combined value of suppliers' sales to other clients and cost savings was reported to be three times the amount of the order by CERN. One problem with surveys is, again, that managers with success stories will be happier to respond than others. Looking for more objective evidence, aggregate statistical approaches have been used for decades for a range of programs, from NASA (*6*) to biotechnology (*7*). Input-output tables representing average national or regional inter-industry linkages and investment multipliers were used to compute the impact of research spending on GDP or productivity. These procedures are basically numerical simulations, and the results are highly dependent on some macroeconomic assumptions (*8*).

We have tried a new empirical strategy based on micro-data: the procurement contract between a firm and its client, the institution managing a research infrastructure, is considered similar to an event that, beyond its short run impact, may or may not change over time the profitability of the firm, net of any confounding factor, such as the economic conditions in the country.

The Large Hadron Collider is an ideal testing ground for our approach. First, because its design and construction have pushed technology beyond previous limits in several fields, such as superconductivity, cryogenics, electromagnets, ultra-high vacuum, distributed computing, rad-resistance materials, fast electronics, etc. (*9*), but they also required large quantities of standard products, such as building work, pipes, heating equipment, electrical power, etc. Thus, there is variability in the technological intensity of procurement, and we take advantage of this fact. Also, the number of suppliers involved, the international scope of the procurement process, the wide range of sectors, and particularly the long time span of the construction process offer additional statistical variability to the empirical analysis.

CERN granted us access to the procurement data for LHC between 1995 and 2008. There were 1,360 suppliers with least one order of over CHF 10,000, for a total of 11,969 orders (Fig. 1). These suppliers of LHC technology were located in 35 countries, including China, Japan, Russia, and the United States, but over 99% of the orders in terms of value were placed with European firms. For each supplier we recorded the location, the year and value of each order, and the activity code (e.g. "23. power cables and conductors"; "58. precision machining work"; "71. films and emulsions"). We classified each order on a technology intensity scale, where at the lower end there were 'off the shelf' non-high-technology products, and at the upper end products at the frontier of technology requiring intensive customization and co-development with CERN (Fig. 2).

Out of the original list of LHC suppliers (which included other laboratories, joint ventures, etc.) we identified 1,060 companies in AMADEUS and ORBIS, two global company

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financial databases maintained by Bureau Van Dijk (*10*). Out of these, we drew the LHC suppliers for which the core financial indicators were available, as far as possible, over the time span 1991-2013. This was a sufficiently long period in order to study the effect of procurement contracts on the firms' profitability. Around 350 companies met this criterion, leading to a sufficiently large and representative sample for the final empirical analysis.

The most interesting performance variable for our research question is the profit margin, defined as the ratio of EBIT (Earnings Before Interest and Taxes) to operating revenues. It is around 4.6% on average in the sample. This financial indicator is a dimensionless ratio, hence not directly affected by turnover size or by inflation, and widely acknowledged by management studies as highly informative about firms' profitability.

Is there any evidence in the data that the profit margin of suppliers of the LHC increased over time after the initial contract with CERN? To answer this question we built a dynamic panel data model. After transforming all the data in first differences, i.e. changes year by year, in order to consider trend effects, we included the lagged dependent variable (profit margins one year before the event) among the controls, the firms' total assets as an additional control for size of the supplier and added time fixed-effects and a time trend variable. To further control for macro-economic conditions, we included yearly GDP change in the country where the firm was located, and yearly GDP change in the OECD area. The event of the contract with CERN is recorded as zero prior to the first order being received, and one thereafter. Finally, each supplier was classified according to the technological intensity of the first order event.

After controlling for the other covariates, the estimated CERN effect coefficient for the sample is positive and statistically significant, suggesting that being a supplier of the LHC is correlated to increased firm profitability. But to what extent is this effect driven by the technological intensity of the procurement? This was our main question, and a simple way to test this was to split the sample in two: high-tech and non-high-tech suppliers, according to the above mentioned classification. We find that CERN effect vanishes for non-high-tech firms (the coefficient is still positive but no longer statistically significant), while it is confirmed as highly statistically significant, and with a higher coefficient, for high-tech firms.

The interpretation of these findings is straightforward. Had we found that a CERN effect was significant also for firms involved in non-high-tech procurement, one may have thought that what we observed was mainly the possible impact of a generic reputational effect in increasing market opportunities or claiming higher prices. But the clear-cut finding that the CERN effect was important for high-tech firms, but not for the others, suggests that a learning process leading to product and process innovation ultimately boosted the profitability of high-tech firms. We cannot exclude that a specific reputational effect may have played a role for these firms as well. They can advertise their success in dealing with the demanding requirements of LHC technology, possibly a convincing marketing argument. This combination of innovation and reputation effects is, after all, exactly what previous narratives and surveys would have suggested, but without being able to show the objective statistical evidence on profitability that we have detected.

There are two messages arising from these findings, both with some implications for science policy. First, it would be helpful if the institutions managing the research infrastructures made the information on their procurement available for independent inquiry, as CERN did for

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us. Matching these data with the long-term financial data of the firms in the supply chain seems both feasible and informative.

Moreover, governments and funding agencies should take note that a non-negligible part of taxpayers' money is paid back to society in the form of increased profitability for the high-tech firms, particularly of innovative small-medium enterprises (*11*): around 75 per cent of CERN suppliers in our data have less than 250 employees. While perhaps in some distant future scientists and engineers may find a practical application for the discovery of the Higgs boson, in a relatively short time (within a decade or so for the median order during the construction of the LHC) there are already market responses to investments in science. These responses are mediated by high-tech firms involved in the procurement of large-scale research infrastructures, and, in principle, the economic impacts can be quantified. Naturally, there are other propagation channels (*12*) of the social benefits of Big Science, such as human capital and cultural effects (*13*) and technology transfer (14). We do not claim that any project can be justified because of technological spillovers alone, but it is worth trying to record and measure them against the investment costs.

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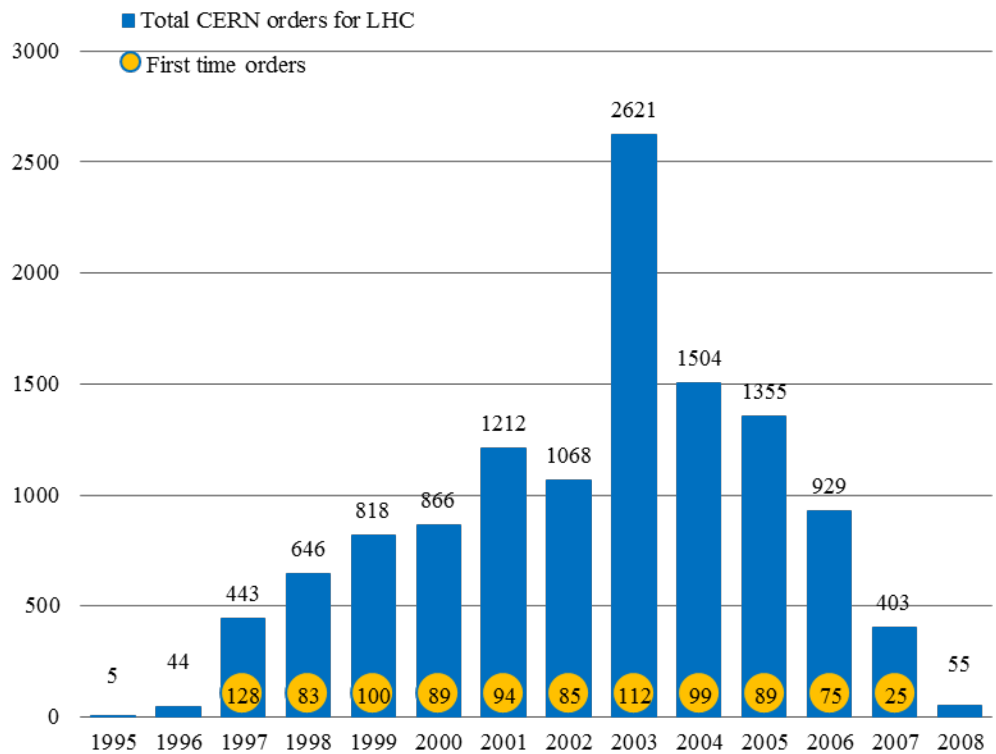

Fig. 1. Distribution by year of LHC procurement orders and of first-time orders to a supplier. Total CERN orders each year is the sum of the number of all the orders above CHF 10,000 in that year, including multiple orders to individual firms. First time orders are the number of orders that were agreed with a firm for the first time in that year. (First orders of 1995=2; 1996=17; 2008=4). Source: Our processing of CERN data.

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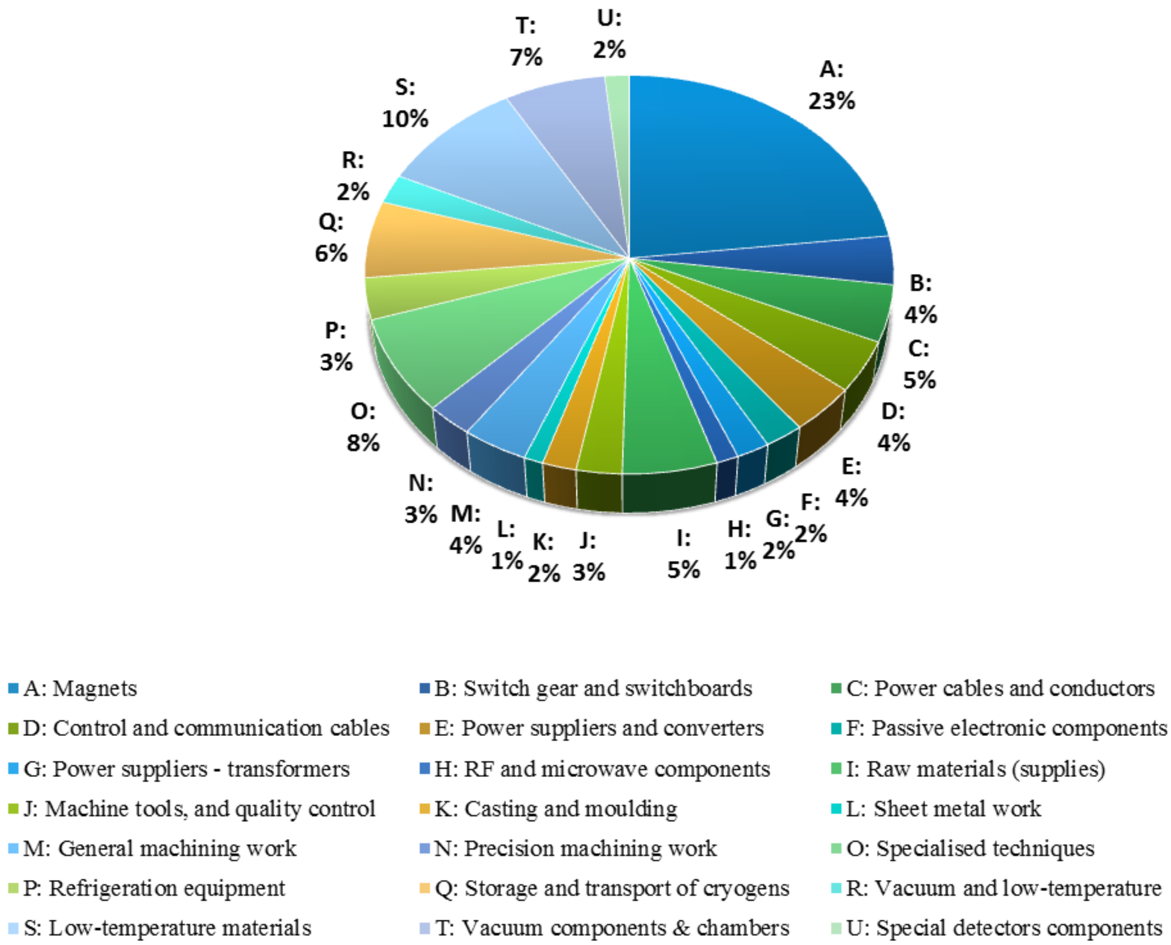

Fig. 2. Distribution of high-tech CERN orders for LHC by activity code. Percent share of number of orders. Minor items omitted. Source: our processing of CERN data.

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Supplementary Materials for

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This file includes:

Supplementary Text
Figs. S1 to S2
Tables S1 to S3
References (*15*)

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Supplementary Text

These Supplementary Materials text contain the details of the research supporting the Policy Forum paper "The economic impact of CERN procurement: evidence from the Large Hadron Collider". It is in four parts: Context, Data, Methods, Results.

1. Context.

Construction work for the Large Hadron Collider at the European Organization for Nuclear Research (CERN) started in 1993 and lasted until 2008. The LHC began operating in 2009 and it is foreseen to continue for at least another decade. It is the largest particle accelerator in the world and its technology is extremely complex. Protons and atomic nuclei are accelerated by subjecting them to electric fields and made to collide with each other, with the goal of studying the structure of matter. To do so, particles are collimated into focused beams through strong magnetic fields. The beams travel in a pipe in which an ultra-high vacuum has been created, and are brought to collide in experimental areas where the debris of the collisions are accurately measured by detectors, managed by international Collaborations. When observing particle collisions, the experiments produce about 1 GB of data per second, which are either analyzed inside by LHC Collaborations, or sent to a number of other computer centers around the world, connected through the worldwide LHC computer grid. The main technological features of LHC are available at (*15*).

2. Data

We present here data on CERN procurement related to the LHC; classification of orders by technological intensity; suppliers of LHC and their distribution by sector; distribution of suppliers by country; financial data of suppliers; macroeconomic controls.

2.1 Procurement orders data

Our main source of original data is CERN Procurement and Industrial Services (http://procurement.web.cern.ch/procurement-strategy-and-policy), which is in charge of coordinating all the supplies and services needed by the laboratory. Experiments, such as ATLAS and CMS, have some procurement autonomy and their orders are not fully covered here. CERN Procurement regularly monitors and reports all supply activities to the management and the Member States and in 2015 it provided us with several extractions from the full dataset of orders specifically intended to implement the construction of the LHC. The construction period considered is 1995-2008, i.e. before the accelerator started regular operation. Only orders above a CHF 10k threshold have been included, as we wanted to exclude a large number of marginal suppliers for which knowledge spillovers from LHC procurement are unlikely.

The total number of orders selected with these criteria was 11,969. Around 99% of the orders were placed between 1996 and 2007 with a peak in 2003. Figure 1 plots the distribution of all the orders by year. It also shows the distribution by year of the initial procurement events, i.e. the number of times a different company became a CERN supplier for the LHC. These first events mark the beginning of a potential learning process. This is our variable of interest. The subsequent time profile is, however, also informative: the average number of years in which a company received at least one order in that year is 2.3 (standard deviation 1.94, minimum 1 and maximum 11 years). This implies that the direct impact of the orders on company profitability could not last on average more than around 2-3 years, and we are interested to study economic effects also beyond these initial years. The first-year events in our study are evenly spread between 1997-2006, differently from total orders, that show a peak in 2003. Around 95 new suppliers were involved in the LHC in any of the years of the above mentioned decade. We take advantage in the empirical analysis of the fact that we do not have just one 'before-after' group of events, but a sequence of ten such groups. For example, a company entering in the CERN procurement system in year 2000 potentially can be observed for 10 years before the event (including year 2000, as we have financial data 1991-2013, see Section 2.5) and 13 years thereafter. For a company entering in one of the last groups, e.g. 2007, we have potentially 6 years of 'after' observations and 18 years of 'before' observations.

2.2 Classification of orders by technological intensity

CERN orders in the original database are classified by an "activity code", a number that identifies the type of product. The classification system is up to 3-digit level, with the latter being extremely detailed. We focused on the 2-digit level, which included around 100 items and was adequately detailed for our analysis. In some cases we also inspected the 3-digit level to better interpret the technological content of the order.

After a preliminary analysis to understand the overall distribution of the orders by code, we identified the specific activity codes that were more likely to be associated with high technological intensity goods and services supplied for the construction of the LHC. The code descriptors in some cases were generic (for example "28-Electrical engineering" or "45-Software"). To minimize classification errors we sampled 300 orders for a more in-depth analysis. These orders were placed with 207 different suppliers, representing around 14% of all the 1442 suppliers that received at least one order for the LHC during the period considered. The sampled orders were then evaluated in detail by CERN experts and classified in terms of technological intensity according to a five-point scale. The scale was intended to capture differences in both the specificity of the products and the degree of collaboration between CERN and its suppliers. It included the following classes:

Class 1: most likely "off-the-shelf" orders with low technological intensity;

Class 2: off-the-shelf orders with an average technological intensity;

Class 3: mostly off-the-shelf, but usually high-tech and requiring some careful specification;

Class 4: high-tech orders with a moderate to high intensity of the specification activity to customize products for LHC;

Class 5: products at the frontiers of technology with intensive customization and co-design involving CERN staff.

As a further step, the high-tech activity codes were identified as those included in Classes 3-4-5. Finally, this analysis was used to classify the suppliers of LHC into two broad groups, according to the opportunity they had to deliver high-tech orders in the initial event, see Figure S1.

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2.3 Suppliers of the LHC by sector

According to the activity code assigned to the first order, around 61% of the companies in the CERN dataset belonged to the high-tech category. There was some risk of misclassification, because it may have been the case that over time a non-high-tech company was able to supply high-tech orders and vice versa, as many companies received several orders, not necessarily with the same activity code. In fact, on average around nine orders were allocated to each contractual partner, several of them in the same year. Considering high-tech and non-high-tech companies separately, the number of years in which an order was allocated was respectively 2.48 (Std Dev: 2.03; Min: 1; Max: 11) and 2.03 (Std Dev: 1.73; Min: 1; Max: 11), which suggested a slightly greater continuity of procurement relations between CERN and the high-tech companies. Inspection of the data suggested that the first order in the series was, in general, a good predictor of the technological intensity of subsequent orders.

We also wanted to compare our classification of companies by technological intensity with the industrial sector to which they belonged, which is a more generic classification. To do so we recovered the company NACE Rev2 code (Statistical classification of economic activities in the European Community, http://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF) from the global company databases AMADEUS and ORBIS, maintained by Bureau Van Dijk (see the following section). Table S1 provides the distribution by 2-digit NACE code of the companies identified by matching the CERN database and the AMADEUS and ORBIS data. Looking at the firms' distribution by NACE code, around 50% of the suppliers we analyzed were in the manufacturing sector (but the actual share in terms of manufacturing firms indirectly involved by CERN procurement was higher as several firms classified as "Wholesale Trade" also delivered some manufactured goods). Using the NACE classification apparently does not capture the technological intensity of the orders or of the firm itself. Thus, to correctly interpret our analysis, when we refer to a "high-tech company" we mean a company that - in whatever NACE sector it is classified - was selected by CERN as a supplier of a high-tech order in the first place.

2.4 Distribution of the sample by country

Our sample comprised only the CERN suppliers included in the AMADEUS and ORBIS databases. The AMADEUS database collects balance-sheet records for European companies and contains financial information on over 7 million companies, while the ORBIS database also includes companies from the rest of the world. Exploiting these sources, we were able to identify 1,060 companies out of the 1,360 contracting units listed in the original CERN database. Matching of the different sources unavoidably reduced the number of observations (for example, because some suppliers are not firms but other laboratories, or simply because their financial data are not recorded). Figure S2 summarizes the distribution of the companies across countries, both in the original CERN database and in our sample, also highlighting the number and share of high-tech companies according to our classification. The former were located in 27 different countries: 22 were from European Union and five from outside. We found no financial data for LHC suppliers in: Belarus, China, India, Pakistan, Romania, Taiwan, and United Arab Republic. Almost 96% of the companies were located in Europe. In terms of loss of data, when moving from the CERN dataset to AMADEUS-ORBIS financial data, France and Switzerland were less represented in our sample than in the original procurement data. These are the two countries where the CERN is located, but the relative under-representation in our sample is not a matter of concern, as in fact a large number of firms from these countries are included in our analysis.

2.5 Financial data

Following the technological intensity classification provided above, 62.4% of the companies in our sample could be classified as high-tech suppliers (with a very modest over-representation of less than 2% relative to the original CERN data). Exploiting the AMADEUS and ORBIS databases, we searched for information on firms' performance indicators over the time span 1991-2013. We focused particularly on the profit margin, defined as the ratio of EBIT (earnings before interest and taxes) to operating revenues. Over the time span considered, the average value of the EBIT margin in the sample was 4.58%. For the companies classified as high-tech, the sample mean value of the EBIT margin was slightly higher at 4.62%. For non-high-tech companies the average EBIT margin was 4.52%. Hence, in terms of descriptive statistics the two subgroups do not greatly differ in their average or median performance, see Table S.2. This is an important empirical feature, as our findings discriminate the different responses to first procurement events by the two groups of firms, despite their similar average profitability in the first place.

As there may be a size effect in the ability of a firm to capture technology spillovers, we also recovered data on companies' total assets (the sum of fixed and current assets) and used this information as a micro-control for firms' size in our regression analysis. For the median company total assets were €5.604 million in the full sample, €6.828 and €4.576 million for high-tech and non-high-tech companies, respectively. The mean value of total assets in the full sample is much higher (€962.363 million: €1,132.241 million respectively for high-tech companies and €772.260 million for non-high-tech ones). These high averages were influenced by the presence in our sample of about 20 companies that were outliers in terms of very large size. The fact that the distribution of companies by assets is highly skewed reflects the usual 'pyramid' structure of the industry. Trimming the size distribution of firms for empirical analysis was also tested, with limited changes in the results.

2.6 Macroeconomic controls

On the demand side GDP growth may have an influence on the EBIT margin because a higher GDP growth may increase the demand for goods and the profitability of firms. We use two controls: yearly GDP growth of each country where suppliers were located and average yearly GDP growth in the OECD area to account for foreign market opportunities. (Source of data: World Bank, http://databank.worldbank.org/data/home.aspx).

3 Methods

We were interested in studying the effect that becoming a CERN supplier had on company performance, distinguishing between high-tech and non-high-tech firms and taking advantage of the time variations in the procurement events. In our data, at the beginning of the period we consider (1991), no firm is a CERN supplier for the LHC. At

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the end of the period all firms are CERN suppliers. In the middle years there is a sequence of events occurring between 1995 and 2008, and a transition of status for each firm in different years. Our general approach was to estimate the effect that receiving an order from CERN had, over time, on a firm-level performance variable, controlling for firm-level characteristics, the macroeconomic situation, a time-trend variable and firm-level fixed-effects. Given the potential existence of trends that might have affected the results of our estimates, the performance variable and the variables included in the vectors of controls were taken in first-differences, i.e. changes year by year. Specifically, the empirical model we are estimating is the following:

$$\begin{aligned}\Delta EBITmargin_{ict}^{j} &= \beta CERN_{ict} + \gamma_1 \Delta TotalAssets_{ict} + \Delta EBITmargin_{ict-1}^{j} + \delta_1 \Delta GDP_{ct} \\ &+ \gamma_2 \Delta GDP\_OECD_t + \rho year_i + \delta_t + \mu_i + u_{it}\end{aligned}$$

where the superscript $J=H$, N identifies high-tech and non-high-tech companies.

- $\Delta \mathrm{EBITmargin}_{ict}^{j}$ is the change of firm's *i* profit margin, located in country *c*, at time *t*, and defined as the ratio of EBIT (earnings before interest and taxes) to operating revenues;
- $CERN_{ict}$ is a dummy variable that takes value 0 before the first year the company received an order from CERN and 1 thereafter;
- $\Delta \mathrm{TotalAssets}_{ict}$ are defined as changes in the sum of fixed and current assets and account for variations in firm size that may affect its profitability;
- $\Delta \mathrm{EBITmargin}_{ict-1}^{j}$ is the one-year-lagged value of the profit margin change, which is included to account for the company's past performance;
- ΔGDP_{ct} and $\Delta \mathrm{GDP\_OECD}_t$ are changes, respectively, in the GDP growth rates of the country where the firm is located, and of the OECD Area, and allow us to control for respectively idiosyncratic and systemic economic shocks.
- $year_t$ is a trend variable controlling for potential time-patterns and takes values from 1 to 23, which is the time-span in years covered by our data (1991-2013);
- δ_t is a vector of time fixed-effects.
- μ_i is a vector of time-invariant unobservable firm-specific characteristics;
- the coefficients to be estimated are β, for the CERN effect; γ_1, γ_2 for the firm level controls; δ_1, δ_2 for the macroeconomic controls, ρ for the trend variable.
- Finally, the error term u_{it} is clustered by country, allowing for error correlation within the same country.

In this setting, OLS regression would lead to biased estimates of the vectors of regressors' coefficients due to the potential correlation between unobservable firm-specific characteristics that do not vary over time and the set of explanatory variables. Hence, we estimate the model using a Fixed-Effect (FE) regression that allows us to capture the impact of variables that change over time. FE regression controls for time-invariant differences between observations, therefore eliminating the potential bias due to the omission of fixed unobserved firm-specific variables, like, for example, a firm's quality of management, corporate governance, reputation, etc. Moreover, the result of the

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Hausman Test, a test that discriminates between Fixed- and Random-effect models, also suggests that, given our data, the preferred alternative is the FE regression.

4 Results

The results of Fixed-Effect regressions are presented in Table S3. The coefficient of the CERN effect, our variable of interest, is positive and statistically significant for the sample of all the suppliers (*p value* = 0.032). The result is driven by the high-tech suppliers, as for these firms the coefficient is greater and highly statistically significant for the high-technology suppliers (*p value* = 0.001), but not for the others (*p value* = 0.256), suggesting that only high-tech suppliers' profitability responds to procurement in the long term. Among the controls, a size effect of the change in total assets is significant for non-high-tech suppliers. Past change in profit margin is inversely correlated to current profit change, in a statistically highly significant way, suggesting a smoothing process over time. Among the macroeconomic controls the coefficient of the OECD area GDP change is significant and positive for high-tech companies. Years fixed effects are always positive and most of them are highly significant. Trimming the sample for outliers, or using the full 1 to 5 technological scale by scoring each firm with an average score, or trying alternative estimation methods consistently confirms the main finding presented in Table S3 (second column). As the dependent variable is defined as a change year by year of the profit margin, the estimated coefficient of the CERN effect roughly corresponds *ceteris paribus* to around one point increase of the profit margin, relative to the average levels reported in Table S.2.

Detailed data and statistical codes for this paper are available at: http://www.eiburs.unimi.it/?page=procurement_data

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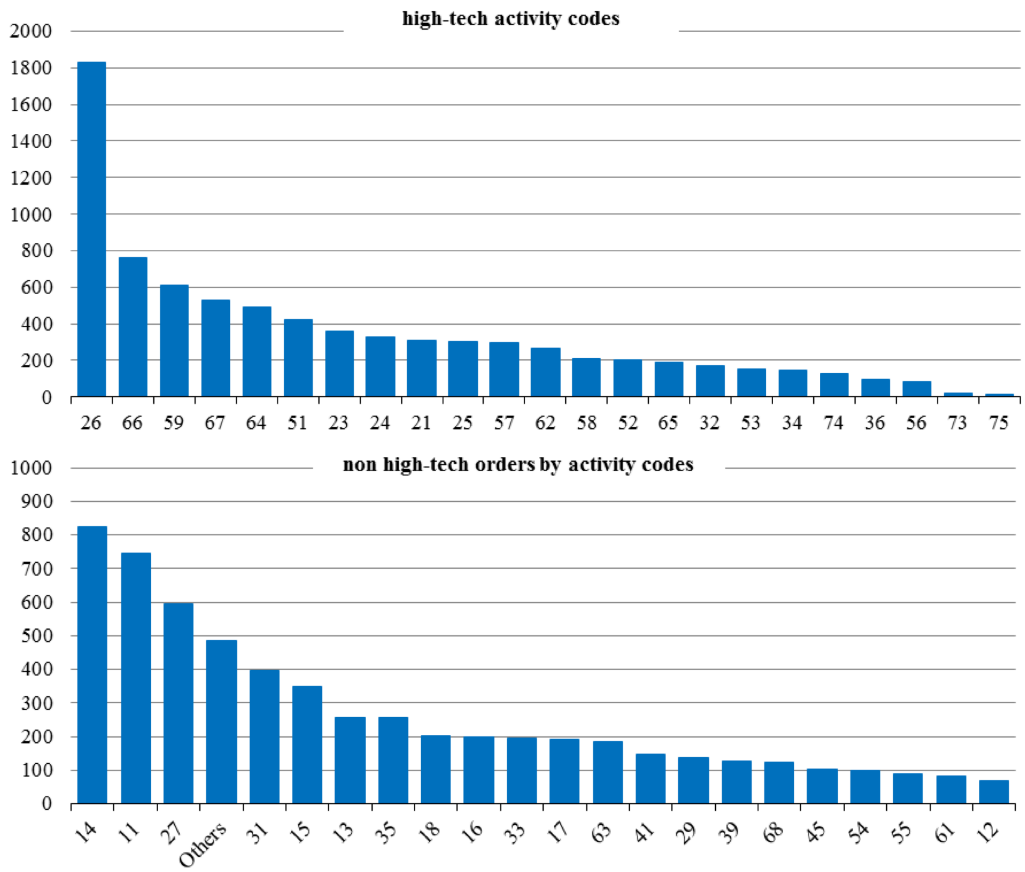

Fig. S1. Distribution of CERN procurement orders for LHC by activity code. Number of orders.

High-tech: 26. Magnets **66.** Low-temperature materials **59.** Specialized techniques **67.** Vacuum components & chambers **64.** Storage and transport of cryogens **51.** Raw materials (supplies) **23.** Power cables and conductors **24.** Control and communication cables **21.** Switch gear and switchboards **25.** Power suppliers and converters **57.** General machining work **62.** Refrigeration equipment **58.** Precision machining work **52.** Machine tools, workshop and quality control equipment **65.** Measurement equipment (vacuum and low-temperature technology) **32.** Passive electronic components **53.** Casting and molding (manufacturing techniques) **34.** Power suppliers - transformers **74.** Special detectors components **36.** RF and microwave components and equipment **56.** Sheet metal work (manufacturing techniques) **Others.** Wire chamber elements and Calorimeter elements.
Non high-tech: 14. Electrical Installation Work **11.** Building Work **27.** Measurement and Regulation **Others.** Electronics, Electrical Engineering, Data Communication, Data-Processing Peripherals, Power Transformers, Radiation Protection, Circuit Boards, Interfaces , Scintillation Counter Components, Vacuum and Low-Temperature Technology, Storage Systems, Consumables Items for Data-Processing, Storage (Data-Processing) **31.** Active Electronic Components **15.** Heating and Air Conditioning Equipment (Supply and Installation) **13.** Installation and Supply of Pipes **35.** Functional Modules & Crates (See Also 44 and 48 Series) **18.** Civil Engineering and Buildings **16.** Hoisting Gear **33.** Electronic Measuring Instruments **17.** Water Supply and Treatment **63.** Gas-Handling Equipment **41.** Computers and Work-Stations **29.** Electrical Engineering

Components **39.** Electronic Assembly and Wiring Work **68.** Low-Temperature Components **45.** Software **54.** Forging (Manufacturing Techniques) **55.** Boiler Metal Work (Manufacturing Techniques) **61.** Vacuum Pumps **12.** Road works. Source: Our processing of CERN data.

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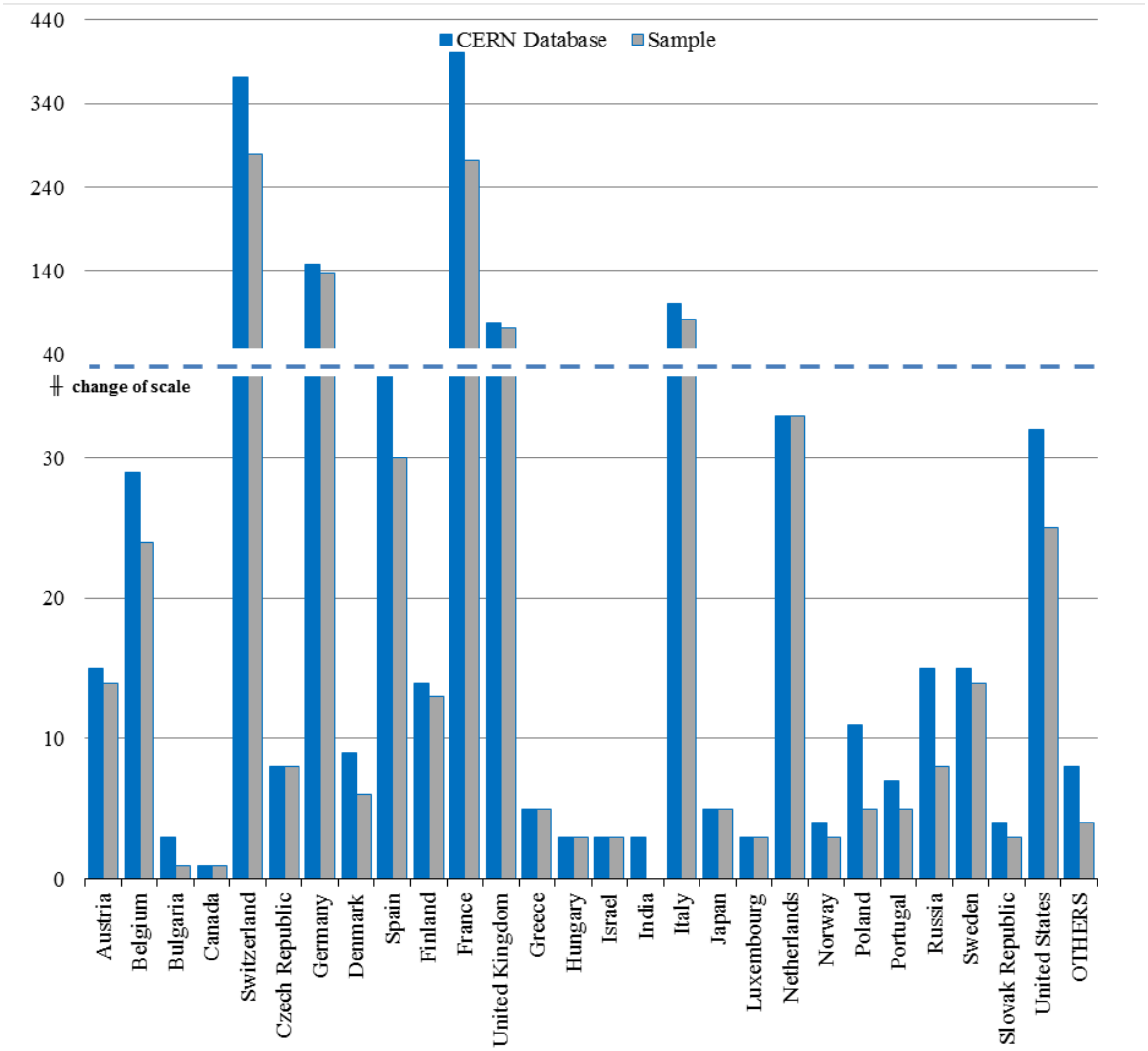

Fig. S2. Distribution of LHC suppliers across countries. Number of companies having received at least one order over CHF 10,000 by country where the company is located. CERN data compared with our sample. Source: Our processing of CERN data.

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Table S1. LHC suppliers distribution by NACE code. NACE Rev2 Classification. **Other includes**: **13**. Manufacture of textiles; **16**. Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials; **38**. Waste collection, treatment and disposal activities; **49**. Land transport and transport via pipelines; materials recovery; **58**. Publishing activities; **63**. Information service activities; **69**. Legal and accounting activities; **74**. Other professional, scientific and technical activities; **81**. Services to buildings and landscape activities; **84**. Public administration and defense; **91**. Libraries, archives, museums and other cultural activities; **94**. Activities of membership organizations; **95**. Repair of computers and personal and household goods. Source: Our processing of CERN and AMADEUS-ORBIS data

NACE code 2 digits	n° of firms	%	NACE code 2 digits	n° of firms	%
20. Manufacture of chemicals and chemical products	13	1.31	43. Specialized construction activities	55	5.56
22. Manufacture of rubber and plastic products	18	1.82	45. Wholesale and retail trade and repair of motor vehicles	3	0.30
23. Manufacture of other non-metallic mineral products	11	1.11	46. Wholesale trade, except of motor vehicles and motorcycles	207	20.93
24. Manufacture of basic metals	31	3.13	47. Retail trade, except of motor vehicles and motorcycles	5	0.51
25. Manufacture of fabricated metal products, except machinery	98	9.91	61. Telecommunications	6	0.61
26. Manufacture of computer, electronic and optical products	134	13.55	62. Computer programming, consultancy	20	2.02
27. Manufacture of electrical equipment	87	8.80	64. Financial service activities, except insurance	20	2.02
28. Manufacture of machinery and equipment n.e.c.	89	9.00	70. Activities of head offices; management consultancy	13	1.31
30. Manufacture of other transport equipment	7	0.71	71. Architectural and engineering activities; technical testing	40	4.04
32. Other manufacturing	11	1.11	72. Scientific research and development	18	1.82
33. Repair and installation of machinery and equipment	20	2.02	77. Rental and leasing activities	3	0.30
35. Electricity, gas, steam and air conditioning supply	3	0.30	82. Office support and other business support activities	10	1.01
41. Construction of buildings	13	1.31	85. Education	7	0.71
42. Civil engineering	11	1.11	Other (1)	26	2.59

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Table S2. EBIT margin descriptive statistics. EBIT margin = EBIT/Operating Revenues. 25th and 75th are percentiles. Source: Our processing of CERN and AMADEUS-ORBIS data

	average	std. dev.	25th	median	75th
Total sample	4.58%	12.94	1.21%	4.26%	8.45%
High-tech	4.62%	13.44	1.35%	4.46%	8.53%
Non-hi-tech	4.52%	11.98	0.95%	3.84%	8.15%

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Table S3. Regression results

	EBIT MARGIN (%)		
	Full Sample	**High-Tech Firms**	**Non High-Tech Firms**
CERN Effect	0.673***	1.007***	0.642
	(2.35)	(4.24)	(1.19)
Firm Level Controls			
ΔTotal Assets[1]	-0.006	-0.061	0.028***
	(0.36)	(0.65)	(2.61)
ΔEBIT margin, 1-year lagged value	-0.341***	-0.351***	-0.285***
	(14.72)	(10.46)	(7.63)
Macroeconomic Controls			
ΔGDP growth rate, firm's country	-0.030	-0.061	0.062
	(0.17)	(0.29)	(0.19)
ΔGDP growth rate, OECD Area	0.383***	0.416*	0.264
	(2.99)	(1.94)	(0.84)
Year	-0.004	-0.051	0.049
	(0.08)	(0.95)	(0.74)
Years Fixed-Effects	Yes	Yes	Yes
Constant	-2.803***	-2.511***	-3.239**
	(4.09)	(2.69)	(2.40)
Number of observations	4856	3017	1676

[1] in millions. Standard Errors are clustered by country. *t* statistics in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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