Can R&D Subsidies Spread Growth?*

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21 August 2026

Abstract Do R&D subsidies spread growth beyond recipient firms? We study France's Crédit d'Impôt Recherche, exploiting quasi-experimental variation in subsidy access generated by the certification of R&D consultancies. IV estimates show that subsidies increase technical employment with an elasticity of .16, technical wages with an elasticity of .14 and non-technical employment with an elasticity of .09, pointing to increased demand for technical workers. This spreads along the value chain to unsubsidized firms, where employment responses for technical workers are half as large as the direct effects, spreading growth and innovation-related activity.

Key Words: R&D Subsidies; Spillovers; Industrial Policy.

JEL Codes: D22, H25, L23, O38.

*We are particularly grateful to Liang Bai, Banu Demir, Fabrizio Leone, Javier Miranda, Max Nathan, Henry Overman, Ariell Reshef, Seyhun Sakalli, Michel Serafinelli and Farid Toubal for insightful discussions, as well as Kirill Borusyak for econometric wisdom. The paper has also benefited from discussions and comments from numerous seminar participants at KCL-Collège de France Junior Research Day, King's College London, Queen Mary University, City University, OECD, EU-SPRI Annual Conference, ETSG, Economics of Global Interaction (Bari), CMA-Durham Workshop, CUNY Queens, Shaping Globalization Workshop, Conference AFSE EPP, Geographical Inequalities Sheffield, IWH (Halle), FIW, INSEAD, Brunel University, Freie University, PSE Lunch Seminar STEP, LSE Spatial Disparities RPN Workshop, DIEW 2024, Birkbeck Alumnus Day and Queen Mary.

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1 Introduction

Industrial policies are often justified by the expectation that firm-level innovation generates benefits beyond recipient firms. Many governments use direct subsidies or tax-based incentives to increase private R&D, but the broader economic value of these programs depends on whether the induced activity generates positive externalities. If subsidies simply reallocate activity toward supported firms, their social returns may be limited. Can R&D subsidies spread growth?

We study this question in the context of France's Credit d'Impot Recherche (CIR), one of the world's largest R&D tax credit programs. The CIR was implemented in 1983 and substantially overhauled in 2008, becoming France's largest business support program and a central tool for promoting innovation, competitiveness, and private investment. Its performance, however, has drawn mixed reviews. While the CIR has increased R&D spending, its effects on business growth and foreign direct investment appear more limited (Commission nationale d'évaluation des politiques d'innovation (CNEPI), 2021). Moreover, firms may position their R&D activities to maximize subsidy claims without undertaking new innovation strategies or investments. Understanding both the direct effects of the CIR and its spillovers to related industries is therefore central to evaluating the broader effects of R&D incentives.

The question is also relevant beyond France. Recent policy initiatives such as the US CHIPS Act and the European Chips Act similarly aim to support strategic industries while crowding in broader economic benefits. Whether these policies succeed depends partly on whether subsidized activity propagates across firm networks and regions. The CIR, with over four decades of implementation and a large recent expansion, provides a useful setting to study how innovation incentives affect regional development and how those effects travel through production linkages.

To illustrate the potential dynamic we have in mind, consider the example of Bordes, a town in southwestern France with limited headquarters presence but rising subsidy-linked employment. The left panel of Figure 1 shows the area in 2005, largely residential with sparse industrial activity. By 2021, the right panel reveals notable industrial expansion, a visual reflection of how policy-induced innovation can reconfigure regional development patterns, even in traditionally peripheral areas.

Figure 1: Bordes Commune in Southwestern France

(a) 2005 (b) 2021

Notes: Maps of the commune Bordes, in the Pyrénées-Atlantiques department in southwestern France for 2005 and 2021. Sources: Institut national de l'information géographique et forestière (https://remonterletemps.ign.fr/).

We ask whether R&D subsidies impact local industries and extend their impact beyond by generating spillovers across the value chain. Using a quasi-experimental approach, we estimate whether CIR exposure increases employment and firm entry within subsidized Industry–Commuting Zone (CZ) cells, and whether those effects propagate to related upstream and downstream industries. We combine administrative records on CIR subsidies with employer data and input-output linkages. We first use a multiple-period difference-in-differences design to estimate how employment evolves following initial CIR exposure at the Industry–CZ level. We then address the endogeneity of subsidy amounts using variation in firms' access to the CIR generated by the certification of R&D consultancy agencies. These consultancies helped firms navigate the complexity of the subsidy application process by identifying eligible R&D expenditures and managing potential audit risks. Certification also provided a quality signal, reducing information asymmetries and increasing firms' confidence in claiming eligible activities. By lowering the costs and uncertainty associated with claiming the CIR, certification increased firms' effective access to the program without altering its rules, providing plausibly exogenous variation in local subsidy exposure.

We find that subsidies have significant and positive effects on employment within treated Industry–CZ cells. Using a long-difference specification and an instrumental variable strategy based on the rollout of certified CIR consultancies, we estimate an elasticity of .16 from CIR subsidies to Technical employment and .09 to Non-Technical employment. The larger Technical response is consistent with R&D support increasing demand for innovation-related labor, but the positive Non-Technical response indicates that the employment effects are not limited to narrowly technical occupations.

Wage effects also point to a stronger labor-market response among Technical workers. The IV estimates imply an elasticity of .14 for Technical wages, while the corresponding estimate for Non-Technical wages is insignificant. Thus, the stronger employment response among Technical workers is accompanied by higher Technical wages, consistent with R&D subsidies increasing demand for innovation-related labor along both the employment and wage margins. Subsidies also increase local net firm entry. The instrumental variable estimates imply an elasticity of .08 for the number of firms in treated Industry–CZ cells, showing that the policy affects the extensive margin of local economic activity.

Beyond direct treatment effects, we find evidence that CIR exposure generates economically meaningful employment spillovers through production networks. Instrumental variable estimates show positive effects both downstream and upstream. Downstream industries experience employment elasticities of .03 for Non-Technical workers and .08 for Technical workers, while upstream industries experience elasticities of .06 and .09, respectively. The effects are therefore broadly similar across the two sides of the value chain, particularly for Technical workers. These estimates show that subsidy-induced growth propagates in both directions along the value chain to firms that do not themselves receive the subsidy. The positive upstream effects are consistent with subsidized innovation increasing demand for inputs, supplier capabilities, and complementary technical services, while the positive downstream effects indicate that customers and related users also expand in response to subsidy-induced growth.

This section continues with a literature review. Section 2 describes the CIR policy, and Section 3 details the data and descriptive statistics. Section 4 specifies our econometric models for estimating the impact of subsidies on Industry–CZ cells using a difference-in-differences framework. Section 5 addresses endogeneity using an instrumental variable strategy based on the rollout of certified R&D consultancies and studies spillovers through production networks. Section 6 concludes.

Related Literature

This paper contributes to three related literatures: the effects of firm subsidies and place-based industrial policy, the propagation of firm-level shocks through local and production networks, and the evaluation of R&D tax incentives, particularly the French CIR.

First, our paper relates to a growing literature studying the effects of firm subsidies and tax incentives on investment, employment, and local economic activity. A broad literature finds that investment incentives can generate sizeable responses in firm activity. For example, Zwick and Mahon (2017) document large investment responses to accelerated depreciation in the United States, while Maffini et al. (2019) find that corporate tax incentives increase investment and employment, with particularly strong effects among smaller firms. Other policies generate more limited employment responses despite affecting investment (Yagan, 2015). In an innovation setting, Howell (2017) shows that early-stage R&D grants increase subsequent innovation, revenue, and external financing, particularly among financially constrained firms. Our contribution differs from much of this literature by focusing not only on activity directly exposed to the subsidy, but also on whether the resulting employment growth propagates to firms that do not themselves receive the policy.

The papers closest to ours study these indirect employment effects of firm subsidies. Lerche (2025) examines investment tax credits targeted toward manufacturing firms in former East Germany and finds substantial direct employment effects together with highly localized spillovers, particularly among economically connected firms. Siegloch et al. (2025) similarly finds that regional investment subsidies generate employment gains outside directly treated manufacturing firms, with approximately 0.48 additional jobs in untreated construction and retail for each manufacturing job generated by the policy. These studies show that the employment consequences of firm subsidies can extend substantially beyond their direct recipients. Our results are consistent with this evidence, but identify a different margin of propagation. Rather than focusing primarily on spatial proximity or non-tradable local employment, we trace CIR-induced activity through specific buyer–supplier relationships within local labor markets.

The magnitude of our estimates is also broadly consistent with these recent findings. Our IV estimates imply direct employment elasticities of approximately 0.16 for technical workers and 0.09 for non-technical workers. In industries linked through the production network, the corresponding spillover elasticities range from approximately 0.03 to 0.09. The percentage employment response in linked, unsubsidized industries is therefore roughly one-third to two-thirds of the corresponding direct response, depending on worker type and whether the industry is upstream or downstream. These ratios are not directly equivalent to the jobs-per-job multipliers estimated in some of the place-based policy literature, since the underlying treatment and employment bases differ. Nevertheless, they indicate that the indirect employment response is economically substantial relative to the direct effect and falls within the broad range of propagation documented in recent studies of firm subsidies.

Second, our paper contributes to the literature on how shocks propagate through production networks and local economies. A large literature documents that firm-level shocks can affect other firms and workers through several channels. Moretti (2010) shows that growth in tradable employment generates additional employment in local non-tradable sectors, highlighting a local demand multiplier. Greenstone et al. (2010) finds productivity gains among incumbent establishments following large plant openings, while Gathmann et al. (2020) documents persistent negative effects of mass layoffs on neighboring firms. Related work provides evidence of knowledge and co-location externalities associated with firm entry (Fons-Rosen et al., 2017) and of employment reallocation across economically connected industries (Helm, 2020). Bilgin et al. (2024) use Turkish firm-to-firm transaction data, showing that robot adoption generates productivity and employment spillovers vertically, wherein they can disentangle these positive flows from business stealing effects. In contrast, we study how a policy-induced expansion in innovative activity propagates upstream and downstream through production relationships and across worker types.

Our mechanism is more closely related to recent work tracing policy shocks through input-output relationships. Atalay et al. (2023) finds that place-based industrial subsidies affect firms connected to subsidized producers through supplier and customer relationships, while Navarra (2023) documents substantial propagation of subsidies along supply chains. We complement this work by distinguishing upstream from downstream responses and by separating technical from non-technical employment.

This occupational dimension is useful because it allows us to distinguish a general expansion in local employment from a response concentrated in workers more directly associated with innovation. We find that spillovers are positive in both directions of the value chain and are broadly similar in magnitude across upstream and downstream industries, particularly for technical employment. This pattern suggests that subsidy-induced growth propagates to both suppliers and customers, while the particularly strong response of technical employment is consistent with increased demand for innovation-related capabilities throughout the production network. The skill bias in the response also relates to work emphasizing complementarities between innovation policy and access to skilled labor (Akcigit et al., 2020).

Finally, our paper contributes to the literature evaluating R&D tax incentives and the French CIR. Existing studies of R&D tax credits have focused primarily on whether fiscal incentives increase firms' own R&D expenditures, innovation inputs, patenting, or employment. In France, studies exploiting the major 2008 CIR reform generally find that the policy increased private R&D activity, although estimates of its effectiveness vary across firms and outcomes (Mulkay and Mairesse, 2013; Salies, 2017). Related work on the Credit d'Impot Innovation, a subsidy targeted toward innovation expenditures by SMEs, finds positive effects on employment, turnover, and patent applications (Bunel et al., 2019). Other work suggests that smaller firms may be particularly responsive to R&D tax incentives, motivating proposals to target the CIR more strongly toward small and medium-sized firms (Aghion et al., 2022).

Much less is known about whether R&D tax incentives generate real effects outside the firms and industries that receive them. This is important for evaluating such policies: if subsidies primarily reimburse activity that firms would have undertaken anyway or redistribute workers and activity across firms, their aggregate benefits may be limited. Conversely, if subsidized innovation raises employment and generates additional activity among suppliers and customers, evaluations based only on recipient firms will understate the broader effects of the policy. We address this gap by combining administrative CIR records, employer reported data on wages, hours worked, occupations, and input-output relationships to estimate both the direct local employment effects of the CIR and its propagation to unsubsidized firms in connected industries. Our results show that the employment effects extend meaningfully beyond directly exposed industries and are particularly pronounced for technical workers, providing evidence that R&D subsidies can diffuse through production networks rather than remaining confined to their direct recipients.

2 The CIR and Consultancy Registration Policies

While multiple policies targeting R&D and local areas exist in France, the largest since 2008 is the Crédit d'Impôt Recherche (CIR). Here we describe its economic context, and other support policies in France. For a more detailed overview of the policy and other policies and policy context see Klebaner and Voy-Gillis (2023).

2.1 History of the CIR

The Crédit d'Impôt Recherche (CIR) was first introduced in 1983 as a temporary plan to stimulate investment in R&D, targeting industrial and commercial sectors. The previous financial law in place allowed firms to claim exceptional depreciation on their research equipment and tools, but firms had little incentive to increase their investment in human and physical capital towards R&D activities. is still in place today, and any industrial, commercial or agricultural organization subject to corporate tax in France is eligible for this research tax credit.

The 2008 reform of France's Crédit d'Impôt Recherche (CIR) fundamentally altered the structure of the scheme, moving from a mixed system which combined a small base credit with a higher incremental component (up to 45% on increases in R&D spending), to a purely volume based approach. The new system offered a uniform 30% tax credit on all eligible R&D expenses up to €100 million, with a reduced rate of 5% beyond that threshold. This simplification aimed to improve predictability and accessibility, particularly for SMEs, while eliminating the need to demonstrate year-on-year R&D growth. The reform led to a sharp increase in the number of participating firms and significantly raised the fiscal cost of the program, which grew from under €1 billion pre-reform to nearly €6 billion annually. Since then, the 2008 reform has made the CIR the main R&D support system for firms in France.[1]

[1] Timeline of the updates in the policy can be found in Salies (2017), https://spire.sciencespo.fr/hdl:/2441/59b98fs2bu8neb8h5au501rtll/resources/evaluation-cir-ofce-avril-2017-755839.

To be part of the scheme, firms need to fill a form enabling the identification of the firm and a breakdown of R&D related expenditures for reimbursement.[2] In addition, firms are asked to provide a summary of each of the projects selected for declared expenditure complying with the conditions of the CIR. They must also detail information on how the amounts are used, such as labor costs and associated hours, invoices, allocation of time on projects, spanning the firm's activities and employees.[3] Given the high time cost in filing the application, the tax incentive scheme for private corporate R&D favors large companies.[4] Applications are evaluated by the French Ministry of Higher Education and Research and Ministry of Finance who evaluate eligible activities.

Basing subsidies on the incremental component before 2008 often disadvantaged service firms, which tend to have more volatile or flat R&D investment patterns (e.g., software development or process innovation). The shift to a volume-based credit made the CIR more accessible to firms with stable or less rapidly growing R&D spending, a common feature in service-oriented R&D. The new simplicity and predictability of the volume-based regime made it easier for service-sector firms to assess eligibility and justify claims.

2.2 CIR Consultancy Certification

The R&D tax credit system in France is known for its complexity, prompting many firms, especially small and medium-sized enterprises (SMEs), to rely on specialized consultancies to file their claims. In response to growing concerns in the 2010s, the government identified several issues with the existing system: high fees charged by private R&D consultancies, aggressive or borderline-legal optimization practices, and unequal access to the CIR based on firm size or geographic location.

In 2015, the French government introduced a voluntary regulatory framework aimed

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[2]See https://www.impots.gouv.fr/sites/default/files/formulaires/2069-a-sd/2023/2069-a-sd_4244.pdf for an example for the form.

[3]See https://www.economie.gouv.fr/files/files/directions_services/dgfip/controle_fiscal/prevention/dossier_justificatif_cir.pdf for a help file when completing an application.

[4]Other schemes are available for smaller firms: Credit d'Impôt Innovation (CII), a product-based development subsidy is available for firms with less than 250 workers, with a turnover inferior to 50 million euros. CIFRE is a scheme that financially helps firms to hire PhD students.

at increasing transparency, enforcing quality standards, and broadening access to the tax credit system through consultancy firms advising on the CIR and Crédit d'Impôt Innovation (CII).[5] Coordinated by the Médiateur des entreprises, the initiative established a "référencement" system whereby firms could apply to be listed as adherents to a formal charter of professional conduct. This charter outlined mandatory principles and best practices, including clear disclosure of fees, avoidance of aggressive or noncompliant claims, and the promotion of balanced, transparent contractual relationships. While participation was not compulsory, the referenced firms were positioned as more reliable partners for companies navigating complex tax credit procedures.

By 2016, 26 firms with multiple branches, advising on over €1.5 billion of the €5.5 billion in total CIR-CII claims, had joined the scheme. The initiative represented a soft regulatory response to growing concerns over opportunistic behavior in the R&D tax consultancy market, aiming to enhance client protection and reduce the risk of fiscal disputes without imposing formal licensing or enforcement mechanisms.

Certification could improve firms' access to the CIR through several related channels. First, the référencement system provided firms with a signal of consultancy quality and professional conduct, reducing uncertainty about which advisers could reliably assist with a claim. Second, the charter required greater transparency over fees and contractual terms, reducing some of the information asymmetries associated with hiring an outside consultant. Third, certified consultancies could assist firms with identifying eligible R&D expenditures, preparing the required technical and financial documentation, and organizing claims in a manner consistent with CIR requirements. This was particularly relevant given the administrative burden of documenting eligible projects, employee time, labor costs, and other R&D expenditures described above. Finally, greater confidence in the compliance of claims could reduce the perceived risk associated with subsequent audits or fiscal disputes.

Importantly, certification did not change the statutory generosity of the CIR or which firms and expenditures were formally eligible for the tax credit. Rather, it affected the costs, information, and uncertainty involved in accessing an existing program. Therefore certification reduced barriers to claiming the CIR by providing firms with a more

[5]We do not consider the CII here as the maximum amount claimable, 20% on up to 400,000 euros is small compared to the CIR.

transparent and reliable channel for navigating the application process. The effects of this change in access should be larger where certified consultancies were more available and where there were more firms potentially able to use their services.

2.3 Potentially Confounding Policies in France

Until 2008, the largest policy was the CICE, a subsidy for low wage workers which is given unconditionally to firms. While this policy is possibly important for inequality and the welfare of low wage workers, we are not concerned about them impacting our outcomes of interest. Given the subsidies were given unconditionally, it's also very possible they had little more effect than acting as a lump sum transfer to firms. Other examples of firm targeted policies in France include the Zones Franches Urbaines' (ZFUs), Prime d'Activité (Activity Bonus), Pole Competitivité (Competitiveness Clusters) and CIFRE which supported hiring PhD educated researchers. We briefly discuss each here.

ZFUs are a French enterprise zone program that mainly cause reallocation within a CZ (Mayer et al., 2017) suggesting the minimal interaction with the CIR at our level of aggregation. Activity Bonus is a salary top up eligible to professional employed European (or long staying) adult residents which may increase workforce participation but should not interact with the CIR in any meaningful way. Competitiveness Clusters attempt to crowd in innovation across industries and receive funding from the public investment bank BPIFrance as well as national, regional and local levels. Using a research survey revealing if firms are enrolled in the program, Ben Hassine (2020) find no evidence of spillovers and a very modest employment effect of less than 1.5 workers per treated firm based on a matching estimator. Given this modest impact on our outcomes of interest, any bias on our estimates would be slight. Finally, the CIFRE is a joint PhD training and hiring program to strengthen collaboration between firms and academic labs. Access to this is broad across France and as the employment costs of PhD students are eligible for the CIR which we instrument for, this should be accounted for in our estimates. While it's an empirical question how any of these policies might interact with the CIR, throughout we will use long lags and fixed effects at the Commuting Zone that will absorb much of the heterogeneity across regions and industries, for instance non-industry specific spillovers from universities as found by

Bergeaud and Guillouzouic (2024).

We now turn to a description of the data used and descriptive statistics on the reach of CIR across firms in France.

3 Data and Descriptive Statistics

This section describes the administrative data, sample construction, and variables used in the empirical analysis. We build a panel of French firms, establishments, and Industry–CZ cells for 2009–2019 by linking administrative records on employment, wages, R&D tax-credit claims, firm characteristics, and production-network relationships. The core unit of observation in the empirical analysis is an Industry–CZ cell. We use these cells to study both the direct effects of R&D subsidies on treated local industries and the indirect effects on linked upstream and downstream industries.

3.1 Administrative Sources and Linkage

We combine four main data sources. First, we use French administrative records from the DADS and DSN files. DADS is the annual declaration of social data and DSN is the later monthly social declaration system, which replaced many prior employer reporting requirements and is based on payroll data transmitted at the establishment level (Institut national de la statistique et des études économiques (Insee), 2018). These files provide near-universal coverage of salaried employment in France and include establishment identifiers, firm identifiers, occupation codes, wages, hours worked, contract characteristics, and workplace location. The key firm identifier is the SIREN, a nine-digit identifier assigned to each legal unit, while the key establishment identifier is the SIRET. A SIRET identifies an establishment and is composed of the SIREN of the legal unit and an establishment-specific NIC code (Institut national de la statistique et des études économiques (Insee), 2025a, 2019). These identifiers allow us to link workers to establishments, establishments to firms, and firms to subsidy records.

Second, we use administrative records on claims to the Crédit d'Impôt Recherche (CIR), drawn from the GECIR database maintained by DGFiP and the Ministry of Higher Education and Research. These records report whether firms claim the CIR and the annual amount claimed. We merge CIR claims to the employer reported data on wages, hours worked, and occupations using firm identifiers. Our main treatment variable is subsidy exposure at the Industry–CZ level, constructed by aggregating CIR claims among firms associated with a given industry and commuting zone.

Third, we use information on certified R&D consultancy agencies. These agencies assisted firms in preparing CIR applications, and their certification provides the variation used in the instrumental-variable strategy. We assign consultancy exposure to commuting zones using the location of certified agencies and interact this exposure with the initial number of firms in each Industry–CZ cell. This produces a measure of changes in access to CIR support generated by the certification of consultancies.

Fourth, we use INSEE input-output tables to construct production-network linkages across industries. Input-output tables describe flows of intermediate inputs across sectors and allow us to identify industries that are strongly linked through buyer-supplier relationships (Institut national de la statistique et des études économiques (Insee), 2020). For each treated industry, we define upstream industries as sectors that supply inputs to the treated industry and downstream industries as sectors that purchase output from the treated industry. In the spillover analysis, we focus on the two strongest upstream and downstream linkages by expenditure share.

3.2 Geography, Industries, and Headquarters

We define local labor markets using INSEE *zones d'emploi*, which we refer to as commuting zones (CZs). INSEE defines a zone d'emploi as a geographic area in which most workers live and work and in which establishments can find most of the labor force needed to fill local jobs (Institut national de la statistique et des études économiques (Insee), 2025b). This geography is well suited to studying the local labor-market effects of R&D subsidies because it captures economically integrated labor markets rather than administrative boundaries.

Industries are defined using the French NAF classification. We assign establishments to industries using the firm or headquarters industry when necessary. In the data, the overwhelming majority of multi-establishment firms operate within a single industry, so assigning establishments to the firm's main industry introduces little ambiguity. We identify firm headquarters using administrative information on the *siège social*. For multi-establishment firms, the headquarters is the establishment reported as the firm's legal or administrative seat; for single-establishment firms, the establishment is coded as the headquarters. Headquarters information is used to assign CIR claims to the firm's primary local industry cell and to study how subsidy exposure maps onto the geography of firm activity.

3.3 Labor-Market Outcomes and Occupation Groups

The DADS/DSN data provide the employment and wage outcomes used throughout the paper. We classify workers into technical and non-technical occupations using occupation codes from the French *Professions et Catégories Socioprofessionnelles* (PCS) classification. Following Charnoz et al. (2018) and Harrigan et al. (2021), we define "technical" workers as occupations closely related to ICT, engineering, product and process design, maintenance, and R&D-related activities. This classification captures workers most directly involved in innovation, technology adoption, and technical production processes. All other occupations are classified as non-technical.

Table 1: Occupation Classifications

Skill Level	Occupation	Label
	Main Category 1: Jobs in Support Activities	
Low	Office Workers, Clerks and Sellers	S1
Middle	Mid-Level Administrative Managers, Mid-Level Professionals	S2
High	Heads of Businesses, Top Managers and Professionals	S3
	Main Category 2: Jobs in Production Activities	
Low	Industrial, Manual Workers, Drivers, Skilled Transport, Wholesale	P1
Middle	Supervisors and Foremen	P2
High	Science and Educational Professionals	P3
Middle-High	Technicians, Technical Managers and Engineers	Techies

Notes: The table reports the occupation classification we will use through out the paper. Skill level stands for the different skill categories (low, medium and high). The label of occupation stands for the official French occupation classification (CSP) label. And the last column is the variable label that can be used in some graphs and tables.
Sources: Charnoz et al. (2018) and Harrigan et al. (2021)

For each establishment-year, we compute employment by worker type, total employment, and average wages. We then aggregate these variables to the Industry–CZ–year level. The main employment outcomes are the number of technical workers and non-technical workers in each cell. Wage outcomes are constructed separately for technical and non-technical workers as average annual earnings per worker. In the long-difference specifications, outcomes are transformed into log changes across the pre- and post-certification periods.

3.4 CIR Subsidy Measures

The main subsidy variable is the annual amount of CIR claimed by firms in each Industry–CZ cell. We aggregate firm-level CIR claims to the cell-year level and construct two complementary measures. In the event-study analysis, a cell is defined as treated beginning in the first year in which any firm in the cell receives a CIR subsidy. In the elasticity analysis, we use the long difference in log subsidy amounts between the pre-period and post-period. Specifically, we compare cumulative subsidy exposure before and after the certification of R&D consultancies.

The long-difference specifications compare outcomes across two periods, 2009–2014 and 2015–2019. For each outcome, we compute the log of cumulative values in the post-period minus the log of cumulative values in the pre-period. For subsidy exposure, we compute the analogous long difference in cumulative CIR claims. This construction smooths year-to-year volatility in claims and aligns the outcome window with the timing of the consultancy certification shock.

3.5 Production-Network Spillovers

To study spillovers, we use input-output linkages to identify industries connected to treated cells through buyer-supplier relationships. For each industry, upstream industries are those that sell intermediate inputs to the treated industry, while downstream industries are those that purchase outputs from the treated industry. We rank linked industries by the strength of the input-output relationship and retain the top two upstream and top two downstream industries for the main spillover analysis.

We then construct spillover exposure at the linked Industry–CZ level. The spillover sample excludes firms that directly receive the CIR subsidy in the linked cells, allowing us to focus on indirect effects on non-recipient firms. This distinction is important because linked industries may themselves receive subsidies; excluding direct recipients helps isolate employment responses generated by exposure to subsidized activity elsewhere in the local production network.

3.6 Sample Construction

The baseline sample consists of Industry–CZ cells observed over 2009–2019. For the event-study analysis, treatment is defined by the first year in which a cell receives a CIR subsidy. For the elasticity estimates, we use a long-difference sample of cells with positive measured subsidy exposure in the relevant period. This restriction allows the coefficient on subsidy exposure to be interpreted as an elasticity while excluding cells with effectively zero measured exposure.

Table 2 summarizes the baseline long-difference sample used in the elasticity analysis. The sample contains 3,133 Industry–CZ cells. Between 2009–2014 and 2015–2019, technical worker-years increase from 1.88 million to 2.27 million, while firm observations increase from 5.08 million to 5.29 million and establishment observations increase from 5.64 million to 5.92 million. Aggregate CIR claims in the estimation sample rise from EUR 27.33 billion to EUR 29.19 billion across the two periods.

Table 2: Baseline Industry–CZ Sample

	2009–2014	2015–2019	Change (%)
Technical worker-years	1,877,200	2,265,490	20.7
Firm observations	5,076,933	5,290,166	4.2
Establishment observations	5,639,084	5,916,597	4.9
Total CIR claims (EUR bn)	27.33	29.19	6.8
CIR claims per firm obs. (EUR)	5,384	5,517	2.5

Notes: The table uses the baseline Industry–CZ sample. Technical employment, firm observations, establishment observations, and CIR claims are cumulative over each period. CIR claims are reported in current euros.

The final dataset links subsidy claims, employment outcomes, firm and establishment counts, wages, and production-network linkages at the Industry–CZ level. This structure allows us to estimate direct effects of R&D subsidies on treated local industries and indirect effects on related upstream and downstream industries.

Table 3 compares observations with positive CIR claims to observations without CIR claims in the pre-period and post-period. CIR observations are far more technology intensive than non-CIR observations. In 2015–2019, CIR observations average 4.04 technical workers per firm observation, compared with 0.07 among non-CIR observations. CIR observations also account for most technical employment despite representing a much smaller number of firm observations. This difference is consistent with the program's targeting of innovation-intensive activities and motivates the distinction between technical and non-technical employment outcomes in the empirical analysis.

Table 3: CIR and Non-CIR Observations

	CIR observations		Non-CIR observations	
	2009–2014	2015–2019	2009–2014	2015–2019
Technical worker-years	1,330,444	1,623,404	916,734	1,106,571
Firm observations	359,673	401,944	18,446,377	16,575,683
Establishment observations	555,474	624,450	19,753,066	17,855,858
Technical workers per firm obs.	3.70	4.04	0.05	0.07
Total CIR claims (EUR bn)	27.75	29.58	0.00	0.00
CIR claims per firm obs. (EUR)	77,142	73,589	0	0

Notes: The table compares observations with positive CIR claims to observations without CIR claims. Counts and claims are cumulative over each period. CIR claims are reported in current euros.

CIR exposure is also highly concentrated across industries. Table 4 ranks A38 industries by total CIR claims in 2015–2019. The top ten A38 industries account for 79.4% of post-period CIR claims. The largest categories are professional and technical services, scientific R&D, IT and information services, transport equipment, and computer, electronic, and optical products. This concentration is consistent with the policy's focus on R&D-intensive activities and reinforces the need to control for industry composition and to use within-industry–commuting-zone variation in the empirical analysis.

Table 4: Top A38 Industries by Post-Period CIR Claims

A38	Industry	CIR 2009–2014 (EUR bn)	CIR 2015–2019 (EUR bn)	Share 2015–2019 (%)	Tech. worker-years 2015–2019
MA	Legal, accounting, engineering	3.93	5.38	18.2	406,453
MB	Scientific R&D	3.11	3.65	12.3	66,654
JC	IT and information services	2.68	3.24	11.0	392,228
CL	Transport equipment	3.04	2.52	8.5	165,174
CI	Computer, electronic, optical	2.82	2.47	8.4	79,819
KZ	Finance and insurance	0.65	1.84	6.2	68,297
JA	Publishing, audiovisual, broadcasting	1.11	1.28	4.3	61,364
GZ	Wholesale and retail trade	1.19	1.22	4.1	175,407
CE	Chemicals	1.46	1.05	3.6	48,308
CK	Machinery and equipment	0.96	0.85	2.9	69,955

Notes: Industries are ranked by total CIR claims in 2015–2019. The top ten A38 industries account for 79.4% of post-period CIR claims.

Having laid out the data, policy, and descriptive features of the sample, we now turn to an event study of the impact of the CIR at the Industry–CZ level. While CIR awards are clearly endogenous, this provides evidence of the dynamic effect on the relevant cells which we will later quantify with an IV strategy in long differences.

4 Difference in Difference Estimates

Here we estimate the impact of the CIR using a difference-in-differences (DiD) estimator applied to Industry–CZ cells. We define treatment to occur when any firm in a cell receives a subsidy. Our key outcomes of interest are Technical and Non-Technical employment and the number of firms within each cell. This section proceeds with our econometric model and then estimates these impacts.

4.1 Econometric Model

We estimate the effect of a firm in an Industry–CZ cell, indexed by (i, l), receiving R&D subsidies for the first time on cell outcomes. Our empirical approach uses a difference-in-differences framework, where we model outcomes as:

$$\text{Outcome}_{i,l,t} = \sum_{k=-8,,k\neq-1}^{8} \beta_k \cdot \text{Treated}_{i,l,t+k} + \alpha_{i,l} + \alpha_t + \varepsilon_{i,l,t}. \tag{1}$$

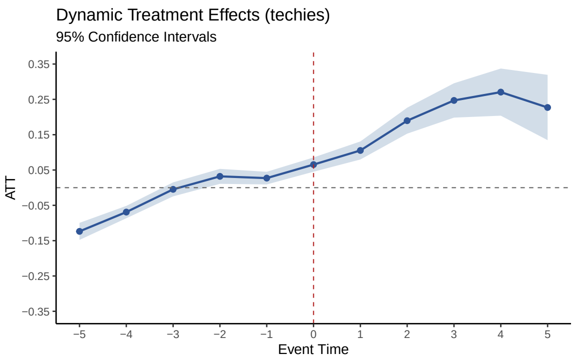
Here, $\text{Outcome}_{i,l,t}$ denotes the outcome of interest in Industry–CZ cell (i, l) in year t, including log employment by worker type and the number of firms. Treatment begins in the first year in which any firm in the cell receives a CIR subsidy and is defined relative to this initial treatment date. The coefficients β_k trace the dynamic effect of treatment k years before or after first receipt of the subsidy, with $k = -1$, the year immediately preceding treatment, serving as the omitted reference period.

Because Industry–CZ cells first receive subsidies in different years, we estimate these dynamic effects using the multiple-period difference-in-differences estimator of Callaway and Sant'Anna (2021). Rather than relying on a conventional two-way fixed-effects event-study regression, this approach first estimates group-time average treatment effects, $ATT_{g,t}$, separately for cells first treated in year g and for each calendar year t. Treated cells are compared with cells that provide a valid untreated counterfactual, thereby avoiding comparisons in which already-treated cells serve as controls for cells treated at a later date. This is important in our setting because both the timing and the effect of initial subsidy receipt may vary across Industry–CZ cells.

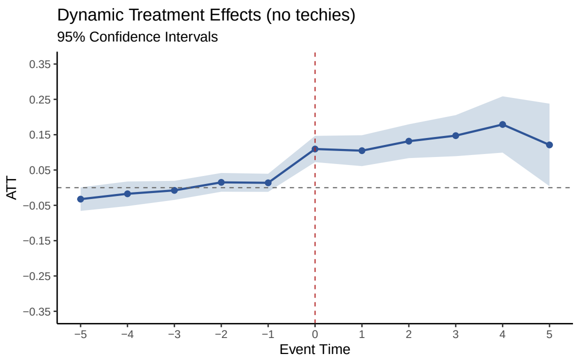
We then aggregate the estimated $ATT_{g,t}$ parameters by event time, $k = t - g$, to obtain the dynamic treatment effects reported in the event-study figures. Under the parallel-trends assumption, these estimates capture the average change in outcomes associated with first subsidy receipt relative to the evolution of outcomes among comparable untreated cells. The pre-treatment coefficients provide a diagnostic for differential trends prior to treatment, while the post-treatment coefficients characterize how employment and firm activity evolve following initial CIR exposure.

4.2 Employment Effects

Figures 2a and 2b show the results of estimating Equation (1) with Technical and Non-Technical employment as outcomes. Both employment outcomes increase around and after initial CIR receipt, with a larger and more persistent response for Technical employment. The pre-treatment estimates are not completely flat, particularly for Technical workers, which is one reason we treat these event studies as descriptive evidence on the dynamics around treatment rather than as our main causal estimates. Following treatment, Technical employment rises steadily over the next several years, while Non-Technical employment also increases but by less. Below, we use the consultancy certification instrument to estimate the magnitudes of these effects using plausibly exogenous variation in subsidy exposure. Overall, the event-study patterns are consistent with an innovation-intensive hiring response within treated Industry–CZ cells.



(a) Technical Worker Employment



(b) Non-Technical Worker Employment

Figure 2: Dynamic Treatment Effects by Worker Type

Figure 3 shows the results of estimating Equation (1) with the number of firms in the cell as the outcome. Firm counts are relatively stable before treatment and increase following initial CIR receipt, with the response building over the first several post-treatment years. This extensive-margin response is consistent with CIR exposure being associated not only with higher employment but also with an expansion in the number of firms operating in the treated local industry. As with the employment event studies, we use the IV estimates below to quantify the causal magnitude of this relationship.

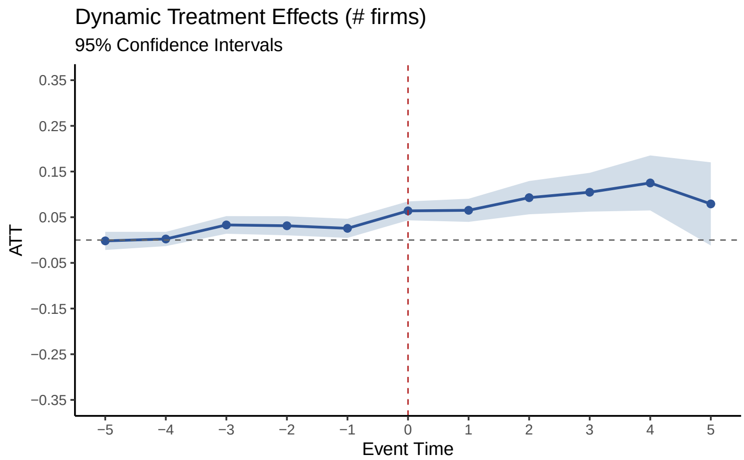
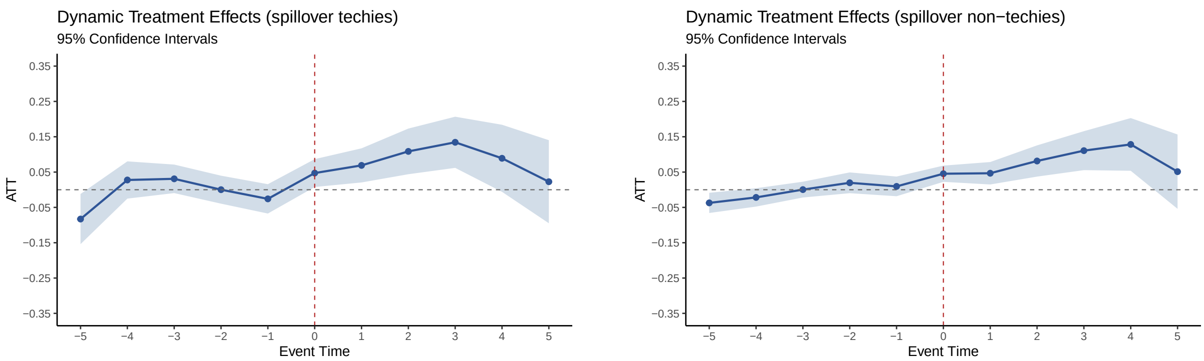


Figure 3: Dynamic Treatment Effects on Firm Count

4.3 Within-Cell Spillovers

We next examine whether the employment response extends beyond firms that receive the CIR directly. Figures 4a and 4b repeat the event-study analysis using Technical and Non-Technical employment at firms in the treated Industry–CZ cell that do not themselves receive the subsidy. These outcomes allow us to examine whether initial CIR exposure is associated with broader employment growth within the local industry rather than only employment expansion among recipient firms.



(a) Technical Worker Employment

(b) Non-Technical Worker Employment

Figure 4: Dynamic Treatment Effects on Employment at Non-Recipient Firms

The event-study estimates indicate that employment at non-recipient firms also increases following initial CIR exposure. Technical employment rises after treatment and remains positive over the following several years, while Non-Technical employment displays a similar, somewhat more gradual increase. Here the pre-treatment estimates are plausibly flat, likely due to the fact that treated non-CIR Industry-CZ cells are in the same Industry-CZ as the treated firms. The Figures show that the positive post-treatment patterns for both worker groups are consistent with CIR-induced activity extending beyond subsidy recipients to other firms operating in the same local industry. In the IV analysis below, we return to these within-cell spillovers using variation in subsidy exposure generated by consultancy certification.

To address endogeneity in selection and the level of subsidies, the next section quantifies subsidy effects using an instrumental variable based on a 2015 reform certifying R&D tax consultancies, which expanded access to the program.

5 Subsidy Elasticity Estimates

This section estimates both the direct effects of subsidies on treated Industry-CZ cells and spillover effects on local industries in the value chain. From a policy standpoint, understanding elasticities of employment with respect to subsidy exposure is informative for quantifying effectiveness. However, since both the decision to award a subsidy and the amount received are endogenous, we require an instrumental variable strategy. In particular, selection bias arises because high-tech and fast-growing firms are more likely to apply for and receive subsidies, potentially inflating estimates of employment growth and spillovers. Even conditional on being selected, variation in subsidy levels can still be endogenous, implying that the DiD estimates above lack granularity. To address this, we interact the number of certified application agencies with the first period number of firms as an instrument. This instrumental variable (IV) strategy will help correct for selection bias in our difference-in-differences framework.

We next lay out the 2SLS model we estimate the impact of consultancy certification on both local industry subsidy amounts and other indications of the actual reach of certification. We then quantify the impact of increased subsidies examining outcomes motivated by the DiD results above which illustrate an effect at the Industry-CZ level.

5.1 Econometric Model

We estimate outcomes with respect to R&D subsidies using a long-difference specification across two 5-year periods (2010–2014 and 2015–2019). Outcomes include occupational employment within the treated cell and other cells in the value chain, as well as number of firms and average wages in each cell. The elasticity of interest is captured by the coefficient β in the following regression equation:

$$\Delta\text{Outcome}_{o,i,l} = \beta\Delta\text{Subsidy}_{i,l} + \gamma_l + \epsilon_{i,l} \tag{2}$$

Here $\Delta\text{Outcome}_{o,i,l}$ represents the long difference in each outcome, such as log employment for occupation o in industry i and location l, while $\Delta\text{Subsidy}_{i,l}$ is the long difference in subsidies awarded to firm headquarters in the same industry-location cell. These differences are constructed as follows:

$$\Delta\text{Outcome}_{o,i,l} = \ln\left(\sum_{t=2015}^{2019} \text{Outcome}_{o,i,l,t}\right) - \ln\left(\sum_{t=2009}^{2014} \text{Outcome}_{o,i,l,t}\right), \tag{3}$$

$$\Delta\text{Subsidy}_{i,l} = \ln\left(\sum_{t=2015}^{2019} \text{Subsidy}_{i,l,t}\right) - \ln\left(\sum_{t=2009}^{2015} \text{Subsidy}_{i,l,t}\right). \tag{4}$$

where the terms in the sums represent the annual values of each variable. The inclusion of location (γ_l) fixed effects allows us to control for underlying trends in advancing or declining regions. As we want to interpret β as an elasticity, we balance the sample on cells with at least 100 euro of subsidy awards in at least one year of each period.[6]

Our identification strategy is based on increased subsidy access following consultancy certification in 2015 as detailed above in Section 2.1. Although firms could claim the CIR directly, doing so required identifying eligible R&D expenditures, preparing supporting technical and financial documentation, and managing the possibility of subsequent tax audits. Specialized R&D consultancies could reduce these administrative and informational costs. Certification provided an additional signal of consultancy quality and compliance, increased transparency over fees and contractual practices, and reduced uncertainty for firms considering the use of an external adviser. This policy change motivates our instrument which exploits cross-sectional variation in the local share of certified consultancies and their interaction with the scale of potential

[6]The results are similar with a zero euro cutoff, this cutoff is essentially zero at the level of the cell.

beneficiaries in a given industry–commuting zone cell. The instrument is defined as:

$$\Delta \text{Access}_{i,l} = \text{Log Initial Firm Count}_{i,l} \times \text{Consultancy Share}_l \tag{5}$$

where Consultancy Share_l captures the proportion of agencies ever certified operating in location l, and the second term counts the (log) average number of firms of the first period in Industry–CZ cell (i, l). We interpret the instrument as a change in access because government certification did not exist prior to 2015. The exclusion restriction assumes that the certification reform affects firm outcomes only through increased access to R&D subsidies through tax credits. This interpretation is supported by the fact that certification changed neither the generosity of the CIR nor the activities and firms formally eligible for the tax credit.

We now proceed to estimate Equation (6) by 2SLS using a first stage regression:

$$\Delta \text{Subsidy}_{i,l} = \theta \Delta \text{Access}_{i,l} + \gamma_l + \epsilon_{i,l} \tag{6}$$

to instrument for changes in subsidy claims.

5.2 First Stage Results

We begin by presenting the first-stage results from our instrumental variable strategy. Table 5 reports estimates of the impact of the instrument on the long-difference in R&D subsidy amounts awarded at the Industry–CZ level, $\Delta\text{Subsidy}_{i,l}$. The results confirm a strong first-stage relationship: Industry-CZ cells with a higher share of certified agencies and more firms experienced greater increases in subsidy receipts. The F-statistic of 12.57 suggests the instrument is strongly predictive of subsidy variation, although below the threshold suggested by Keane and Neal (2024). Given our conservative approach of long differences which reduce the number of observations, we are less concerned about this F-statistic passing the more conventional test level of 10.

Table 5: First Stage Estimates of Certification on Subsidies

Dependent Variable:	ΔSubsidy$_{i,l}$
	(1)
ΔAccess$_{i,l}$	0.0039***
	(0.0011)
Commuting Zone FE	Yes
Observations	3,137
R^2	0.0971
F-statistic	12.57

Clustered (CZ) standard-errors in parentheses.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

The sub-sample of cells complying the most strongly with the instrument are industries above the median in (technical) employment (Table 6, Columns 1 and 2) or above the 90th percentile in technical employment (Table 6, Column 3). Taken together, the results suggest increased subsidy access had a larger effect in helping industries with higher employment and especially those with more technical workers claim tax credits from the subsidy.

Table 6: First Stage Breakdown by Industry Characteristics

Dependent Variable:	$\Delta \text{Subsidy}_{i,l}$			
Threshold:	Top 50 percent		Top 90 percent	
	(1)	(2)	(3)	(4)
$\Delta \text{Access}_{i,l}$	0.0048**	0.0026***	0.0043***	0.0044**
	(0.0019)	(0.0008)	(0.0015)	(0.0018)
Industry Technical Employment > Threshold	0.0900***		0.1159***	
	(0.0328)		(0.0422)	
$\Delta \text{Access}_{i,l} \times$ Industry Technical Employment > Threshold	-0.0010		-0.0011	
	(0.0008)		(0.0008)	
Industry Employment > Threshold		0.2844***		0.0909
		(0.0338)		(0.0598)
$\Delta \text{Access}_{i,l} \times$ Industry Employment > Threshold		-0.0003		-0.0009
		(0.0003)		(0.0009)
Commuting Zone FE	Yes	Yes	Yes	Yes
Observations	3,137	3,137	3,137	3,137
R^2	0.09965	0.12072	0.10001	0.09817

Clustered (CZ) standard-errors in parentheses.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

To further examine which industries respond to the increase in access generated by consultancy certification, Table 7 allows the first-stage relationship to differ between manufacturing and non-manufacturing Industry–CZ cells. Column (1) reports the baseline first stage, while Column (2) interacts the access instrument with an indicator for manufacturing industries. This provides a direct test of whether certification-induced access to R&D consultancies translated into CIR claims differently across the two groups. The results indicate substantial heterogeneity in the first-stage response across sectors. The point estimates imply a first-stage coefficient of approximately 0.0003 for manufacturing cells, compared with 0.0010 for non-manufacturing cells. Thus, the increase in subsidy claims associated with certification-induced access is substantially smaller among manufacturing industries.

Table 7: First Stage Heterogeneity by Manufacturing Status

Dependent Variable:	ΔSubsidy$_{i,l}$	
	(1)	(2)
ΔAccess$_{i,l}$	0.0039***	0.0010***
	(0.0011)	(0.0003)
Manufacturing		-0.3897***
		(0.0336)
ΔAccess$_{i,l}$ $\times$ Manufacturing		-0.0007***
		(0.0002)
Commuting Zone FE	Yes	Yes
Observations	3,133	3,133
R^2	0.09669	0.14226

Clustered (CZ) standard-errors in parentheses.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

This pattern is consistent with certification being particularly important in industries where identifying and documenting eligible R&D activity may be less straightforward. Manufacturing firms may already have relatively well-established R&D functions, accounting systems, or experience claiming the CIR, reducing the marginal value of improved access to certified consultants. In contrast, R&D activity in non-manufacturing industries such as services may be more difficult to identify or document within the requirements of the tax credit, making the informational and administrative services provided by certified consultancies more valuable. While the estimates do not identify specific mechanisms, they support the idea that the instrument operates through differences in firms' effective access to CIR claims.

5.3 Subsidy Impact on Treated Industry-CZs

We next present the OLS and second-stage estimates of Equation (6) in Table 8. Outcomes are either Technical or Non-Technical employment. The results show positive and significant effects, again with the effect on Technical workers being considerably higher than for other occupations.

Table 8: Subsidies Impact on Treated Industry-CZ Cell Employment

Dependent Variables:	ΔTechnical$_{i,l}$	ΔNon-Technical$_{i,l}$	ΔTechnical$_{i,l}$	ΔNon-Technical$_{i,l}$
	OLS	OLS	IV	IV
	(1)	(2)	(3)	(4)
ΔSubsidy$_{i,l}$	0.1225***	0.0796***	0.1621***	0.0927**
	(0.0102)	(0.0081)	(0.0296)	(0.0443)
Commuting Zone FE	Yes	Yes	Yes	Yes
Observations	3,137	3,137	3,137	3,137
R^2	0.22599	0.18702	0.21819	0.18571

Clustered (CZ) standard-errors in parentheses.

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

The OLS results indicate positive and statistically significant effects of subsidies on both employment groups. However, when correcting for endogeneity using the certification instrument, the point estimate for Technical employment rises to an elasticity of .16, remaining highly significant. In contrast, the effect on Non-Technical employment is more modest and only slightly rises. These findings show that the technical employment response is stronger, consistent with the hypothesis that R&D subsidies disproportionately benefit high-skill labor as firms direct resources to innovation. However, given the small share of Technical workers in the workforce, the increase in aggregate employment is much closer to the Non-Technical estimate. The inclusion of all firms within each industry–CZ cell, including non-beneficiaries, may also introduce business stealing or escape the competition effects, so these estimates capture the overall measured impact not the effect solely on recipients. In Appendix A we explore heterogeneity by groups of over and under 35, finding little difference but weak support that the non-technical employment increases are driven by younger workers.

Table 9 repeats the estimation of Table 8 using wages of Technical and Non-Technical workers within each Industry–CZ cell as outcomes. The OLS estimates indicate positive wage responses for both occupational groups. The IV estimate for Technical workers remains positive and statistically significant, with an elasticity of 0.141. In contrast, the IV elasticity for Non-Technical wages is smaller, at 0.055, and is not significant. Together with the employment estimates above, these results indicate that the labor-market response to increased R&D subsidy exposure is particularly pronounced for Technical workers, for whom subsidies increase both employment and wages, consistent with a textbook outward shift of technical worker demand.

Table 9: Subsidies Impact on Treated Industry-CZ Cell Average Wages

Dependent Variables:	ΔTechnical$_{i,l}$	ΔNon-Technical$_{i,l}$	ΔTechnical$_{i,l}$	ΔNon-Technical$_{i,l}$
	OLS	OLS	IV	IV
	(1)	(2)	(3)	(4)
ΔSubsidy$_{i,l}$	0.1449***	0.0837***	0.1411***	0.0549
	(0.0124)	(0.0083)	(0.0292)	(0.0418)
Commuting Zone FE	Yes	Yes	Yes	Yes
Observations	3,137	3,137	3,137	3,137
R^2	0.22692	0.19108	0.22687	0.18475

Clustered CZ standard-errors in parentheses.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

Finally, examining the impact of subsidies on the number of firms in each cell in Table 10, we find that indeed subsidies increase net firm entry in each cell, in line with the subsidy attracting new, innovative activity as by Tables 8 and 9. Here, the OLS estimates of subsidies increase, with the IV estimates providing a net entry elasticity with respect to subsidies of .08. The increase from OLS is modest and the elasticity is in line with the increase in non-technical workers of .09. This gives us greater confidence that the direct effect of the subsidy is as expected on industry-CZ cells.

Table 10: Subsidies Impact on Treated Industry-CZ Cell Firm Count

Dependent Variables:	$\Delta\text{Firms}_{i,l}$	$\Delta\text{Firms}_{i,l}$
	OLS	IV
	(1)	(2)
$\Delta\text{Subsidy}_{i,l}$	0.0503^{***}	0.0756^{***}
	(0.0070)	(0.0148)
Commuting Zone FE	Yes	Yes
Observations	3,137	3,137
R^2	0.15178	0.14551

Clustered (CZ) standard-errors in parentheses.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

5.4 Within-Cell Employment Spillovers

We next examine whether the employment effects of R&D subsidies extend to firms within the treated Industry–CZ cell that do not themselves receive the CIR. This provides a more direct test of whether subsidy-induced growth remains concentrated among recipient firms or spreads to other firms operating in the same local industry. We construct Technical and Non-Technical employment outcomes using only employment at non-recipient firms within each treated Industry–CZ cell and estimate the same OLS and IV specifications as above. Table 11 reports the results.

Table 11: Employment Spillovers to Non-Recipient Firms Within Treated Cells

Dependent Variables:	$\Delta\text{Technical}_{i,l}$	$\Delta\text{Non-Technical}_{i,l}$	$\Delta\text{Technical}_{i,l}$	$\Delta\text{Non-Technical}_{i,l}$
	OLS	OLS	IV	IV
	(1)	(2)	(3)	(4)
$\Delta\text{Subsidy}_{i,l}$	0.0621^{***}	0.0342^{***}	0.3751^{***}	0.1569^{**}
	(0.0117)	(0.0117)	(0.0594)	(0.0608)
Commuting Zone FE	Yes	Yes	Yes	Yes
Observations	3,133	3,133	3,133	3,133
R^2	0.11854	0.11198	-0.13321	0.05940

Clustered (CZ) standard-errors in parentheses.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

The estimates indicate substantial positive employment spillovers to firms that do not themselves receive the CIR. These within-cell elasticities are larger than the corresponding estimates for total employment in treated Industry–CZ cells, where the IV elasticities are approximately .16 for Technical employment and .09 for Non-Technical employment. This difference should not be interpreted as implying that more jobs are created at non-recipient firms than in the treated cell as a whole. The outcomes are measured over different employment bases: employment at non-recipient firms often represents a smaller base, so a given absolute employment response can translate into a considerably larger percentage change.

Several additional mechanisms may contribute to the larger percentage response among non-recipient firms. Firms operating in the same industry and local labor market may benefit from knowledge diffusion, worker mobility, increased demand for specialized local inputs and services, or other agglomeration effects generated by the expansion of subsidized R&D activity. These effects may be especially important for Technical employment if innovation-related knowledge and workers circulate across nearby firms. The IV estimates also identify the effect of subsidy variation among Industry–CZ cells whose CIR claims respond to certification-induced access, and these cells may be precisely those in which local innovative activity and interactions across firms are particularly strong. While we cannot distinguish among these mechanisms with the present specification, the positive estimates provide evidence against a pure business-stealing interpretation in which subsidized firms expand only by drawing employment away from other firms in the same local industry. Instead, CIR-induced growth appears to coincide with employment expansion among nearby non-recipient firms, providing a first form of spillover before we turn to propagation across upstream and downstream industries.

5.5 Spillovers Across the Value Chain

Finally, we investigate spillover effects from R&D subsidies along the top two buyer and supplier industries linked to a treated cell. To better isolate indirect effects, the outcomes include only employment at firms in linked cells that never receive the CIR subsidy directly. Table 12 reports estimates separately for technical and non-technical employment.

Table 12: Employment Spillovers to Upstream and Downstream Industries

	Downstream Industries		Upstream Industries	
Dependent Variables:	ΔTechnical	ΔNon-Technical	ΔTechnical	ΔNon-Technical
	(1)	(2)	(3)	(4)
Panel A: OLS				
$\Delta\text{Subsidy}_{i,l}$	0.0055*	0.0089***	0.0088**	0.0038*
	(0.0030)	(0.0021)	(0.0036)	(0.0022)
Commuting Zone FE	Yes	Yes	Yes	Yes
Observations	3,137	3,137	3,137	3,137
R^2	0.41020	0.37625	0.53275	0.56501
Panel B: IV				
$\Delta\text{Subsidy}_{i,l}$	0.0800***	0.0279**	0.0918***	0.0640***
	(0.0104)	(0.0108)	(0.0231)	(0.0244)
Commuting Zone FE	Yes	Yes	Yes	Yes
Observations	3,137	3,137	3,137	3,137
R^2	0.29519	0.36046	0.41124	0.42747

Clustered (CZ) standard errors in parentheses.
Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The OLS estimates are positive but small, with elasticities below 0.01. These estimates should be interpreted primarily as conditional correlations because observed changes in CIR claims are endogenous: they need not correspond to exogenous shocks to subsidy exposure across industries. In contrast, the IV specification isolates variation in subsidy claims generated by the certification-induced increase in access to R&D consultancies. The IV estimates are substantially larger. Downstream employment elasticities are 0.080 for technical workers and 0.028 for non-technical workers, while upstream elasticities are 0.092 and 0.064, respectively.

These spillovers are economically meaningful relative to the direct effects estimated in treated cells. The direct IV elasticities are 0.162 for technical employment and 0.093 for non-technical employment. Hence, the employment response in linked, unsubsidized industries is roughly one-third to two-thirds of the corresponding direct response. This magnitude is broadly in line with recent studies of firm and place-based subsidies, which find substantial indirect employment responses in connected or local industries (Lerche, 2025; Siegloch et al., 2025; Atalay et al., 2023; Navarra, 2023).

The upstream effects are consistent with a production-network mechanism in which expansion among subsidized firms raises demand for inputs, specialized suppliers, and complementary services. Positive downstream effects indicate that the effects also propagate toward customers and users of subsidized industries. Taken together, the results suggest that the employment effects of CIR subsidies extend beyond directly exposed industries and diffuse through local production networks.

6 Conclusion

This paper examines the localized employment effects and production-network spillovers generated by France's R&D tax credit program, the Credit d'Impot Recherche. We first estimate difference-in-differences specifications at the Industry–CZ level to examine how local employment responds to initial exposure to the CIR. We then implement an instrumental variable strategy based on increased subsidy access generated by the certification of R&D consultancy agencies. The results show that R&D subsidies increase employment in directly exposed local industries, with particularly strong effects for Technical workers. Subsidies also increase local net firm entry and generate sizable employment spillovers across linked industries through input-output relationships.

Our findings highlight several important patterns. First, the direct employment effects are positive for both Technical and Non-Technical workers. The IV estimates imply an elasticity of approximately 0.16 for Technical employment and 0.09 for Non-Technical employment. The larger Technical response is consistent with the view that R&D support disproportionately raises demand for workers involved more directly in innovative activity, and IV estimates of a rise in Technical wages further support this. The positive Non-Technical response indicates that the employment effects extend beyond narrowly defined technical occupations but this is not accompanied by a significant increase in wages. Second, subsidies increase the number of firms operating within treated local industries, with an IV elasticity of approximately 0.08. Third, we find evidence that subsidies increase employment within cell to non-subsidized firms, supporting the view of a positive growth response across the cell level. The CIR therefore appears to affect both employment within existing local industries and the extensive margin of local economic activity.

Finally, we document positive employment spillovers along local supply chains. These effects are present both downstream and upstream among firms in linked industries that do not themselves receive the CIR subsidy. The IV estimates imply downstream elasticities of approximately 0.08 for Technical workers and 0.03 for Non-Technical workers, while the corresponding upstream elasticities are approximately 0.09 and 0.06. These spillovers are economically meaningful relative to the direct effects in treated cells, amounting to roughly one-third to two-thirds of the corresponding direct employment response.

From a policy perspective, the evidence suggests that R&D subsidies can generate substantive growth beyond recipient firms. The results also highlight the importance of the institutional infrastructure surrounding industrial policy: certified intermediaries appear to shape firms' access to the program and thereby influence the geography and incidence of subsidy effects. As the increase in CIR claims associated with certification-induced access is smaller among manufacturing industries, this suggests that the consultancy channel was especially important outside manufacturing. This is particularly relevant because much of the existing evidence on subsidies focuses on manufacturing. Our results therefore suggest that reducing informational and administrative barriers to R&D support may be especially consequential in services.

Future work could extend these insights by examining effects within business groups, exploring spillovers on innovation outcomes directly, such as patents or product launches, and tracing how the effects of subsidies cascade further through the value chain. These questions are particularly relevant in light of new industrial policies such as France 2030, which may amplify both the direct and indirect effects documented here. Taken together, our results suggest that modern industrial strategy can generate positive and directed employment spillovers beyond directly subsidized firms and industries, but that fully evaluating these policies requires tracing their effects across both local labor markets and production networks.

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A Heterogeneity by Worker Age

We examine whether the effects of CIR exposure differ between younger and older workers. We divide workers into those aged 15–34 and those aged 35 and above, following the age categories available in the data. One motivation for this split is that some features of the CIR may affect workers at different career stages differently. In particular, the CIR contains an additional incentive for firms hiring newly recruited doctorate holders.[7]

[7] Under the CIR's *jeune docteur* provision, eligible personnel expenditures for a newly hired doctorate holder receive more generous treatment in the CIR base during the first 24 months following the worker's first qualifying permanent post-doctorate contract, subject to conditions on the firm's research

Table 13 reports the employment results. Among workers aged 15–34, the IV elasticity of technical employment with respect to CIR exposure is 0.136 and statistically significant at the one-percent level. The corresponding non-technical elasticity is 0.079 and is not statistically significant. For workers aged 35 and above, the IV elasticities are 0.185 for technical employment and 0.105 for non-technical employment, with both estimates significant at the one-percent level.

Table 13: Subsidies Impact on Treated Industry-CZ Cell Employment by Age

Dependent Variables:	ΔTechnical$_{i,l}$	ΔNon-Technical$_{i,l}$	ΔTechnical$_{i,l}$	ΔNon-Technical$_{i,l}$
	OLS	OLS	IV	IV
	(1)	(2)	(3)	(4)
Panel A: Workers aged 15–34				
ΔSubsidy$_{i,l}$	0.1268***	0.0848***	0.1359***	0.0790
	(0.0104)	(0.0090)	(0.0431)	(0.0685)
Commuting Zone FE	Yes	Yes	Yes	Yes
Observations	3,137	3,137	3,137	3,137
R^2	0.19937	0.17429	0.19905	0.17411
Panel B: Workers aged 35 and above				
ΔSubsidy$_{i,l}$	0.1190***	0.0757***	0.1850***	0.1052***
	(0.0104)	(0.0080)	(0.0322)	(0.0351)
Commuting Zone FE	Yes	Yes	Yes	Yes
Observations	3,137	3,137	3,137	3,137
R^2	0.21051	0.18438	0.18973	0.17754

Clustered CZ standard-errors in parentheses.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

Table 14 reports the corresponding wage outcomes. For younger workers, the IV coefficient is 0.183 for technical workers and 0.121 for non-technical workers, with the latter significant at the ten-percent level. For older workers, the corresponding estimates are 0.135 and 0.056, with only the technical-worker estimate statistically significant.

workforce. The provision is intended to encourage firms to recruit doctorate holders early in their research careers. Our age split does not identify workers eligible for this provision and is not intended as a test of this specific policy component.

Table 14: Subsidies Impact on Treated Industry-CZ Cell Wage Outcomes by Age

Dependent Variables:	$\Delta\text{Technical}_{i,l}$	$\Delta\text{Non-Technical}_{i,l}$	$\Delta\text{Technical}_{i,l}$	$\Delta\text{Non-Technical}_{i,l}$
	OLS	OLS	IV	IV
	(1)	(2)	(3)	(4)
Panel A: Workers aged 15–34				
$\Delta\text{Subsidy}_{i,l}$	0.1687***	0.0957***	0.1827***	0.1207*
	(0.0180)	(0.0108)	(0.0580)	(0.0727)
Commuting Zone FE	Yes	Yes	Yes	Yes
Observations	3,137	3,137	3,137	3,137
R^2	0.16084	0.15492	0.16064	0.15246
Panel B: Workers aged 35 and above				
$\Delta\text{Subsidy}_{i,l}$	0.1446***	0.0839***	0.1354***	0.0555
	(0.0127)	(0.0085)	(0.0266)	(0.0399)
Commuting Zone FE	Yes	Yes	Yes	Yes
Observations	3,137	3,137	3,137	3,137
R^2	0.32866	0.19151	0.32843	0.18560

Clustered CZ standard-errors in parentheses.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

Overall, the age decomposition does not reveal large quantitative differences in the CIR response across younger and older technical workers. Technical employment and wage outcomes respond positively in both age groups. The results therefore suggest that the labour-market effects of CIR exposure are not concentrated exclusively among workers at the beginning of their careers, but extend across a broader range of technical workers. There is weak evidence that younger non-technical workers are driving the increase in non-technical employment, but this is only suggestive.