

Can Firm Subsidies Spread Growth?*

Elodie Andrieu[†]

John Morrow[‡]

8 September 2025

Abstract How do firms diffuse resources along the value chain and how large are such spillovers? We estimate the effects of France's R&D subsidies during a period of substantially increased funding, using increased access from consultancy certification as an instrument. While most studies focus on manufacturing, over half of the treated firms are in services. Subsidies increase local industry technical employment with an elasticity of .12 and firms with an elasticity of .05. Subsidies also increase local upstream employment with an elasticity of .05 but downstream employment asymmetrically, twice as large as upstream but with almost zero effect on technical employment. This suggests directed innovation spillovers along the value chain.

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

JEL Codes: D22, H25, L23, O38.

*We are particularly grateful to 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-Colège 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.

[†]Paris School of Economics.

[‡]Queen Mary University of London, CEP and CEPR.

1 Introduction

Well-designed industrial policies can mobilize and distribute resources in ways that generate positive returns and externalities. Many governments enhance firms' incentives to invest in R&D through direct subsidies or tax-based incentives. In France, the *Crédit d'Impôt Recherche (CIR)*, implemented in 1983 and overhauled in 2008, has become the country's largest business support program, aimed at bolstering competitiveness and attracting private investment in innovation.

However, the CIR's performance has drawn mixed reviews. While it has led to increases in R&D spending, its impact on business growth and foreign direct investment appears limited ([Strategie, 2021](#)). Moreover, firms may tactically position their R&D to maximize subsidy claims without committing to new innovation strategies or investments. Therefore understanding the direct impact of the policy and spillovers remain critical to understanding the broader effects of R&D incentives. Recent global policy initiatives like the US CHIPS Act and the European Chips Act similarly aim to reshore strategic industries and crowd in positive externalities. While these efforts may stimulate domestic investment, their effectiveness in diffusing benefits across firm networks remains uncertain. The CIR, with over four decades of implementation and recent increases in funding and emphasis, provides a valuable lens to examine whether and how such incentives promote regional innovation ecosystems.

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.

This paper explores whether this subsidy can extend its impact beyond treated local industries, generating spillovers across them. Using a quasi-experimental approach, we analyze whether subsidies encourage local industries and whether such growth affects related industries. The study focuses on three core outcomes: local employment, net firm entry, and spillovers along the value chain.

Figure 1: Bordes Commune in Southwestern France



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 find that subsidies have a significant and positive effect on technical employment within treated Industry–Commuting Zone (CZ) cells. Using a long-difference specification and an instrumental variable strategy that exploits new certification of CIR consultancy agencies, we estimate an elasticity of .12 from the CIR subsidy to technical worker employment. These effects are not mirrored for non-technical workers, suggesting that the employment gains are driven primarily by high-skill, innovation-adjacent occupations and will not move aggregate employment much. However, subsidies do increase firm count with an elasticity of .05 in addition to increasing local industry wages.

Beyond direct treatment effects, we uncover compelling evidence of economic spillovers from CIR exposure to non-treated firms through input-output relationships. Instrumental variable estimates show that subsidy exposure in local industries leads to significant employment gains upstream, with an elasticity of .05. In downstream sectors, the effect is even larger for production and support workers with an elasticity of .11. However, technical workers exhibit an elasticity of close to zero. This exhibits a funneled innovation diffusion pattern where suppliers adopt or adapt innovations and hire technical workers, while buyers do not, instead expanding their production and support teams with an elasticity twice as large as upstream. These asymmetric spillovers underscore the importance of supply-chain linkages in amplifying the effects of innovation policy and point to diffusion outside directly subsidized industries.

This section continues with a literature review, while Section 2 describes the CIR policy and Section 3 details data and descriptive statistics of the policy. Section 4 specifies our econometric models to estimate the impact of the subsidy on industry-commuting zone cells with a difference in difference specification. Section 5 addresses endogeneity in these estimates with an instrumentation strategy using the rollout of tax consultancies that improved access to the subsidy. Section 6 concludes.

Related Literature

Our study has parallels with [Lerche \(2025\)](#) estimates the impact of investment tax credits on manufacturing firms in former East Germany that differentially targeted SMEs. Using difference-in-differences and matched employer–employee data, Lerche finds that small firms increased capital stock by 17.7% and employment by 12.0% relative to large firms. Spillovers are strongest in downstream industries and consumer-facing sectors like retail also benefit. In contrast, the French CIR is accessible by all sectors and firm sizes and offer a higher level of credit than the East German policy, but is focused on innovative activities.

Our study also relates to a broad literature on the direct investment effects of tax incentives and subsidies. [Zwick and Mahon \(2017\)](#) examine U.S. bonus depreciation and find sizable investment responses. [Maffini et al. \(2019\)](#) show that corporate tax incentives raise both investment and employment, particularly for smaller firms. [Yagan \(2015\)](#) provide quasi-experimental evidence that temporary bonus depreciation increases investment but has limited employment effects. [Howell \(2017\)](#) uses quasi-experimental variation from the U.S. Department of Energy’s SBIR grant program to show that early-stage R&D subsidies substantially increase patenting, revenue, and venture capital investment, particularly for financially constrained firms.

Our spillover results relate to the general equilibrium spillover literature such as the well known study by [Moretti \(2010\)](#) highlighting the effect of new manufacturing jobs on local non-tradable employment. Similarly, [Greenstone et al. \(2010\)](#) documents that large plant openings raise total factor productivity of incumbent plants in the same county and industry. More recently [Gathmann et al. \(2020\)](#) shows that mass layoffs have persistent negative effects on neighboring firms. [Fons-Rosen et al. \(2017\)](#) find ev-

idence of knowledge spillovers from firm entry and [Navarra \(2023\)](#) and [Atalay et al. \(2023\)](#) find evidence of spillovers from subsidies upstream. [Helm \(2020\)](#) finds employment shifts where impacted employment affects economically close but non-impacted industries. As we find technical skill biases in spillovers, this aligns with the importance [Akcigit et al. \(2020\)](#) place on combining subsidy and higher education policy for enabling growth.

Several studies have examined the impact of CIR policy. Most recently, they have exploited the major reform implemented in 2008, such as [Mulkey and Mairesse \(2013\)](#) and [Salies \(2017\)](#). One exception is [Bunel et al. \(2019\)](#), who evaluate the *Crédit d'Impôt Innovation*, a related 2013 policy targeting innovation through subsidies for Small and Medium-sized Enterprises (SME). Using a DiD design and propensity score matching, they find the policy increased employment, turnover and patent applications. Such studies tend to conclude that SMEs are more efficient in transforming R&D tax credits into R&D investments or patents, in line with the recommendations in [Aghion et al. \(2022\)](#), who suggest the French tax credit focus on small and medium firms. Much less is known on the spillovers R&D subsidies can create, especially in the service sector and on the structure of internal R&D inputs (e.g. workforce composition) which is the focus here.

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, targetting industrial and commercial sectors. The previous financial law in place allowed firms to an 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. The CIR regulation is still

into 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 €5 billion annually. Since then, the 2008 reform has made the CIR the main R&D support system for firms in France.¹

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.,

¹Timeline of the updates in the policy can be found in *Salies (2017)*, <https://spire.sciencespo.fr/hdl:/2441/59b98fs2bu8neb8h5au501rt11/resources/evaluation-cir-ofce-avril-2017-755839.pdf>, page 19))

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

³See 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.

⁴Other 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.

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 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. This suggests that indeed certification reduced barriers to access, providing a more reliable channel for navigating claims. Since service firms often face greater uncertainty in

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

audits, especially where R&D outputs are intangible or embedded in client solutions, this also asymmetrically benefited service firms.

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 Compétitivité (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, [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 (to be completed)

Here we describe the data, sample used, and variables built using French administrative datasets at the firm and establishment level from 2009–2019. While firm-level balance sheet data from the Fichier Approché des Résultats d’Exercice (FARE) is widely used in empirical research on French firms, our analysis also incorporates more granular labor and innovation data. A somewhat novel source here is the “Déclaration Annuelle de Données Sociales” (DADS), the Annual Declaration of Social Data, which provides near-universal coverage of all business establishments in France with at least one salaried employee in a given year. The DADS reports each establishment’s unique identifier (SIRET), which is composed of the SIREN (firm-level identifier) and NIC (establishment-level code), as well as the firm to which it is attached, enabling linkage across organizational levels. In addition to identifying information, the DADS provides rich workforce details, including occupation codes (PCS), contractual wages, hours worked, contract type (e.g., full-time, part-time), age and gender composition, and geographic location, allowing identification of commuting zones, départements, and postcodes.

To capture firm-level innovation behavior, we merge these data with CIR grant records from the GECIR database, administered by the French Ministry of Research and INSEE, which contains information on whether firms claimed the Crédit d’Impôt Recherche (CIR), the amounts claimed, and their industry and firm characteristics. Finally, we draw on Input-Output tables provided by INSEE to measure sectoral linkages and construct upstream and downstream exposure measures, allowing us to control for sector-level technological spillovers and market structure. Together, these linked datasets enable a comprehensive, multi-level analysis of firm behavior, workforce composition, and innovation activity over time.

Having laid out the data, policy and descriptions of relevant data features, we now turn to estimating the impact of the CIR at the industry-commuting zone level.

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 employment and the number of firms within each cell to evidence the subsidy is having an effect. This section proceeds with our econometric model then estimates these two impacts.

4.1 Econometric Model

We estimate the effect of a firm in an industry-CZ cell, indexed by (l, i) , 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:

$$\text{Outcome}_{l,i,t} = \sum_{k=-4, k \neq 0}^4 \beta_k \cdot \text{Treated}_{l,i,t+k} + \alpha_{l,i} + \alpha_t + \varepsilon_{l,i,t} \quad (1)$$

Here, $\text{Outcome}_{l,i,t}$ denotes (log) employment by worker type or number of firms in cell (l, i) at time t , and $\text{Treated}_{l,i,t+k}$ is an indicator for whether the cell has received a subsidy k years before or after year t which begins when a firm in cell (l, i) receives its first subsidy in the study period. Estimation follows the approach of de [Chaisemartin and dHaultfoeuille \(2020\)](#), with interactions between cell and time fixed effects allowing us to isolate average treatment effects relative to not-yet-treated units.

4.2 Employment Effects

Figure 2 shows the results of estimating Equation (1) with employment as an outcome. Techie employment increases significantly more in percentage terms than other employment following subsidy award at over 10 per cent in the Industry-CZ cell. These estimates suggest the effect on techie employment is roughly double that of the effect on labour in general which is composed of support and production workers. While we do not claim any causality here, the results do show a techie intensive impact on hiring for treated cells.

Figure 2: Effect of First Time Subsidy on Employment

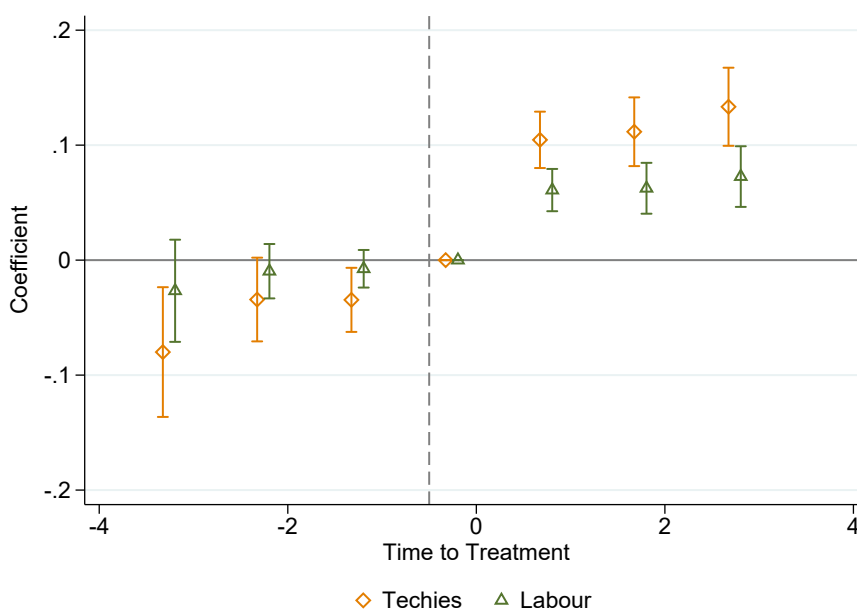
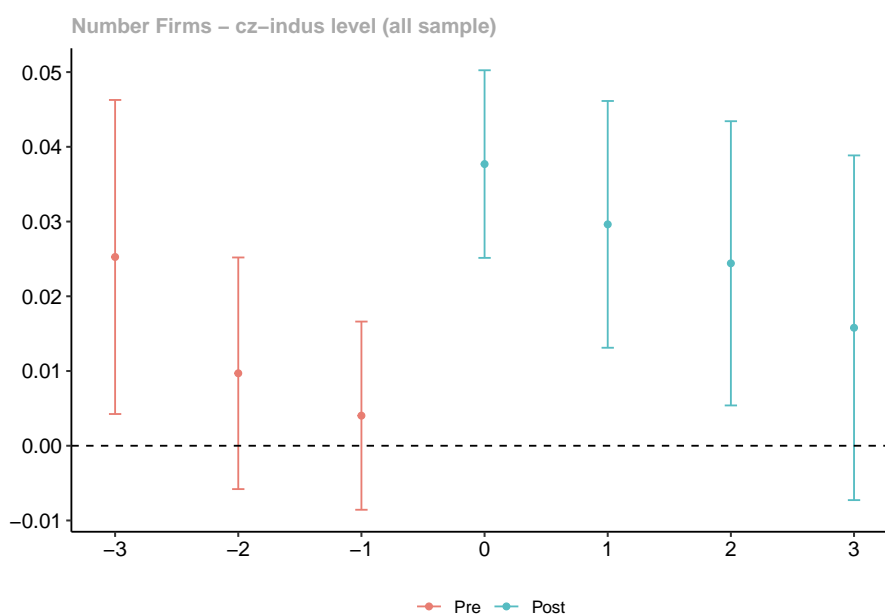


Figure 3 shows the results of estimating Equation (1) with the number of firms in the cell as the outcome. The number of firms clearly increases by about 4 percent after treatment after which the effect subsides. This necessarily implies an increase in net firm entry within the Industry-CZ cell. Thus the subsidy increases employment and the number of firms in each cell, expanding local industry.

Figure 3: Effect of First Time Subsidy on Firm Count



To address endogeneity in selection and 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.

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 recipient establishments 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:

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

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:

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

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

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 non-zero subsidy awards in at least one year of each period.

Our identification strategy is based on increased subsidy access following consultancy certification in 2015 as detailed above. 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 beneficiaries in a given industry–commuting zone cell. Specifically, the instrument is defined as:

$$\Delta\text{Access}_{i,l} = \text{Consultancy Share}_l \times \text{Initial Subsidy Establishments}_{i,l} \quad (5)$$

where $\text{Consultancy Share}_l$ captures the proportion of agencies ever certified in location l , and the second term counts the (log) average number of establishments of the first period in Industry–CZ cell (i,l) .⁶ The instrument is labeled as a change in access since pre-2015, consultancy registration by the government was not available and therefore implying a ‘treatment’ of zero. The instrument is designed to measure increased exposure between more certified consultancies and more innovative activity. The underlying identification strategy assumes that certification reduced the cost and risk of using agencies, thereby increasing firms’ likelihood of accessing and optimizing CIR claims. The exclusion restriction assumes that the certification reform affects firm outcomes only through increased access to R&D subsidies through tax credits.

⁶Results using consultancy in levels and log levels are similar.

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

$$\Delta\text{Subsidy}_{i,l} = \theta\Delta\text{Access}_{i,l} + \gamma_i + \gamma_l + \epsilon_{i,l} \quad (6)$$

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 1 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 close to 50 suggests the instrument is strongly predictive of subsidy variation, above the threshold suggested by [Keane and Neal \(2024\)](#).

Table 1: First Stage Estimates of Certification on Subsidies

Dependent Variable:	$\Delta\text{Subsidy}_{i,l}$
	(1)
$\Delta\text{Access}_{i,l}$	0.1232*** (0.0179)
Commuting Zone FE	Yes
Observations	4,287
R ²	0.07401
F-statistic	???

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 with are higher in employment (Table 2, Column 1) but composed of fewer firms (Table 2, Column 2). Taken together, the results suggest increased subsidy access had a larger effect in helping high employment but more concentrated industries claim tax credits from the subsidy.

Table 2: First Stage Breakdown by Industry Employment and Firm Count

Dependent Variable:	$\Delta\text{Subsidy}_{i,l}$	
	(1)	(2)
$\Delta\text{Access}_{i,l}$	-0.2143*** (0.0522)	0.4384*** (0.0897)
$\Delta\text{Access}_{i,l} \times \text{Industry Employment Above Median}$	0.3044*** (0.0529)	
$\Delta\text{Access}_{i,l} \times \text{Industry Firms Above Median}$		-0.3027*** (0.0819)
Commuting Zone FE	Yes	Yes
Above/Below Median FE	Yes	Yes
Observations	4,287	4,287
R ²	0.08463	0.07549

Clustered (CZ) standard-errors in parentheses.

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

5.3 Subsidy Impact on Treated Industry-CZs

We next present the OLS and second-stage estimates of Equation (6) in Table 3. Outcomes are either Techies or Non-Techies (support and production workers combined). The results show positive and significant effects, again with the effect on Techies being considerably higher than for other occupations.

Table 3: Subsidies Impact on Treated Industry-CZ Cell Employment

Dependent Variables:	$\Delta\text{Techies}_{i,l}$	$\Delta\text{Non-Techies}_{i,l}$	$\Delta\text{Techies}_{i,l}$	$\Delta\text{Non-Techies}_{i,l}$
	OLS	OLS	IV	IV
	(1)	(2)	(3)	(4)
$\Delta\text{Subsidy}_{i,l}$	0.0688*** (0.0058)	0.0460*** (0.0048)	0.1173*** (0.0189)	0.0207 (0.0153)
Commuting Zone FE	Yes	Yes	Yes	Yes
Observations	4,287	4,287	4,287	4,287
R ²	0.15204	0.14310	0.12803	0.13303

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 Techie employment rises in magnitude to an elasticity of .12, remaining highly significant. In contrast, the effect on Non-Techie employment is modest and insignificant. These findings show that the employment response is driven by Techie occupations, consistent with the hypothesis that R&D subsidies disproportionately benefit high-skill labor as firms direct resources to innovation. Given the small share of techies in the workforce, this does not leave appreciable scope for increases in aggregate employment. The inclusion of all firms within each industry-CZ cell, including non-beneficiaries, may also introduce business stealing or escape the competition effects, which could attenuate or overstate the overall measured impact.

Table 4 repeats the estimation of Table 3 with outcomes being the average wage of the Techie and Non-Techie groups in each cell. Here we see an increase in wages in the IV, although the large increase from the OLS estimates suggest caution in interpreting the values precisely. Nonetheless, the labor market effects are consistent with subsidies increasing growth of beneficiary Industry-CZ cells.

Table 4: Subsidies Impact on Treated Industry-CZ Cell Average Wages

Dependent Variables:	$\Delta\text{Techies}_{i,l}$	$\Delta\text{Non-Techies}_{i,l}$	$\Delta\text{Techies}_{i,l}$	$\Delta\text{Non-Techies}_{i,l}$
	OLS	OLS	IV	IV
	(1)	(2)	(3)	(4)
$\Delta\text{Subsidy}_{i,l}$	0.0092*** (0.0023)	0.0016 (0.0019)	0.1052*** (0.0118)	0.0314*** (0.0040)
Commuting Zone FE	Yes	Yes	Yes	Yes
Observations	4,280	4,287	4,280	4,287
R ²	0.07199	0.08996	-0.52621	0.00370

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 5, we find that indeed subsidies grow the number of firms in each cell, in line with a labor demand shifting out as suggested by Tables 3 and 4. Here, the OLS estimates of subsidies are an underestimate, with the IV estimates providing a net entry elasticity with respect to subsidies of .05.

Table 5: 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)
$\Delta\text{Subsidy}_{i,l}$	0.0293*** (0.0041)	0.0473*** (0.0063)
Commuting Zone FE	Yes	Yes
Observations	4,287	4,287
R ²	0.10820	0.10154

Clustered (CZ) standard-errors in parentheses.

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

5.4 Spillovers Across the Value Chain

Finally, we investigate spillover effects from R&D subsidies along the top two buyer and supplier linked cells to a treated cell using both OLS and IV estimators. Here we consider only firms in the buyer and supplier cells that never receive the subsidy to better isolate the effect of spillovers from other firms' activities. Table 6 reports the effect of subsidy exposure in linked industries on employment outcomes for both occupational groups. The OLS estimates show both positive and negative spillovers for employment. The IV shows a large positive spillover to Non-Techie workers which make up the bulk of employment. What is somewhat surprising is the absence of a positive spillover on Techies given the innovation directed activities we might expect from subsidized firms, especially given the Techie intensive effects estimated in treated cells.

Table 6: Employment Spillovers to Top Two Upstream and Downstream Industries

Dependent Variables:	Δ Techies	Δ Non-Techies	Δ Techies	Δ Non-Techies
	OLS	OLS	IV	IV
	(1)	(2)	(3)	(4)
Δ Subsidy _{<i>i,l</i>}	0.0491*** (0.0081)	-0.0125*** (0.0043)	-0.0002 (0.0061)	0.0937*** (0.0162)
Commuting Zone FE	Yes	Yes	Yes	Yes
Observations	4,164	4,164	4,164	4,164
R ²	0.39648	0.60594	0.22539	-0.53833

Clustered (CZ) standard-errors in parentheses.

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

Next we further disaggregate the instrumental variable estimates to separately examine upstream and downstream spillovers. Table 7 reports results for Techie and Non-Techie occupations, split by whether the subsidy exposure originates from industries supplying to (upstream) or buying from (downstream) the treated industry.

Table 7: Employment Spillovers Upstream versus Downstream

Dependent Variables:	Upstream		Downstream	
	Δ Techies	Δ Non-Techies	Δ Techies	Δ Non-Techies
	IV	IV	IV	IV
	(1)	(2)	(3)	(4)
Δ Subsidy _{<i>i,l</i>}	0.0504*** (0.0184)	0.0560*** (0.0093)	-0.0175* (0.0101)	0.1078*** (0.0175)
Commuting Zone FE	Yes	Yes	Yes	Yes
Observations	4,154	4,154	4,154	4,154
R ²	0.13481	0.06364	0.16862	-0.02553

Clustered (CZ) standard-errors in parentheses.

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

Disentangling spillovers to upstream and downstream industries in Table 7 reveals that R&D subsidies generally generate positive and statistically significant upstream spillovers to all workers, with an elasticity of .05. In contrast, downstream spillovers are primarily concentrated among Non-Techie occupations, with an elasticity of .11, and (weakly) negative effect on Techie employment. These positive and negative elasticities are masked when the upstream and downstream nature of links are not considered. These patterns suggest that innovation incentives propagate through supply chains in asymmetric ways: innovation activity appears to propagate upstream on par with other employment effects, while stronger employment gains on Non-Technical workers propagate downstream.

6 Conclusion

This paper examines the localized employment effects and spillovers generated by France's R&D tax credit program the Cr dit d'Imp t Recherche. After examining DiD treatments to industry-commuting zone cells, we implement an instrumental variable strategy based on increased subsidy access in the presence of certified consultancy agencies. We show that R&D subsidies directly stimulate technical worker employment. Subsidies also generate sizable spillovers across firms through input-output

linkages.

Our findings highlight several important patterns. First, the direct employment effects are concentrated in technical occupations, aligning with the notion that R&D support tends to benefit knowledge-intensive segments of the labor market, but in terms of total employment this would be negligible. Second, subsidies increase net local firm entry within the same industry and drive up local wages in the industry, putting pressure on non-subsidized firms. Third, and crucially, we document robust spillover effects along local supply chains. These propagate asymmetrically wherein upstream industries have an employment elasticity with respect to the subsidy which is about half that of the treated industry. Downstream industries have an employment elasticity for non-technical workers almost as large as the the treated industry, and a small and potentially negative employment elasticity for technical workers. This suggests a channel of innovation flowing upstream but not downstream.

These results carry both policy and methodological implications. From a policy perspective, the evidence supports the view that well-targeted R&D subsidies can foster not only firm-level innovation but also broader labor market benefits across the value chain. However, our findings also suggest that policy effectiveness hinges on the institutional infrastructure, such as certified intermediaries, that shapes firms' access to and ability to optimize this tax credit program.

Future work could extend these insights by exploring effects within business groups, examining the role of spillovers on innovation outcomes directly (e.g., patents or product launches), or by following cascading effects through the value chain. Taken together, our results affirm the potential of modern industrial strategy to generate positive, and directed, positive spillovers.

References

- Aghion, P., N. Chanut, and X. Jaravel (2022). Renforcer l'impact du credit d'impôt recherche.
- Akcigit, U., J. G. Pearce, and M. Prato (2020). Tapping into talent: Coupling education

- and innovation policies for economic growth. Technical report, National Bureau of Economic Research.
- Atalay, E., A. Hortaçsu, M. Runyun, C. Syverson, and M. F. Ulu (2023). Micro-and macroeconomic impacts of a place-based industrial policy. Technical report, National Bureau of Economic Research.
- Bergeaud and Guillouzouic (2024). PROXIMITY OF FIRMS TO SCIENTIFIC PRODUCTION. *Annals of Economics and Statistics* (153), 105.
- Bunel, S., B. Hadjibeyli, et al. (2019). Évaluation du crédit d'impôt innovation. Technical report, Institut National de la Statistique et des Etudes Economiques.
- De Chaisemartin, C. and X. d'Haultfoeuille (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American economic review* 110(9), 2964–2996. Publisher: American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.
- Fons-Rosen, C., V. Scrutinio, and K. Szemerédi (2017). Colocation and knowledge diffusion: evidence from million dollar plants. *Working Paper*. Publisher: London School of Economics and Political Science. Centre for Economic . . .
- Gathmann, C., I. Helm, and U. Schönberg (2020). Spillover effects of mass layoffs. *Journal of the European Economic Association* 18(1), 427–468. Publisher: Oxford University Press.
- Greenstone, M., R. Hornbeck, and E. Moretti (2010). Identifying Agglomeration Spillovers: Evidence from Winners and Losers of Large Plant Openings. *Journal of Political Economy* 118(3), 536–598.
- Hassine, H. B. (2020). Competitiveness clusters: what outcomes since 2005? Technical report, France Stratégie.
- Helm, I. (2020). National industry trade shocks, local labour markets, and agglomeration spillovers. *The Review of Economic Studies* 87(3), 1399–1431.
- Howell, S. T. (2017). Financing innovation: Evidence from r&d grants. *American economic review* 107(4), 1136–1164.

- Keane, M. P. and T. Neal (2024, August). A Practical Guide to Weak Instruments. *Annual Review of Economics* 16(1), 185–212. Publisher: Annual Reviews.
- Klebaner, S. and A. Voy-Gillis (2023, April). The political economy of French industrial policymaking. *Review of Evolutionary Political Economy* 4(1), 49–74. Publisher: Springer Science and Business Media LLC.
- Lerche, A. (2025, August). Direct and Indirect Effects of Investment Tax Incentives. *American Economic Review* 115(8), 2781–2818.
- Maffini, G., J. Xing, and M. P. Devereux (2019). The Impact of Investment Incentives: Evidence from UK Corporation Tax Returns. *American Economic Journal: Economic Policy* 11(3), 361–389.
- Mayer, T., F. Mayneris, and L. Py (2017, July). The impact of Urban Enterprise Zones on establishment location decisions and labor market outcomes: evidence from France. *Journal of Economic Geography* 17(4), 709–752.
- Moretti, E. (2010, May). Local multipliers. *American Economic Review* 100(2), 373–77.
- Mulkay, B. and J. Mairesse (2013). The r&d tax credit in france: assessment and ex ante evaluation of the 2008 reform. *Oxford Economic Papers* 65(3), 746–766.
- Navarra, E. (2023). The effects of corporate subsidies along the value chain. *Available at SSRN 4337015*.
- Salies, E. (2017, April). Etudes d’impact du crédit d’impôt recherche (CIR). Research report, OFCE.
- Strategie, F. (2021). Evaluation du credit d’impot recherche. *Avis de la Commission nationale d’evaluation des politiques d’innovation*, 1–138.
- Yagan, D. (2015). Capital Tax Reform and the Real Economy: The Effects of the 2003 Dividend Tax Cut. *American Economic Review* 105(12), 3531–3563.
- Zwick, E. and J. Mahon (2017). Tax Policy and Heterogeneous Investment Behavior. *American Economic Review* 107(1), 217–248.