Fraunhofer ISI Discussion Papers *Innovation Systems and Policy Analysis* No. 87

Measuring the Causal Economic Effects of Scientific Research

Evidence from the Staggered Foundation of the SENAI Innovation Institutes in Brazil

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Place: Karlsruhe
Date: November 2024

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Recommended citation

Schubert, T.; Darold, D.; Will, M. (2024): Measuring the Causal Economic Effects of Scientific Research – Evidence from the Staggered Foundation of the SENAI Innovation Institutes in Brazil, Discussion Papers *Innovation Systems and Policy Analysis* No. 87. Karlsruhe: Fraunhofer ISI

Published

November 2024

ISSN

1612-1430

Doi

10.24406/publica-3768

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Abstract

How to estimate the economic returns of public science is a longstanding but equally challenging topic in quantitative science studies. In this paper, we exploit the staggered foundation of the SENAI Innovation Institutes (ISI) in Brazil since 2012, to estimate their effects on GDP using a difference-in-differences (DiD) approach. Building on historical and institutional insights from interviews on the foundation process, we unravel the conditions under which the parallel trends assumption is likely to hold. Our analysis reveals that these institutes significantly contribute to GDP per capita, with an average treatment effect of 985 BRL (approximately €160). Moreover, by relying on detailed project-level data, we were able to show that the effects come almost exclusively from genuine research projects and not from the provision of scientific services, such as metrology. Finally, tentative calculations suggest that the SENAI institutes may account for about 0.66% of Brazil's overall GDP, emphasising the importance of applied science in regional economic development and providing insights into effective collaboration between research and industry.

1 Introduction

The analysis of the economic returns and effects of science has a long tradition in quantitative science studies. Almost 70 years ago, Zvi Griliches (1958) analysed the social returns of hybrid corn-related innovations by comparing the costs of their development with market values. Extending this idea, many studies since the 1970s have sought ways to measure the economic returns of science with various methodologies, including multiplier analyses (Glückler et al. 2015), regression approaches (Schubert and Kroll 2016b; Bertoletti et al. 2022; Agasisti and Bertoletti 2022) or macroeconomic simulation models (Allan et al. 2022). Yet, while these methods come with their specific advantages and disadvantages, they all face the pressing need to establish causality. In the context of the economic effects of science, credibly claiming causal links is, however, notoriously difficult because scientific organisations are usually not randomly located across space; they are deeply intertwined with and embedded in economic and cultural centres with whom they co-evolve, over the course of decades, if not centuries. Hence, causes and effects are blurred in a by nature deeply co-evolutionary process, even at a level of substance. Irrespective of the level of statistical sophistication, it is therefore usually not only technically almost impossible to identify causal economic effects of science, it would also conceptually be besides the point. Nonetheless, it remains a problematic fact that the numbers reported in most existing analyses reflect – to a not insubstantial degree – associations rather than causation remains problematic. Specifically with a view to the potential setting up of new institutions or sites, a methodology that identifies the potential direct, causal effect of interventions not yet decided would add much, specifically from a policy perspective.

In this paper, we seek to address this gap by exploiting evidence from a unique case: the SENAI Innovation Institutes (ISI) in Brazil. The ISI institutes are private, not-for-profit research institutes focusing on applied sciences – mostly in natural sciences, engineering and life sciences – which make revenues by cooperating with contracting firms, for which they provide various types of research-related services. 27 ISI institutes have been founded sequentially since 2011 (26 up to 2019) and they are spread over the country. The staggered foundation offers a unique opportunity of a quasi-experimental setting usually unavailable in the studies analysing the effects of public science. Specifically, we will make a case that the characteristics of the regional selection process was driven by fixed effects like selection based on long-term regional characteristics and therefore satisfy conditions under which parallel trends will hold (Ghanem et al. 2022). Thus, the characteristics of the foundation process – specifically, how regions were selected – allow us to estimate the causal effects of the SENAI ISI institutes on regional GDP. Moreover, our detailed data allows us to separate the effects based on the types of collaboration projects with firms, which gives us unique insights into which types engender the strongest economic effects.

Our results suggest that the staggered foundation of the SENAI institutes had substantial economic effects in terms of GDP. Overall, we estimate the average treatment effect on the treated regions (ATT) in terms of GDP per capita to be 985 BRL. This effect comes almost exclusively from genuine research projects involving R&D, while more service-oriented projects such as metrology or technical consultancy appeared to cause little or no effect. Finally, we provide some tentative macroeconomic projections, which suggest that the SENAI institutes may be causally linked to about 0.66% of the overall Brazilian GDP.

2 Background

Studies measuring the economic value of public science can be subdivided into microeconomic studies that measure the effects of firm performance and macroeconomic studies that measure the effects on whole economies, such as regions or countries. While the former group of studies is broad (Robin and Schubert 2013b; Maietta 2015; Comin et al. 2019), they rely on very different kinds of datasets and thus identifying assumptions. We will therefore omit this group from our review and focus on studies estimating macroeconomic returns in the next section.

2.1 The Macroeconomic Returns of Scientific Research

Most analyses estimating the macroeconomic effects of public research have relied on multiplier analysis, using either Keynesian or input-output multipliers (Glückler et al. 2015). These studies rely on taking into account clearly identifiable and attributable expenditure streams, such as induced investments or consumption by staff or students, to which, in turn, multipliers are applied. While estimating rates of returns, typically defined as GDP increase divided by costs, these studies contain several sources of bias that limit their economic interpretability (Schubert and Kroll 2015). The measurement of expenditure that flows into the region is, in many cases, economically problematic for the purpose of measuring social returns. For example, the increase induced by student consumption in the host region seems hardly interpretable. The students would have consumption expenditures in their home region irrespective of their student status. So, what is calculated is value of the university is merely a regional redistribution and from a welfare aspect ceteris paribus a zero-sum game. Moreover, multiplier analyses ignore the value of knowledge (Glückler et al. 2015), which is arguably the most genuine contribution of scientific organisations. In particular, the latter assumption is conceptually hard to defend and, within the methodological framework, impossible to tackle. A number of studies have specifically tried to address both problems by resorting to econometric estimations of the macroeconomic effects of public science organisations. In this setting, some sort of regression approach is used to allow an economic outcome variable in a given region (often GDP) to be explained by variables measuring the activity of public science organisations in the same regression. Studies falling into this category include Schubert and Kroll (2013), Schubert and Kroll (2016b), Bertoletti et al. (2022), Agasisti and Bertoletti (2022) and Allan et al. (2022). A common finding of these studies is that estimated returns are much larger than those resulting from multiplier analyses, underscoring the paramount importance of knowledge generation as a contribution of science. For example, Schubert and Kroll (2013) – using fixed-effects panel regressions for German NUTS 3 regions – estimate that about 8% of German GDP is attributable to its university system.

Nonetheless, while conceptually clearer in their interpretation, these studies are also subject to methodological criticisms. Notably, like all regression approaches, the key challenge is to establish causality – a non-trivial task with field data, which is subject to various sorts of selection effects. While these studies make considerable econometric efforts to ensure causality – e.g., in their study of the economic effects of the Fraunhofer Society in Germany, Allan et al. (2022) provide a series of confirming placebo tests – ultimately, the ability to provide causal effects rather than mere associations requires the identification of some sort of exogenous variation. Thus, even when studies rely on DiD estimations (Schlegel et al. 2022; Pfister et al. 2021), their reliability rests less on their choice of econometric estimators and more on whether the specific case is likely to provide such a source of exogenous variation. In the next section, we will explain the institutional and historical details of the foundation of the SENAI institutes in Brazil to argue that this case appropriately provides such exogenous variation.

2.2 History and Role of the SENAI Innovation Institutes (ISI)

The SENAI ISIs (*SENAI Innovation Institutes, or Institutos SENAI de Inovação*) were established by SENAI (*Serviço Nacional de Aprendizagem Industrial, or National Service for Industrial Training*) as a response to the evolving needs of the Brazilian industrial sector with regard to advanced research and development capabilities. The foundation of these institutes marked a significant shift in the country's approach to industrial innovation, aiming to bolster competitiveness through cutting-edge technology and applied research.

SENAI itself is the largest private vocational education complex in Latin America. Since its creation in 1942, it has trained more than 73 million workers in 28 industry areas. It is present in more than 2000 Brazilian municipalities and offers a wide variety of courses at all levels of professional and technological education. Additionally, it offers technological services, metrology, consulting through SENAI ISTs (*SENAI Technology Institutes, or Institutos SENAI de Tecnologia*) and, more recently, applied research and innovation through the establishment of SENAI ISIs.

The establishment of the SENAI ISI institutes in 2011 represented an important evolution of SENAI's mission. It started in 2011, driven by a comprehensive dialogue with over 50 business leaders – organised by the MEI (*Mobilização Empresarial pela Inovação, or Business Mobilization for Innovation*) – which highlighted the need for a more robust infrastructure dedicated to industrial innovation. The National Confederation of Industry (CNI) led this initiative, selecting SENAI as the primary institution due to its extensive experience, established credibility and deep-rooted connections within the Brazilian industrial sector. With its 70-year legacy, SENAI was well-positioned to lead the creation of a national network of applied research institutes through the SENAI ISIs.

The development of the SENAI ISI network was not merely an infrastructural endeavour but one that required significant intellectual capital, including business processes and human and relational resources. SENAI partnered with the Fraunhofer Society, a global leader in industrial research and development, to plan, implement and operationalise the ISI network. This collaboration facilitated the determination of actual industrial demand through workshops with over 300 companies across 12 Brazilian states.

When comparing the SENAI ISI network to other research and technology organisations globally, key similarities and distinctions emerge. Modelled after Germany's Fraunhofer Society, SENAI ISIs focus on high-impact industrial projects and emphasise collaboration with both large and small enterprises. Similarly, the Dutch TNO, the Canadian National Research Council (NRC) and the Finnish Technical Research Centre (VTT) highlight the importance of broad scope, national impact and transforming economies through innovation. The SENAI ISI network, with its well-planned establishment and strategic focus, mirrors these successful international models, with the aim of positioning itself as a vital component of Brazil's national innovation system.

The strategic focus was on creating a demand-driven network, ensuring sustainability and broad national coverage. Financially, the infrastructure part of the project was supported by investments from SENAI and loans from the Brazilian Development Bank (BNDES), worth approximately R$ 1 billion in initial investments and R$ 2.2 billion up to now. By 2024, 27 of the 28 planned innovation institutes were operational, employing over 1500 researchers. These institutes have collectively executed projects worth R$ 1.9 billion in partnership with more than 800 industrial companies by 2021.

The ISIs are also integrated into broader national and international research frameworks, with 18 institutes accredited as EMBRAPII units, 23 recognised by the ANP and 14 accredited by CATI. Notably, 56% of the R&D&I projects involve startups and small to medium enterprises, fostering a robust ecosystem of innovation. The network has connected over 185 startups with 90 larger companies through technological challenges.

The impact of the SENAI ISI network extends beyond immediate project outcomes. It has facilitated the practical application of scientific research, translating theoretical knowledge into tangible industrial solutions. This role as an intermediary between universities, research centres and the industry is crucial for maintaining the flow of innovation within Brazil's economic framework.

Therefore, the SENAI ISI network is an exemplary case for measuring the economic effects of scientific research due to its unique setup. The staggered establishment of the institutes across diverse regions provides exogenous variation, ideal for applying the difference-in-differences (DiD) method to estimate causal impacts. This setting minimises pre-existing regional differences, ensuring credible results. Additionally, the institutes' focus on applied research and industry collaboration directly ties economic effects to scientific advancements. The comprehensive data available from their inception further strengthens the analysis. Thus, the SENAI ISI network offers a robust framework for evaluating the true economic returns of scientific research and innovation.

2.3 Locational Choice in the SENAI ISI Case and the Parallel Trends Assumption

Measuring the causal effects of the foundation of SENAI ISI institutes using a DiD approach depends crucially on the validity of the parallel trends assumption, which means that in the absence of treatment, both treated and non-treated regions would have displayed parallel trends in the outcome variable in the post-treatment period. The parallel trends assumption is obviously defined partly in terms of unobservable counterfactuals, since all treated regions in the post-treatment period are only observed in their treated and not in their hypothetical non-treated state. This unobservability makes it impossible to test empirically, but we can theoretically assess its plausibility. Whether it holds or not obviously depends on the locational choice. For example, if the SENAI ISI institutes had been randomly allocated to regions, then randomisation of the locational choice would imply that treatment and non-treatment regions would probabilistically not differ in any respect except for the treatment status. Needless to say, randomisation is an unreasonable assumption in our case, as the locations for establishing the institutes were strategically chosen. However, while – at a trivial level – randomisation implies the validity of DiD, the parallel trend can also hold under weaker assumptions, too, as shown by Ghanem et al. (2022).

One of the conditions under which it can hold is that the locational choice depended only (potentially unobservable within the context of the study) on fixed effects of the regions, i.e., locational choices were made based on (roughly) time-constant structural characteristics of the regions. Examples of such characteristics include economic power, established presence of potential collaboration partners, presence of other scientific organisations, local demand/economic structures or human capital endowments. Based on desk research and insights from SENAI management, we will now make a case that the locational choice was, as expected, non-random and made in a way to a) strategically maximise the prospective success of the institutes and b) achieve a certain level of regional balance. Both mechanisms worked in a way where the key decision-makers relied on stable regional characteristics, which they used as proxies. Thus, our key argument is that the selection was based on fixed effects and consistency conditions – as defined by Ghanem et al. (2022) – can be credibly assumed to apply.

Qualitative Evidence on Locational Choice for SENAI ISI Institutes

To better understand the context and circumstances of SENAI ISI's conception and the selection criteria for branch establishment across the country, an interview was conducted in September 2024 with the current SENAI general director, who has been directly involved in the whole foundation process since its inception.

According to him, the selection of institutes followed a structured process that combined both technical and political considerations. Initially, the primary criterion for selecting locations was the technical capacity of pre-existing local SENAI institutes. The goal was to ensure that these institutes, focused on vocational training, had the necessary infrastructure, expertise and administrative capability to support R&D activities in specific technological areas. In his words, "institutes with high performance willing to implement R&D." Next, thematic competence was assessed, where competencies that have already been developed converge with priority technologies. SENAI sought to align the institutes with fields deemed as national priorities, or "promising technologies," based on international benchmarks, ensuring that emerging technologies would be the focus.

The first institutes were initially concentrated in Brazil's coastal regions, where most of the population and major cities are located. The existing institutes had more developed technical capabilities and administrative infrastructure, making them natural candidates. However, aligned with the National Confederation of Industry (CNI), the assessment was that the geographic distribution was imbalanced. It was, in his words, "*muito litorâneo*," or "too coastal." This imbalance reflects neither the internal political structure, as SENAI is a federated organisation, nor the underlying policy goals of regional development.

To address this geographic imbalance, a political element was introduced into the selection process. This shift led to the prioritisation of inland regions when the technical criteria had been exhausted. The rationale behind this decision was both pragmatic and political. From a development perspective, investing in economically weaker regions was seen as a way to foster innovation across the entire country, not just in areas that were already well-established. Politically, it was important to maintain equity within SENAI's federative system, which included balancing investments among the various state industry federations to ensure regional representation and support.

Thus, the second phase of the selection process involved directing funds to inland states like Amazonas, Pará and Mato Grosso do Sul. This phase sought to ensure that the benefits of the SENAI ISI network extended beyond the country's more developed coastal regions, helping to promote R&D activities in underdeveloped areas. It is important to note that the institutes were thematically oriented, meaning their focus was on specific technological fields rather than serving only local industries. As a result, their client base was often scattered across the country, and their location was largely independent of where their industrial partners were based.

In sum, the location of SENAI ISI institutes was driven by two main factors: pre-existing technical capabilities/proximity to economic centres and the political will for geographic distribution. Both selection mechanisms were implemented by the key decision-makers' reliance on stable regional characteristics, which gives us a good a priori confidence that parallel trends (potentially conditional on covariates) are likely to hold in our setting.

3 Data and Methodology

We utilised two primary data sources: regional macroeconomic statistics and administrative data from SENAI. The regional macroeconomic statistics, which include GDP per micro-region and population data, were sourced from the Brazilian Institute of Geography and Statistics (IBGE). The IBGE is the official government agency responsible for the collection of statistical, geographic, cartographic, geodetic and environmental information in Brazil. The second data source was provided by the SENAI administration and includes detailed administrative data of all SENAI institutes, their projects, respective categories and client locations. This comprehensive dataset encompasses various aspects of SENAI's operations, offering insights into the specific competencies of each institute and the geographical distribution of their clients.

To construct the dataset for econometric analysis, we merged the macroeconomic statistics with the SENAI administrative data using the micro-region as the key. This approach allows us to analyse the economic impact at the regional level, taking into account both the locations of the institutes and their clients, who are spread across the country. This widespread distribution is attributed to each institute's specialisation, which focuses on specific areas of competence rather than regional allocation or concession.

3.1 Econometric Identification Strategy

Our econometric identification strategy aims to estimate the causal effects of SENAI ISI's establishment on regional economic outcomes. To achieve this, we employ a difference-in-differences (DiD) methodology, leveraging the staggered introduction of SENAI ISI institutes across various micro-regions in Brazil.

Our identification strategy benefits from the quasi-experimental setting provided by the non-random and staggered placement of the institutes. The non-random placement relied, as we explained in Section 2.3, largely on regional fixed effects, which is one of the conditions under which the crucial parallel trends assumption of DiD is met. To rule out the possibility that any short-term dynamics in the GDP growth path would bias the estimates, we also included one-year leads and lags of growth in GDP per capita. Moreover, since we know the SENAI ISI institutes, despite being founded equitably across the Brazilian states, were located in urban areas in the states, we also included the population of the hosting municipality. Thus, we ultimately employ a conditional DiD approach, where the central identifying assumption is that parallel trends hold conditionally on leads and lags in GDP per capita and population growth.

3.1.1 The Logics of Difference-in-Differences Estimation

As we saw in Section 2.2, 27 SENAI institutes – spread over the country – have formally commenced operations since 2011, of which 26 were operational by the end of our observation period in 2019. Since our exposition suggested that the location of the individual institutes was to a non-negligible degree based on a principle seeking regional proportionality, we may be tempted to conclude that strategic locational selection of the a priori strongest regions may be less pertinent than in many other countries where public/private research organisations have been founded on a large scale in a short time. In order to fully exploit the opportunities associated with the (at least partly) experimental setting, a staggered difference-in-differences approach is a natural choice.

In general, DiD approaches can be applied when there is data on both a treated and an untreated group of units, for which observations exist for at least one pre-treatment and one post-treatment unit. In the simplest setting of a two-period unstaggered design, treatment occurs at a fixed time and affects only a part of the overall sample, e.g., a policy change affecting only observations in one state but not in another. The idea of DiD is then to determine changes and pre- and post-treatment trends in the outcomes for both the untreated and the treated observations. If these changes differ between the groups, DiD would attribute the differences to the policy change.

While DiD has become a particularly influential method in causal treatment studies using field data, recent advances have made clear that there are many pitfalls associated with its use requiring specific care. First and probably most importantly, attributing the group differences in pre- and post-treatment changes to the policy measures obviously requires non-trivial assumptions, specifically the non-anticipation assumption and the parallel trend assumption. The latter assumption states that both the treatment and control groups would exhibit the same trends post-treatment if both were untreated. Obviously, this assumption involves unobservable counterfactuals because the treatment group is only observed in its treated and not its hypothetical untreated state. To assess the validity of the common trends and the non-anticipation assumption, it has therefore become customary to compare the pre-treatment trends between the groups (in which both were de-facto untreated), asserting that common trends are indicative of a non-violation of the common (post-treatment) trend assumption. Needless to say, this reasoning – inferred from the observable equality of pre-treatment trends and applied to the non-observable equality of post-treatment trends – is inductive and may fail in practice. Nonetheless, it is a tangible and intuitive assumption and, paired with institutional insights into the case, can add great credibility, which more opaque identification assumptions (such as zero correlation between structural error terms and explaining variables) cannot easily do.

A second important aspect concerns the design of the DiD setting. While originally, DiD was developed for the canonical two-periods-two-groups setting, it has also been used in more complex situations, particularly in cases of staggered designs, i.e., when treatment occurs at different times and even when units can switch back and forth between treatment and control group. Recent research by Goodman-Bacon et al. (2019), however, makes clear that although the conceptual logics of DiD extend to more complex designs such as these, the classical regression-based two-way fixed effects (TWFE) estimator will be either not at all consistent or only consistent under very restrictive assumptions. A host of staggered DiD estimators have been developed to address the shortcomings of TWFE.

3.2 Treatment Definition in the SENAI Case

The specifics of the staggered foundation of the SENAI Innovation Institutes suggest an intuitive approach to defining treatment and control groups. Exploiting the foundation dates, it is straightforward to assign the treatment status to all regions that are home to at least one SENAI institute from the year of foundation of the earliest institute in the region. Suppose a region is home to two SENAI institutes, one of which was founded in 2014 and the other in 2015; the region would be considered as treated from 2014 onwards and untreated before. To define what we consider the home region, we draw on insights from the literature on the geography of knowledge spillovers, which suggests that knowledge spillovers are often localised but may well reach beyond very narrow geographic boundaries. For example, Anselin et al. (1997) provide evidence for the US that academic spillovers will often reach beyond the boundaries of metropolitan statistical areas (defined as at least one metropolitan agglomeration and at least 50,000 inhabitants). Similar findings for Germany suggest that up to 90% of the economic effects for universities originate outside the boundaries of the local community (Schubert and Kroll 2016a). Thus, it seems necessary to define the home region in sufficiently broad terms. In our case, we opted for the state level, of which there are 26 in Brazil. For instance, we consider a region treated if there is at least one SENAI institute in the same state. The resulting design has the form of a standard staggered DiD approach, which we can essentially estimate by using any of the recent DiD estimators, which are robust to staggered roll-out, the most common of which is the estimator by Callaway and Sant'Anna (2021).

Obviously, the notion of a home region still rests on the assumption that the economic effects occur on the basis of geographic proximity as reflected by administrative borders. While this assumption is reasonable, it neglects the fact that the geographic patterns of interaction between science organisations and firms that give rise to economic effects can be substantially more complex. In particular, this could be the case for the SENAI institutes. An important reason for complex geographic interaction patterns is that the SENAI institutes are very specialised in terms of topics. Thus, for any firm with a certain activity profile, the institutes are not interchangeable. If the firm sees value in collaborating with SENAI, it can reasonably be expected to select a thematically appropriate institute as a partner, rather than just selecting the closest. While there is certainly a significant distance decay component, because firms may be reluctant to enter into collaborations with partners located very far away, we would expect cooperation patterns to be more spread out than for public science organisations covering a much broader range of activities, notably universities. One way to address this point is to use the location of the cooperating firms rather than the location of the institute. Based on this information, we define treated regions as those regions that, in a given year, were home to at least one firm that had a contractual relationship with a SENAI institute (irrespective of where the latter was located). Because our database covers more than 25,000 different contracts, we define the home region of the firm relatively narrowly by the 5-digit regions, of which there are 510 in Brazil. This regional treatment definition based on partner firm location gives a very fine-grained account based on actual interaction patterns that are not biased by ad-hoc assumptions regarding regional proximity.

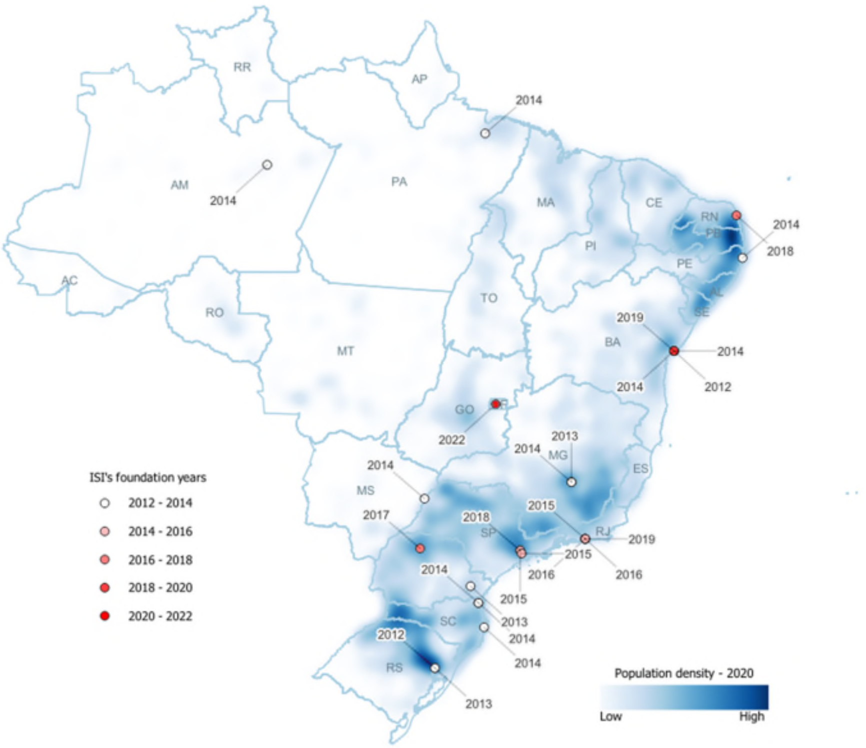
However, it does not result in a standard staggered DiD design because, obviously, regions can, depending on the start and end of individual projects, switch arbitrarily back and forth between treated and untreated states. The estimator provided by Callaway and Sant'Anna (2021) is not fit for such a design. However, Chaisemartin and d'Haultfoeuille (2024) provided an extension of a staggered DiD estimator that can handle such complex intertemporal treatment situations alongside simpler settings, including the standard staggered design. For the sake of comparability, we used the estimator by Chaisemartin and d'Haultfoeuille (2024) throughout and reported the one by Callaway and Sant'Anna (2021) only as a point of comparison for the treatment definition based on the location of the institutes. The choice of estimator, however, did not seem to have much influence in the cases where both should be applicable.

4 Results

4.1 The Evolution and the Development of SENAI

The SENAI ISI network currently consists of 28 operational institutes, the first of which was founded in 2012. These institutes are distributed across 13 federal states, with some states – such as Bahia and Rio de Janeiro – hosting multiple institutes established in different years during the study period. Initially, the institutes were concentrated in densely populated coastal regions, where the largest vocational training centres were located, before gradually expanding to inland areas, which is in line with the two phases of the foundation process we described in Section 2.3. Figure 1 illustrates Brazil's population density along with the locations of the institutes, labelled with their respective foundation years.

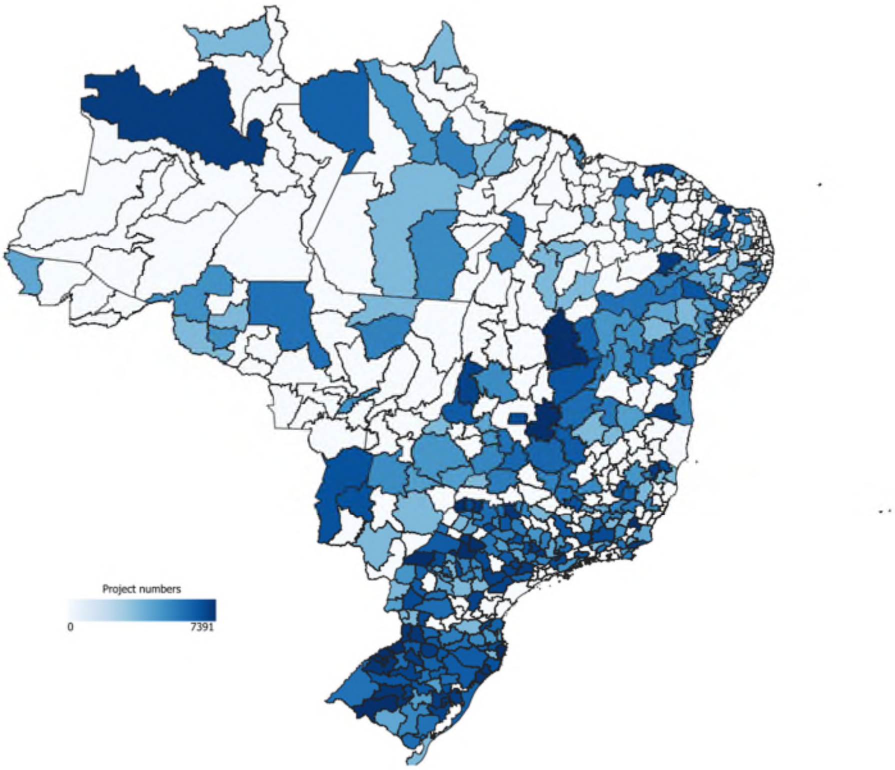
Figure 1: Population density and ISI institutes



Source: own calculations

To better understand our definition of treatment, it would be useful to take a closer look at the official regional classification in Brazil. While there are 26 states at the top level, these are hierarchically divided into 126 intermediate regions, 510 immediate (or micro) regions and 5570 municipalities. While the 26 states were used to define treatment using the location of institutes, we opted to draw on the 510 micro-regions to define treatment based on project locations with ISI clients, i.e., companies that have ordered or commissioned projects with ISI institutes. Of the 510 immediate regions, 313 have at least one project listed, as can be seen in Figure 2, showing the geographic outreach of the institutes' client base.

Figure 2: Project numbers per region



Source: own calculations

Figure 2 reveals a high regional concentration of the projects. While most regions have only a small number of projects, a few regions exhibit disproportionately high project counts and revenues. The top region has 7391 projects, and the leading client accounts for 915 projects. Similarly, revenue per project varies widely, with most generating modest amounts, though a few outliers greatly inflate the average, with one project earning over R$ 25 million as Table 1 shows. This highlights the fact that a small number of high-impact projects and regions account for a disproportionate share of overall activity and financial returns. The figures are interesting because they can imply challenges for DiD estimation, which implicitly assumes that treatment is equally sized. We come back to this issue later with additional robustness checks allowing for continuous treatment.

Table 1: Summary of project statistics

	Regions	Clients	Revenue per Project
Count	313	7402	43.64
Mean	147.00	6.22	23.17
Std Dev	692.61	23.76	329.80
Min	1	1	-1181.14
25%	3	1	0.25
Median	11	2	0.6
75%	56	4	1.54
Max	7391	915	25594.35

Note: Revenue in thousand $

Source: own calculations

Examining the revenue grouped by service types provides us with further details, as seen in Table 2. R&D stands out with the highest average revenue by far, confirming that R&D projects tend to be the most financially impactful, though the variation is substantial, as seen in the large standard deviation and a maximum value of R$ 25.5 million. Technology Consulting shows the highest outlier at over R$ 2.5 million, though it also has a wide range of outcomes. Metrology, with the most entries, has a lower average revenue but a broad range, while specialised services show notable extremes, with a maximum of over R$ 2.3 million. Overall, a small number of high-revenue projects, particularly in R&D, drive much of the financial impact.

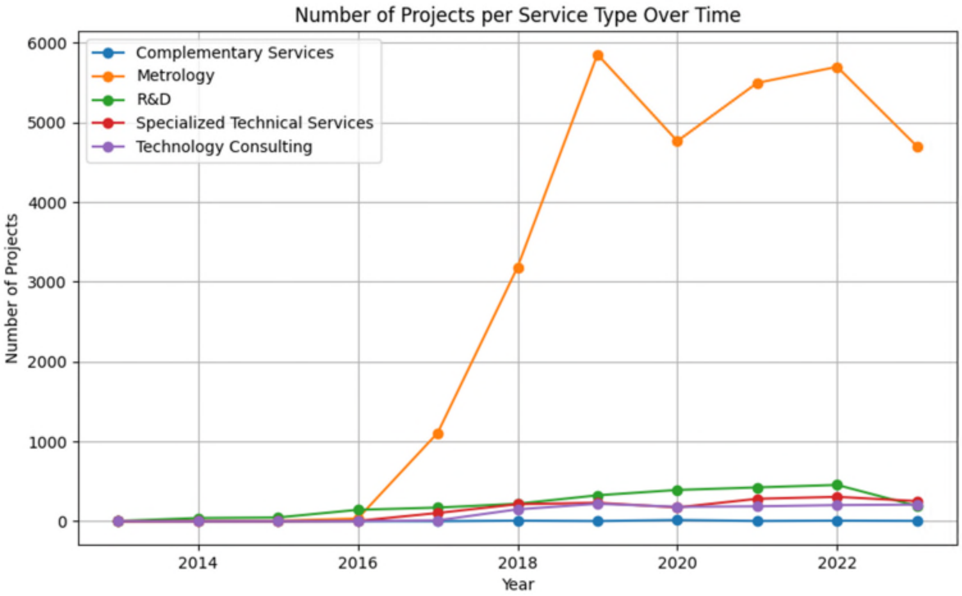
Table 2: Project revenue per service type

	Technology Consultancy	Metrology	R&D	Complementary Services	Specialised Technical Services
Count	1,380.00	38,435.00	2,080.00	39.00	1,709.00
Mean	22,204.52	1,963.12	422,883.19	52,582.76	13,844.97
Std	109,713.31	22,559.62	1,445,190.35	135,812.16	103,146.88
Min	-1,181,149.90	-960.00	0.00	480.00	0.00
25%	1,980.00	229.50	11,660.00	3,630.00	450.00
Median	5,515.00	510.00	78,079.46	19,199.81	1,250.00
75%	20,000.00	1,196.50	320,660.49	51,653.47	3,600.00
Max	2,527,547.10	2,190,876.00	25,594,357.26	843,579.87	2,375,021.00

Source: own calculations

Regarding the evolution over time, there is a consistent upward trend of projects across all service types from 2013 to 2019 and then stabilisation until 2023, as seen in Figure 3. The majority are metrology services, followed by R&D, consultancy and specialised services. The slight dip in 2020 was driven by a decrease in metrology projects, whereas R&D presented a consistent increase over the whole period, peaking in 2022.

Figure 3: Project numbers over time



Source: own calculations

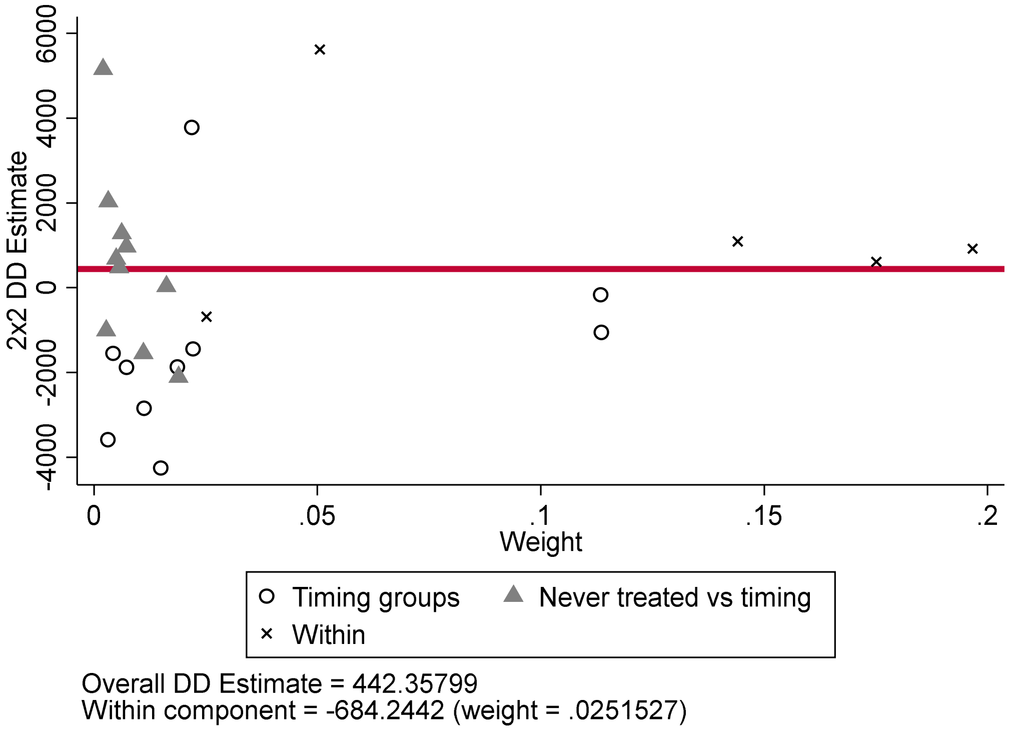
These descriptive statistics lay the groundwork for the subsequent analysis of the economic effects of SENAI ISI institutes, including a macroeconomic perspective.

4.2 The Economic Effects of SENAI

4.2.1 The Importance of Staggered Roll-out

Goodman-Bacon et al. (2019) have shown that the regular TWFE estimator of the average treatment effect of the treated group (ATT) is a weighted sum of all constituent 2x2 DiD designs. Out of these 2x2 designs, the particularly problematic cases are those where later treatment groups are compared to earlier treatment groups. Bias arises unless treatment effects are constant over time. The decomposition results by Goodman-Bacon et al. (2019) make it possible to analyse the significance of these potentially bias-inducing later-vs.-earlier comparisons by calculating the ATT for each individual 2x2 design alongside the aggregation weight. Problems are likely if i) treatment effects differ strongly over the 2x2 designs and ii) if the problematic later-vs.-earlier comparisons have high weights.

Figure 4: **Project numbers over time**



Source: own calculations

The results from the Bacon decomposition are shown in Figure 4, where the label "Timing groups" refers to a set of potentially problematic later-vs.-earlier comparisons. As we can see, the overall TWFE DiD estimate corresponds to a 442 BRL increase in GDP per capita following the foundation of an institute, which, from a normal TWFE regression, would obtain a p-value of 6.7%. We should note that this effect does not include any control variables and is merely a point of reference. Moreover, we can see that the individual ATTs differ substantially as there are, besides many positive ATTs, also a larger number of negative effects. Most importantly, however, the potentially bias-inducing later-vs.-earlier comparisons are - with one exception - all negative, and two of them have very high weights of about 11% each. Thus, the Bacon decomposition suggests that the treatment effects are heterogeneous over time and that they have most likely induced a negative bias. Indeed, when using only the later-vs.-earlier comparisons to estimate the overall treatment effect, we obtain an estimate of 691 BRL, which is thus likely to be more significant than the baseline TWFE estimate, including the biasing comparisons. Overall, the results from the Bacon decomposition suggest that it is highly important to rely on estimators that are robust to heterogeneous treatment effects in staggered designs. We present the results of these estimations in the next subsection.

4.2.2 Estimating the Baseline Effects on GDP per Capita

As discussed in Section 3.2, our data allowed us to define treatment either by relying on foundation dates in combination with institute location or alternatively based on the location of the cooperating firms. The baseline results of these estimations are presented in Table 3.

In the first row, we show the results for the treatment definition based on institute location using the estimators. We can see that the estimates are positive and significant (ATT=1210 BRL, pval<0.01). It is, as suggested by the Bacon decomposition, also larger than the naive TWFE estimate of 442 BRL, which confirms the downward bias of the time-heterogeneous treatment effects in our case. Most importantly, when looking at the placebo test of the joint common trend and non-anticipation assumption, there is no strong evidence of the violation with a p-value of the joint nullity of the pre-treatment effects of 0.12. Indeed, when using the estimator provided by Callaway and Sant'Anna (2021) with the doubly robust option based on inverse probability weighting of tilting (Sant'Anna and Zhao 2020), we obtain similar results (ATT= 936, pval<0.05, pval placebo test=0.20). When looking at the alternative treatment definition based on the firm location, we can only meaningfully provide the estimator by Chaisemartin and d'Haultfoeuille (2024), because of the complex intertemporal treatment assignment, which Callaway and Sant'Anna (2021) do not allow for. The results are, however, quite similar both in terms of size and significance level (C&H firm: 985 BRL, pval<0.01). It should be noted that in this latter case, the test of the common trend assumption does not reach the 5% significance level, even though it is close. In any case, overall, our findings are highly robust to quite different specifications of treatment, providing strong evidence that the foundation of the SENAI institutes has contributed positively to GDP.

Table 3: Staggered DiD estimation

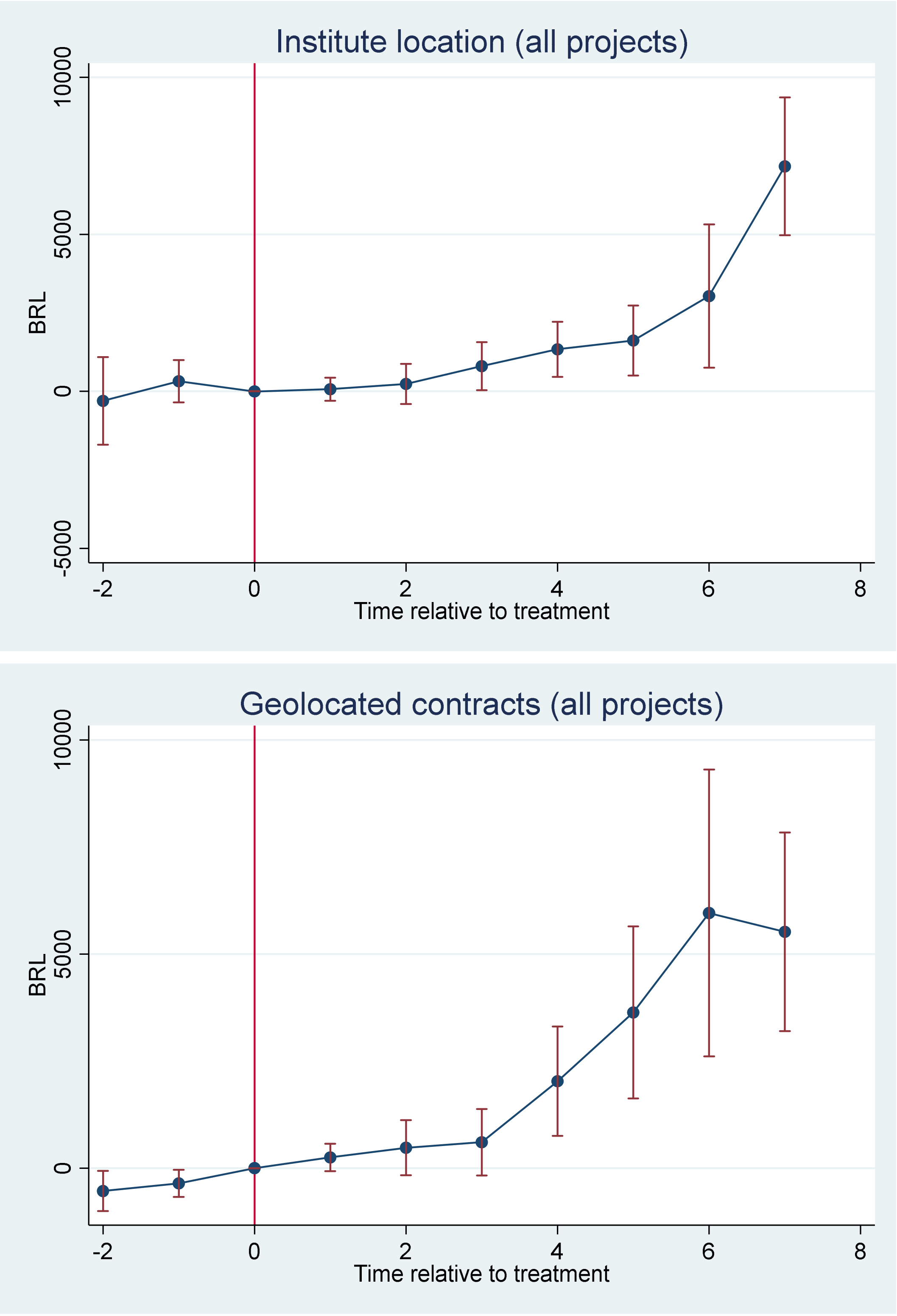
Treatment	ATT		SE	z-val.	p-val. placebo
Institute location	1210.49	**	381.86	3.17	0.12
Firm location	985.08	**	339.39	2.90	0.06

* p<0.05, ** p<0.01, *** p<0.001

Source: own calculations

Event-study representations of the two DiD estimations are presented in Figure 5. What is interesting about these figures is that the effects are increasing over time, with the first two treatments being small and insignificant and the latter being the largest, at more than 5000 BRL. This is well in line with the intuitive principle that the effects of scientific research on the economy do not occur instantaneously and will take time to unfold.

Figure 5: **Event-study plots of the baseline DiD estimations**



Source: own calculations

4.2.3 Assessing the Stable Unit of Treatment Value Assumption

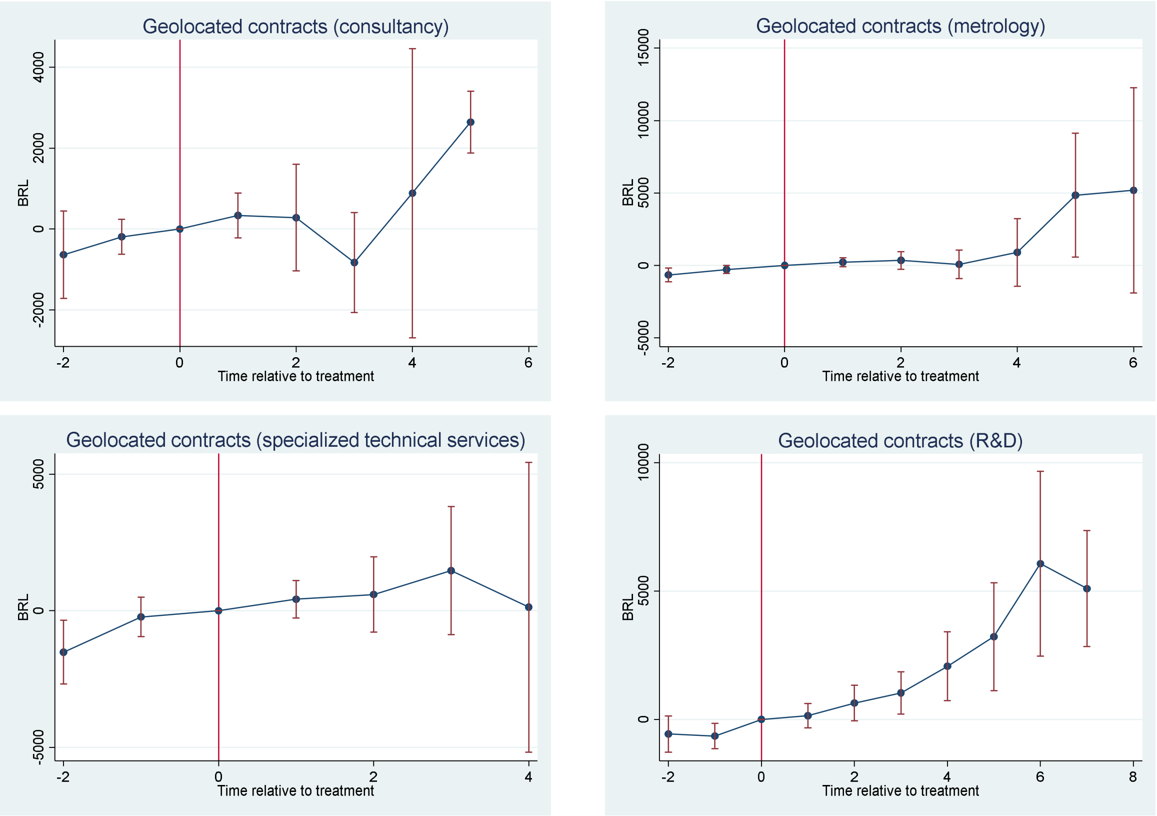
An important objection that could be raised against the implementation of the DiD design is a violation of the Stable Unit of Treatment Value Assumption (SUTVA). This assumption ensures that received treatments are homogenous across units. Random controlled trials are usually tightly monitored and harmonised across recipients. For example, a fixed dosage of a certain drug is administered to patients. However, in our case, treatment differs both qualitatively and in intensity. To assess the influence of such differences, we first analyse whether the effects differ by type of project/contract. Secondly, we assess the influence of intensity by explicitly allowing treatments to be continuous to reflect differences in "dosage." While these analyses confirm the robustness of our previous findings overall, they also deliver additional valuable insights about the mechanisms underlying the effects as well as their size.

4.2.3.1 Effects by Project Type

As we have seen, the SENAI institutes cover quite a large portfolio of activities that range from consultancy projects and technical services such as metrology to genuine R&D projects. The bulk of these activities corresponded to the second category of metrology. An important question from the policy as well as from the managerial side is whether the effects differ by type of project. The treatment definition based on firm location allows for an easy test of differential effects by splitting the treatment definition by project type; i.e., in one variant, the definition of treatment would be based only on consultancy projects, in another, only on metrology projects, and so on. If treatment effects were homogenous, all estimated ATTs would not differ substantially.

Figure 6 presents the associated event-study plots by project type. Although there are a few significant spikes – for consultancy and metrology projects at least – only R&D projects show a clear positive pattern. Indeed, the overall ATTs are only significant for this group of projects (ATT=1800 BRL, pval<0.001), while the ATTs of the other project categories are not. Thus, the results suggest that the overall positive effects of the SENAI institutes are, by far and large, driven by more basic R&D projects rather than consultancy or technical services such as metrology. Such a finding is also in line with findings that the value of scientific organisations comes from their ability to create and make available fundamental advanced knowledge and technologies rather than to generate income from side hustles.

Figure 6: Event-study plots of the baseline DiD estimations by project type



Source: own calculations

4.2.3.2 Differences in Dosage

We know from the descriptive statistics that the intensity of treatment differs considerably between the treated units. In some regions, the treatment is assigned on the basis of just one institute. In other treated regions, such as São Paulo, there are several institutes. Also, there are differences concerning the contract location. In some regions that have been assigned a positive treatment status, there are only one or a few contracts, while the observed maximum is 1209. In simple terms, the treatment "dosage" differs substantially. A solution that has been established so far to address this issue is to define treatment status based on varying cut-offs. Yet this approach remains, of course, arbitrary. However, the estimator by Chaisemartin and d'Haultfoeuille (2024) allows for an extension of dichotomous treatment logics of DiD to the continuous case. We see in Table 4 that the overall results are confirmed, documenting a positive and significant effect overall, with the estimates indicating that an additional institute, on average, raises GDP per capita by 356 BRL and an additional contract by 51 BRL. The p-values on the placebo tests are, as before, not significant and therefore do not provide strong evidence against the common trend and non-anticipation assumptions.

Table 4: **Staggered DiD estimation (continuous treatment)**

Treatment	ATT		SE	z-val.[+]	p-val. placebo
Number of institutes	356.67	*	149.39	2.39	0.17
Number of contracts	51.84	**	20.51	2.53	0.06

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

[+] There is currently no proven asymptotic normality result for the continuous DiD estimator of the ATT. The z-values and resulting significance levels are reported only as points of reference.

Source: own calculations

4.3 The Overall Macroeconomic Value of SENAI

Like the study by Schubert and Kroll (2016a), our data represents a regional breakdown of a total economy and thus does not represent a mere sample. This feature is desirable in order to derive simple estimates of the overall value of SENAI for the Brazilian economy as opposed to just the treated regions. It is, for example, straightforward to provide results for the share of Brazilian GDP explained by the presence of SENAI institutes. It is, however, important to emphasise that these calculations are tentative and should be seen as indicative of the range of the effect size rather than exact estimates.

Table 5: **Share of Brazilian GDP explained by SENAI**

	2011-2020
ATT: GDP per capita	985.00
Average share of treated regions	13.45%
Average population	399,705
Average population in treated regions	1,060,365
Population-weighted share of treated regions	35.68%
ATE (Brazil)	351.48
Average GDP per capita Brazil in 2011-2022	52,894.74
Share of explained GDP per capita	0.66%

Sources: own calculations, Worldbank

Such a calculation is presented in Table 5. We assume the lowest estimated ATT resulting from contractor locations of 985 BRL. Over the course of the observation period, an average of 13% of the regions were treated each year. However, since these regions were, on average, larger by a factor of about 2.65, the population-weighted share of treated regions was 36%. Assuming that the treatment effect of the untreated is zero,[1] we can calculate an estimate of the average treatment effect for Brazil (ATE) by multiplying the ATT by the population-weighted share of treated regions. If we compare the ATE to the overall average GDP of 52,894 BRL, we find that approximately 0.66% of the Brazilian GDP can be attributed to SENAI. This estimate is substantial, particularly in comparison to the overall budget. However, it falls well in line with, for example, the results for the (admittedly much larger) Fraunhofer Society in Germany, to which 1.6% of total GDP (Allan et al. 2022) and 0.55% of labour productivity may be attributed (Comin et al. 2019). It is also in line with research indicating that the returns on innovation-related expenditures may induce multipliers that are often in the double digits (Jones and Summers 2020)[2].

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[1] This assumption is an approximation and may be violated if, for example, treatment leads to relocation of economic activities to treated regions (negative regional spillovers) or if induced economic activities in treated regions also drive economic activities in untreated regions (positive regional spillovers).

[2] We refrain, however, from reporting such multipliers because of quality concerns about cost data in the internal bookkeeping system.

5 Discussion and Conclusion

The literature on the economic effects of science is well established and has mostly pointed to substantial effects for a wide array of variables, including GDP (Schubert and Kroll 2016b; Agasisti and Bertoletti 2022; Glückler et al. 2015), productivity (Comin et al. 2019; Fritsch and Wyrwich 2018) and innovativeness (Robin and Schubert 2013a). However, generating credible causal evidence has always been a non-trivial challenge because scientific organisations tend to have long histories, often coevolving with or sometimes even creating their environments. This coevolution tends to blur clear cause-and-effect relationships and makes it difficult to understand the direction of causality. It has therefore been hard to establish causality in most settings trying to estimate the economic effects of public research.

Recently, a few studies have employed the foundation of scientific organisations in difference-in-differences approaches (Pfister et al. 2021; Schlegel et al. 2022), which provides a promising framework to address the endogeneity challenges. These studies are, however, still limited in number and naturally focus on very specific cases, all of them in Western economies. Our work adds to this stream of literature in two important ways. Firstly, our unique institutional insights into the historic locational selection processes allow us to make a very credible case for the validity of the parallel trends assumption going beyond mere empirical corroboration by placebo tests. So far, existing studies have focussed on broader types of organisations, such as the Universities of Applied Sciences in Switzerland, which, despite sharing a common organisational form, are heterogeneous and highly independent of each other from a legal perspective. Thus, in these studies, an institutional assessment of locational selection criteria naturally faces limitations. Secondly, our specific setting of the SENAI ISI institutes is one of the very few instances where evidence is provided for a catch-up economy.

Overall, our results confirm that public research organisations can have profound impacts on the economy. Focusing on productivity, we estimated the average treatment effect on the treated regions (ATT) in terms of GDP per capita to be at least 985 BRL. This effect was robust in the light of various specification alternatives. It is also economically substantial, given that it implies that about 0.66% of the total Brazilian GDP can be attributed to the SENAI ISI institutes. Indeed, this effect may appear very large given the fact that investment levels are still rather limited, leading to enormous returns on investment. Yet, at the same time, it is known that the returns on innovation and knowledge-related activities are very large. Jones and Summers (2020) report high multipliers of 10–30. In an emerging economy such as Brazil, these effects may even be amplified because, up to now, organisations closing the gap between universities and firms, which are an established part of innovation systems in most advanced economies, have been largely absent. Thus, it is not unreasonable to assume that the SENAI ISI institutes closed a systemic gap in the Brazilian innovation system, which explains the considerable returns. Needless to say, decreasing returns may, of course, set in once the ISI activities are sufficiently expanded. However, at least while spending remains at its current limited level, our results suggest that increased investments appear to be economically warranted.

A highly important observation with regard to high-relevance public research organisations in general concerns the question of which types of projects cause the effects. Most public research organisations – including those in other countries, e.g., Fraunhofer in Germany, SINTEF in Norway, TNO in the Netherlands or RISE in Sweden – engage in a wide variety of activities ranging from genuine research and technological development projects to the provision of technical services, such as metrology, or consultancy. All of these activities can potentially provide benefits for industrial partners. However, our results suggest that, in this case, the economic effects almost exclusively result from research projects. Thus, the social or economic value of public research organisations seems to be associated with their capacity to contribute to research, technology development and innovation. It is apparently much less related to their capacity to provide technical services or consultancy, which commercial actors could also provide. Interestingly, the finding that a higher research focus is associated with higher effects seems to extend beyond the specific Brazilian case. Findings for the Fraunhofer-Gesellschaft in Germany for example suggest that collaborations have a higher effect of firm productivity if the projects aim at technology generation rather than the application of existing technologies (Comin et al. 2019).

This is not to say that public research organisations, such as SENAI, should not engage in these activities. One argument is also that these activities allow for the efficient utilization of technical infrastructures which can be essential in research context. However, it does have important implications for management and policy. Concerning the managerial aspects, the provision of technical services should not be a goal in itself, but a means to sustain a scientific organisation that sees its ultimate objective as providing collaborative applied research with and for industrial partners. Among other things, it can have the functions to establish first relations with industrial partners and sound out their needs – to subsequently then engage in deeper and technologically more advanced collaboration which might also be economically more impactful. As concerns policy, our results suggest that public funding should for the SENAI institutes should for the moment primarily be linked to the performance of research-oriented activities. The case for funding technical services or consultancy, which can essentially also be provided by commercial suppliers, is probably less compelling.

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