Place-Based Industrial Policies and Local Agglomeration in the Long Run*

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September 2025

Abstract

This paper estimates the long-run effects of place-based industrial policy, studying a program implemented in Italy in the 1960s–70s. Leveraging administrative data over a century and exogenous variation in the assignment rules, we document agglomeration of workers and firms in the targeted clusters lasting well beyond the policy's termination. By promoting high-technology industries, the intervention spurred demand for business services and fostered a skilled local workforce. Over time, this produced spillovers from manufacturing to knowledge-intensive services, with sustained gains in local wages and human capital. We illustrate that these persistent effects depend on the initial conditions of host locations.

JEL Codes: J24, N94, O14, O25, R58
Keywords: place-based industrial policy, employment, wages, agglomeration

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1. Introduction

In recent decades, advanced economies have witnessed rising spatial inequality as "left-behind" industrial districts struggled to adapt to technical change and globalization. In response, place-based industrial policies (PBIPs) seeking to bolster local manufacturing and establish industrial clusters have gained traction (Porter, 2000; Kline and Moretti, 2014b; Garin, 2025).[1] The persistent effects of PBIPs on local development remain, however, not fully understood. Leveraging a century's worth of data, this paper studies a historical program to assess whether PBIPs benefit the targeted areas in the long run, exploring the sources of persistence, their spillover effects, and cost-effectiveness.

There is active debate on these programs among economists. While state intervention can correct market failures and have a lasting impact on local development, it might also lead to inefficiencies and misallocation, yielding—at best—only transient benefits (Rodrik, 2019; Heblich et al., 2022). Moreover, PBIPs may not just affect the targeted clusters but also produce spillovers to other industries and areas. Last, their impact may depend on the preexisting conditions of the host locations (Corinth et al., 2025). Shedding light on these issues requires examining the effects of PBIP over time—ideally, before it starts until long after its termination. However, reliable evidence is scant as data on historical policies are hard to find and selection problems complicate causal analysis (Juhász et al., 2024).

This paper takes advantage of a unique historical setting to address these questions. It studies a policy conducted in the 1960s and 1970s to develop industrial clusters in select areas of Southern Italy—the *Industrial Development Areas* (IDAs). Exploiting the criteria ruling the establishment of IDAs for identification, we provide causal evidence of long-lasting effects on employment, firms and the structure of local economies persisting well after the end of the program.

The IDAs were launched in 1960 as part of a broader regional policy called *Extraordinary Intervention in the Mezzogiorno* (EIM). The EIM was introduced by the Italian government to stimulate development in southern regions through infrastructure building and investment subsidies to manufacturing firms. The IDAs were groups of municipalities *within* the EIM jurisdiction identified as suitable hosts for industrial clusters and agglomeration of firms and workers. To facilitate such agglomeration, the government provided a bundle of policy instruments such as a higher subsidy rate on investments (hence a lower cost of capital) for firms located in an IDA, along with infrastructure works tailored to the area's

[1] Several measures passed by the United States Congress in recent years involve the creation of industrial hubs, often in distressed areas, representing *"potentially the most significant place-based policy funding in U.S. history"* (Bartik et al., 2022). This shift towards place-based approaches has also occurred in industrial policies in Europe, the United Kingdom, and China (Fai, 2018; Alessandrini et al., 2019; Gerritse et al., 2024).

needs. Total IDA funding averaged 0.5 percent of national GDP each year between 1960 and the end of the program in the late 1970s.

We first explore whether the policy raised economic activity in the targeted clusters. To measure this, we reconstruct the number of workers and establishments across municipalities over one hundred years (1911 to 2011) by digitizing historical censuses. We then scale these by the municipality's area to build the main outcomes, measuring local agglomeration. The extended time horizon before and after the IDA program allows us to clearly identify its effects and describe how they unfold over time. We complement this dataset with geo-coded records of the projects financed within the policy, and with rich administrative employer-employee data for the Italian private sector starting in 1990.

Valid identification requires isolating exogenous variation in IDA status. The criteria set by the government in the late 1950s to establish IDAs offer a unique source of spatial variation. Each IDA was centered around a large city (the IDA center) and included neighboring municipalities. The key requirement was that municipalities directly bordering the IDA center *had* to be part of the IDA—which we refer to as "contiguity rule". This resulted in a "minimum" IDA border traced by municipalities contiguous to the IDA center. Within this cutoff, all municipalities (the center and contiguous ones) were part of the IDA; outside of it, they could be included or not, leading to a 40-percentage-point jump in IDA status at the border.

We exploit the contiguity rule in a fuzzy regression discontinuity design comparing municipalities within the minimum IDA border to municipalities outside of it. The identifying assumption is that only IDA status changes discontinuously at the cutoff and that areas within and outside of it are otherwise similar. There are indeed no systematic imbalances in lagged outcomes and other relevant covariates at the cutoff before the start of the policy. This is not surprising, as the imposition that municipalities bordering IDA centers be automatically included in the IDA was independent of local characteristics. To account for unobserved time-invariant discontinuities, we rely on a longitudinal design that compares over time municipalities bordering IDA centers to areas just outside of the cutoff—which hinges on a less restrictive parallel trends assumption.

We estimate a positive effect on local employment density emerging while IDAs were in place and continuing to grow afterwards. We measure a discontinuity of about 40 workers per square kilometer (km^2) (50 percent of a standard deviation) at the end of the policy. In 2011, almost four decades after peak funding in IDAs, the jump is still large at 60 workers per km^2 (60 percent of a standard deviation). Higher employment levels in the long run reflect higher local labor force participation, rather than migration into IDAs after their termination. Results also show a persistent rise in local firm density. These *increasing* impacts even after the program's end are somewhat in contrast with the existing evidence on industrial cluster policies—which documents employment effects that are, at best, positive but stabilizing over time (e.g., Garin and Rothbaum, 2024).

Such stark persistence originates from sectors not directly targeted by the policy. By decomposing the baseline effect, we find that manufacturing—the only subsidized sector—drove most of the employment growth during the policy years but leveled off as IDAs were phased out. In contrast, employment in services started to rise while IDAs were in place and kept growing after their termination. While not directly receiving subsidies, the services sector eventually became the main driver of long-run agglomeration in the IDAs.

These spillovers to services raise key questions, which are tackled in the rest of the paper. Why did non-targeted sectors respond to industrial policy? How can these effects be so persistent? To answer, we begin by further decomposing the response of services. While IDAs were in place, the rise of employment and firm density in services occurred exclusively for non-tradables (e.g., retail, hospitality), in line with local multiplier effects (Moretti, 2010). Starting in the 1980s, however, we also document steep growth of knowledge-intensive services (e.g., information technology, business services), suggesting development of a skilled local workforce.

A possible criticism is that these results may not reflect the impact of the IDA policy, but rather urban growth and structural transformations originating from large cities (the IDA centers) and differentially affecting contiguous municipalities and control areas farther away. To address this, we use a complementary design. We match IDA centers with "placebo centers" in the Center-North of Italy and run a triple differences specification that subtracts from the baseline double difference estimated around IDA centers—which compares municipalities bordering IDA centers to those farther away—its counterpart obtained around placebo centers, aiming to net out possible confounding factors. These triple differences estimates are close to our baseline design, and confirm long-run agglomeration in IDAs led by services, especially in knowledge-intensive sectors.

The placebo centers design also allows identification of the policy's spatial spillovers to nearby untreated areas. We compare the control group of the baseline analysis (areas just outside of the minimum IDA border) to its counterpart in the Center-North around municipalities contiguous to placebo centers. We find negative policy spillovers on manufacturing employment equivalent to about one third of the baseline treatment effect estimates. However, this displacement occurs mostly while IDAs were in place—suggesting migration into IDAs in response to subsidies—and shrinks afterwards. There are also small positive spillovers on workers and firms in the services sector in untreated areas.

The transition towards skilled jobs is a result of the *type* of manufacturing stimulated by the policy. We observe a larger share of high-technology manufacturing industries in IDAs, which we argue has led to the subsequent development of knowledge-intensive services in two ways. First, by providing local supply of skilled workers—a thick labor market externality (Hanlon, 2020; Moretti and Yi, 2024), which we document using matched employer-employee data to reconstruct job flows across firms and sectors. Second, through a local multiplier effect in the form of increased demand for business services such as consulting and human resources. We confirm in national input-output matrices that high-technology manufacturing firms demand more skilled services than low-technology ones. While we lack input-output data at the municipal level, we exploit granular administrative data to show that business services jobs are indeed more present in IDAs.

These findings suggest the diffusion of "good jobs" (Rodrik and Stantcheva, 2021). Accordingly, the effect on local wages is positive and long-lasting, there is a persistently larger share of residents with high education and skills, and IDA firms are more productive and invest more than other firms in the long run. We additionally find small changes in municipal spending and other government transfers in the decades after the policy, thus ruling out that continued public investment in IDAs has contributed to persistent effects (von Ehrlich and Seidel, 2018). We argue, instead, that our findings reflect primarily *neighborhood-level* channels linked to path-dependence in residential choices, as well as structural transformation at the *local labor market-level* (Bartik, 2022). To show this empirically, we estimate policy impacts at varying geographical scales, leveraging the placebo centers design combined with synthetic control methods (Abadie and Gardeazabal, 2003).

Turning to cost-benefit analysis, we calculate a long-term cost per job of about €25,000, in line with comparable regional policies studied in the literature. In a more comprehensive assessment following Busso et al. (2013), we find that the gains to local workers, firms and landlords generated by the program *after* its termination compensate for the total costs—abstracting from general equilibrium effects (Cerrato and Filippucci, 2024).

Finally, we argue that a reason why IDAs were successful was a policy design explicitly targeting high-potential areas. To document this aspect, we contrast the experience of IDAs with that of other areas receiving similar subsidies within the EIM program. We conduct a discontinuity analysis at the border separating the EIM jurisdiction from the rest of Italy (Albanese et al., 2024). For manufacturing employment, we estimate a positive but fading effect in treated areas south of the border qualitatively similar to that found for the IDAs. However, knowledge-intensive services did not respond to the intervention. There are also no effects on high-technology manufacturing, wages, or local education and skills. While suggestive, this exercise highlights the role of local preexisting conditions in the design of place-based development policy and reconciles our findings with other studies (reviewed below) documenting null or, at best, short-lived economic benefits of the EIM program. IDAs' target locations were high-potential poles suitable to future agglomeration, skill development and the formation of a local hub. In contrast, areas around the EIM border had less favorable starting conditions such as poor geography, remote locations far away from large cities, and low initial presence of workers and firms: in those places, the effects of government intervention were temporary, and limited to the subsidized industries.

Literature and contributions. This paper contributes to the ongoing debate on place-based policy (for reviews, see Kline and Moretti, 2014b; Neumark and Simpson, 2015). More specifically, our focus is on firm cluster policies (PBIPs), for which most of the existing evidence concerns policy impacts during the intervention or shortly after its end (Falck et al., 2010; Criscuolo et al., 2019; Lu et al., 2019; Lapoint and Sakabe, 2022). The few recent papers studying historical programs have revealed mixed evidence, ranging from positive long-run effects (Giorcelli and Li, 2022; Garin and Rothbaum, 2024) to "boom-and-bust" patterns where targeted areas initially benefit from the intervention but later on fail to diversify away from subsidized industries and to adjust to technological change (Kim et al., 2021; Heblich et al., 2022). We contribute to this literature by investigating how policy can shape the transition of industrial clusters from manufacturing to knowledge-based local economies.[2] Our work offers insights into the mechanisms underlying persistent effects, highlighting the role of local multipliers and labor market externalities in developing high-skill local jobs and businesses.[3] Importantly, we describe how long-run impacts depend on the initial conditions of the targeted locations. These findings emphasize ex-ante design—through successful targeting of host areas—as a key factor in the evaluation of place-based policy (Gaubert et al., 2025).

This paper also relates to the growing body of work on industrial policy (Juhász et al., 2024). Recent studies have uncovered the impact of various types of industrial policy on local development and structural change (e.g., Juhász, 2018; Hanlon, 2020; Mitrunen, 2024; Choi and Levchenko, 2025; Kantor and Whalley, 2025). Our work adds to the existing evidence by illustrating how these interventions can not only stimulate the manufacturing sector but also, eventually, promote a shift towards services—which is not the typical goal of industrial policy. Therefore, our findings also add to the evidence on the *spillovers* of (place-based) industrial policies to non-targeted industries and locations (Greenstone et al., 2010; Atalay et al., 2022; Giorcelli and Li, 2022; Lane, 2022; Siegloch et al., 2022). We present

[2]While we study the manufacturing-to-services transition, Kline and Moretti (2014a) show how place-based policy can shift target regions from agriculture to manufacturing through infrastructure investments.

[3]Gagliardi et al. (2023) show that manufacturing hubs with larger shares of high-skill workers navigated deindustrialization better than others. Our paper highlights the role that policy can play in this process.

a detailed breakdown of the dynamic effects of PBIP across different classes of services, shedding light on how these programs shape local economies. We also provide dynamic estimates of their spatial spillovers to nearby locations, showing some displacement of economic activity away from non-targeted areas during the intervention, but much less so in the long run.

Last, this study shows new evidence on the EIM—the most ambitious regional program in Italy's history (Felice and Lepore, 2017). Prior research (Colussi et al., 2020; Buscemi and Romani, 2022; Albanese et al., 2024) has consistently reported limited economic impacts of the policy, especially in the long run. Instead, we show that government intervention did promote economic development in a few select clusters of Southern Italy—the IDAs—and argue that better initial conditions might explain divergent effects compared to previous evidence. In contemporaneous work, Cerrato and Filippucci (2024) study the aggregate implications of the EIM and do find small welfare gains. We instead examine more in depth a prominent facet of the EIM (the IDAs) and go beyond its direct impacts, using rich administrative micro data to unveil the effects of the program on other sectors and locations and, most importantly, to identify the sources of persistence.

The paper is organized as follows. Section 2 and Section 3 describe the policy and the data, respectively; Section 4 outlines the identification strategy; Section 5 and Section 6 present the baseline results and explore the mechanisms; Section 7 conducts cost-benefit analysis; Section 8 discusses the role of local initial conditions. The last section concludes.

2. Background

The EIM. In the aftermath of World War II, the gap between Southern Italy and the rest of the country was at its peak. In 1950, a regional policy named *Extraordinary Intervention in the Mezzogiorno* (EIM) was put in place (and financed) by the central government to jump-start development in the South—roughly 40 percent of Italy's surface (Law n. 646/1950).[4] The EIM had an initial lifespan of ten years, then prolonged several times until 1992, and was run by a state-owned agency called *Cassa per il Mezzogiorno* (Cassa, henceforth).

At its onset in 1950, the main goal of the EIM was to enhance Southern agriculture and modernize infrastructure. To achieve this, the Cassa performed infrastructure interventions during its first decade of activity (Appendix A.1). A new phase began in the late 1950s, when the focus of the EIM shifted towards industrial policy to support businesses and attract investments in the South (Laws n. 634/1957, n. 555/1959).

[4]GDP per capita in the South was half of that in the Center-North in 1951. See De Philippis et al. (2022) and studies cited therein for details on the Italian North-South divide. The term Mezzogiorno ("Midday") is conventionally used to identify the South of Italy.

To pursue its new mandate, the Cassa conceded investment grants to firms in its jurisdiction. Firms had to apply for a grant to the Cassa for eligible investments, such as building or enlarging plants or purchasing machinery. The subsidy rate depended on firm size, sector, and—crucially—location (more on this below and in Appendix A.1, which describes the grant allocation process). We only observe successful applications, and have no data on subsidized firms except for their sector and location (Section 3 provides more detail). Virtually all grants went to manufacturing firms, especially in heavy industries, with only negligible funding to the services sector (1-2 percent of total subsidies, see Appendix A.1). EIM expenses rose dramatically during the 1970s, reaching yearly peaks of roughly 2 percent of Italy's GDP and 8 percent of aggregate investment.

The IDAs. The core of this industrial policy (and the focus of our paper) were the *Industrial Development Areas* (IDAs), established during the 1960s. The IDAs were clusters of municipalities within the EIM region identified by the government as suitable for industrial concentration, with the goal of "*accommodating agglomeration forces in firm location*" (Cassa's Annual Report, 1958-59, p. 144).

An IDA was created upon initiative of a group of local authorities (municipalities and provinces) called a "consortium", which submitted a development plan to the government. The plan outlined the proposed investments and a list of municipalities to be included in the IDA. For each candidate municipality, the consortium had to report information on economic, demographic and geographic characteristics. The decision to include the individual municipalities proposed by the consortium, and to ratify the creation of the IDA, rested with the government. A total of 14 IDAs were created—see Section 3.[5]

Each IDA was centered around a provincial capital and had to include, by law, at least all municipalities contiguous to the center—a rule we will exploit for identification (Section 4). IDAs could then extend to more municipalities farther away (up to 25 km) from the center, subject to a minimum total population threshold (200,000 people as of 1958). The government imposed that the area showed a "*propensity for industrial concentration*", including requirements related to its geological properties (e.g., low seismicity) and to the presence of basic infrastructure (Ministerial Circular n. 21354/1959).

Government intervention in IDAs consisted of a bundle of policy items aimed at incentivizing investment and providing infrastructural support to the area as expressed in the consortium's development plan. Following approval of the plan, the Cassa could subsidize the investments of consortia in their IDA, such as connections to transport and

[5] We do not observe the initial proposals from consortia, but only the final list of municipalities included in each IDA as approved by the government. This prevents us from using runner-ups as control group as in, e.g., Greenstone et al. (2010) or Kline and Moretti (2014a).

energy services, or the construction of plants and houses for workers. The maximum subsidy rate for these expenses was 85 percent. Moreover, firm investment grants were more generous for firms in IDAs compared to other EIM areas. This was achieved in two ways. First, the investment subsidy rate was larger for IDA firms. Second, while all firms in IDAs could access grants, firms in the rest of the EIM region could do so only if small- or medium-sized and located in small municipalities (Appendix A.1).

The IDA program was de-facto in place until the late 1970s, when grants for IDA firms were equalized to those for other EIM firms. Transfers continued also through the 1980s, but with no distinction between IDAs and other EIM areas. The EIM ended with Law n. 488/1992, which introduced a new set of subsidies also covering firms in the Center-North (Bronzini and de Blasio, 2006; Cerqua and Pellegrini, 2014; Cingano et al., 2022).

3. Data

Identifying the effects of the IDA program over time and disentangling the mechanisms requires rich longitudinal data spanning a long time period. This paper draws on several unique data sources.

EIM transfers. We collect data on interventions from the Cassa from the ASET database.[6] Records for all (about 110,000) firm subsidies are available with information on the grant's amount, year, sector and municipality. We cannot characterize subsidized firms more in detail and have no information on unsuccessful applications. The data also include the infrastructure projects run by the Cassa (about 75,000), reporting the financial resources allocated as well as the project's location and year of approval. We do not observe the infrastructure expenses borne by IDAs' consortia and subsidized by the Cassa.

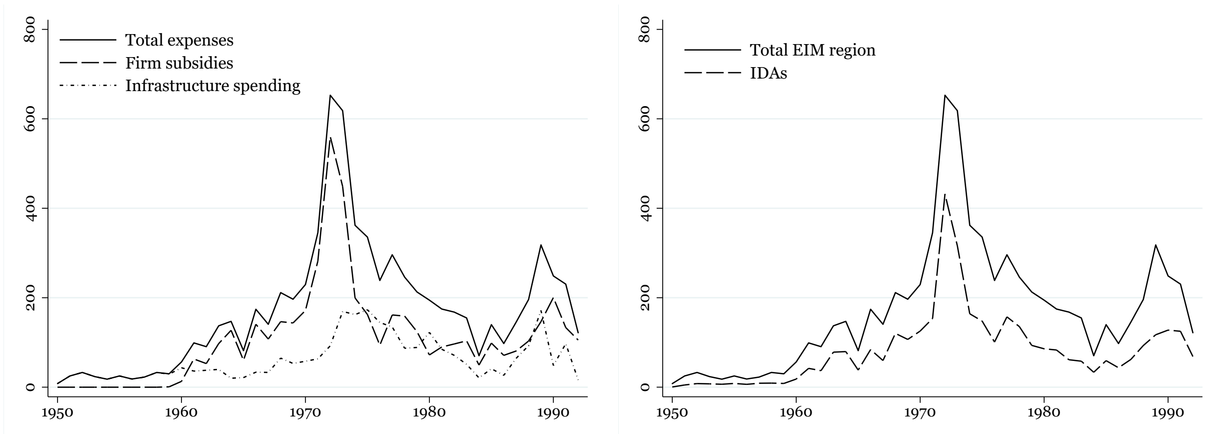
Figure 1 plots EIM expenses over time, scaled by the total population in the EIM region in 1951. As showed in Panel (a), the Cassa only performed infrastructure works during its first decade (the 1950s). A strong industrial push began in the 1960s with a massive rise in firm subsidies. These grants went disproportionately to capital intensive industries such as chemicals and metallurgy (Appendix A.1). Panel (b) shows that most expenses were concentrated in IDAs, especially during the funding peak in the 1960s and 1970s.

The ASET archives also record a list of the IDAs and the included municipalities, which we digitize and plot in Figure 2. A total of 14 IDAs comprising over 300 municipalities have been established throughout Southern Italy. These are indicated by the yellow regions

[6] The ASET project (Archives for Regional Economic Development) was set up in 2013 to catalog the archives and balance sheets of the Cassa. We describe the ASET data in Appendix A.1.

Figure 1. EIM Expenses Over Time

(a) Breakdown across policy items (b) Full EIM area and IDAs



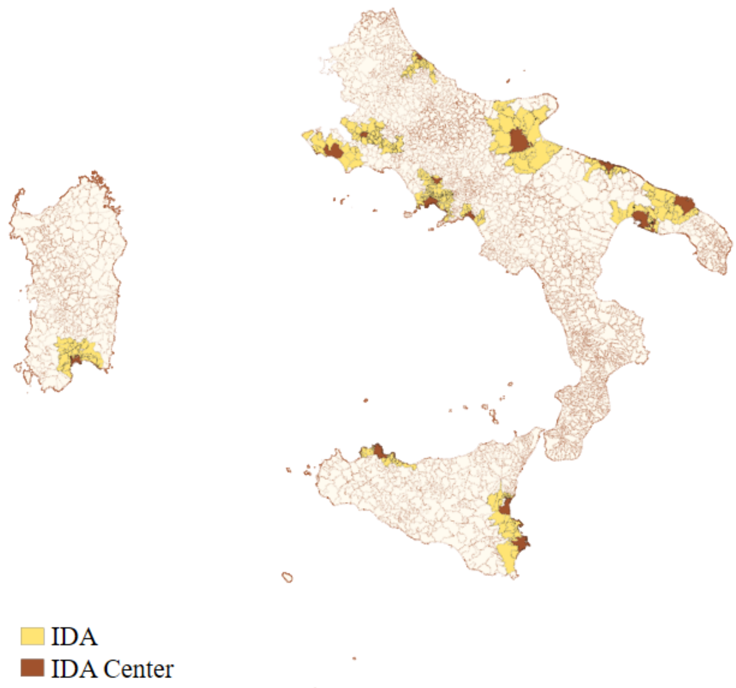
Notes: Flow annual EIM expenses in € (2011 prices) scaled by total population in the EIM region in 1951. Loans to firms are excluded (loans are a small share of total funding, see Appendix A.1). The solid line shows total expenses and is the same in the two panels. Panel (a) shows a breakdown between firm grants (long dashed line) and infrastructure spending (short dashed line). Panel (b) shows expenses separately for IDA municipalities (long dashed line).

surrounding the brown IDA centers (nearly all the main cities of the South). On average, IDA municipalities received funding of around €10,000 (cumulated between 1950 and 1992 and measured in 2011 prices) per 1951 resident. This amount does not change much if excluding IDA centers and is about twice as large as for other EIM municipalities. IDAs absorbed more than half of the total EIM expenses (€165 billion, Appendix A.1), despite accounting for one tenth of the surface of the EIM region and one third of its population.

Industrial censuses. To measure local agglomeration (a key target for the policymaker) we compute municipality-level economic density as the number of workers (or establishments) per km^2—although we will show results for many additional outcomes, including economic density in log rather than levels. We collect data on the number of workers and establishments in Italian municipalities from decennial industrial censuses spanning six decades (1951 to 2011, including an intermediate census in 1996), sourced from the Italian statistical institute (Istat).[7] The data report employment and firm counts in the private sector (the terms "firm" and "establishment" are used interchangeably throughout the paper), across different industries. Appendix A.2 provides more details, including the list of industries. The availability of data well after the end of the policy enables us to tackle key questions on its long-run effects. However, only the 1951 census allows us to evaluate the balancing properties of the outcome *before* the introduction of IDAs in the 1960s, which is essential for identification purposes. We thus reconstruct municipality-level employ-

[7]Because our outcomes are at decennial frequency, the staggered creation of IDAs during the 1960s (see Section 2) cannot be exploited for identification.

Figure 2. The Industrial Development Areas (IDAs)



Notes: The map shows the EIM jurisdiction and highlights IDAs, which are denoted in brown/yellow. IDA centers are in brown and the remaining IDA municipalities are in yellow. The IDA centers are the following provincial capitals: Bari, Brindisi, Cagliari, Caserta, Catania, Foggia, Frosinone, Latina, Napoli, Palermo, Pescara, Salerno, Siracusa and Taranto.

ment and number of establishments long before the start of the IDAs (and of the EIM) by hand-digitizing the 1911 and 1927 industrial censuses, available in the historical archives of Istat. Appendix A.2 describes our reconstruction of historical censuses.

Social security. The third main data source of the paper is the administrative archive on the population of Italian private-sector firms from social security records, available at the Bank of Italy. The data start in 1990 and include information on firm employment counts, 6-digit sector, location, and average wages. Importantly, the granular sector-level information allows us to break down manufacturing activities by technological intensity (high- versus low-technology manufacturing) and service activities by knowledge content (knowledge-intensive versus other services) using the Eurostat classification. We complement the data with income statements collected by Cerved, matched using firm tax identifiers, and reporting detailed balance sheet information for incorporated limited liability companies. Last, we obtain matched employer-employee data by merging the firm dataset with a 7 percent random sample of Italian workers. We collapse the data at a more aggregate level of analysis (the municipality) as we cannot match the administrative firm records with the establishment-level subsidy data from ASET. Appendix A.3 provides more detail on the social security data.

Other data sources. We leverage complementary data sources in the analysis. We obtain municipality-level demographic and labor market data from Istat's decennial population censuses between 1951 and 2011. We also collect data on geographic characteristics (area, mean elevation, slope, seismicity) from Istat. Other sources are the Italian Ministry of the Interior (election data), the Italian Finance Ministry (taxable income), the OpenCoesione database (non-EIM funding, such as Law n. 488/1992 and EU structural funds), AIDA PA (municipality balance sheets), and the Osservatorio del Mercato Immobiliare at the Italian Tax Office (house prices).

4. Identification strategy

The selective nature of the IDA program complicates causal identification of its effects. These clusters were not picked randomly but differed from other areas in many aspects, possibly unobserved and correlated with our outcomes. IDAs were positively selected, as their choice was explicitly informed by agglomeration potential (Section 2). Table 1 confirms this by showing descriptive statistics separately for IDA municipalities and other EIM municipalities. Before the start of the policy, IDAs had a higher density of workers and firms relative to other EIM areas, their geography was better suited to economic development and local residents were more educated and less likely to work in agriculture.

Overcoming these selection issues requires isolating exogenous variation in IDA status. To this end, we examine the criteria ruling the establishment of an IDA, which were set in the late 1950s. As explained in Section 2, IDAs were centered around a provincial capital (the brown IDA centers in Figure 2) and included municipalities in its surroundings (in yellow in Figure 2) up to a minimum population threshold. Importantly, the government required that the minimum set of municipalities forming an IDA should be, by default, the IDA center and all municipalities *directly contiguous* to it.

This "contiguity rule"—all municipalities bordering the center are automatically included in the IDA—can be exploited for identification, as illustrated in Figure 3 Panel (a). The outer boundaries of the contiguous municipalities trace a "minimum" IDA border—the dashed white line in the map—separating municipalities in a within-cutoff region (the IDA center in brown and the contiguous municipalities in orange) and an outside-cutoff region (in blue). The outside-cutoff region includes both municipalities that are part of the IDA (in light blue) and municipalities that are not (in dark blue).[8] Below, we clarify how we choose the specific extension of the outside-cutoff region in our estimation.

[8] As noted in Section 2, IDAs could include municipalities away from the center and contiguous ones, not farther than 25 km from the center. There is no discontinuity in IDA status at the 25 km distance cutoff.

Table 1. IDA and EIM Municipalities: Descriptive Statistics

	IDA municipalities		Other EIM
	All	Excl. centers	municipalities
	(1)	(2)	(3)
Employment density (1951)	48.57	39.88	9.69
	(119.24)	(89.05)	(19.30)
Establishment density (1951)	16.92	15.42	4.74
	(27.27)	(23.84)	(7.45)
Manuf. employment density (1951)	21.80	18.86	4.19
	(60.12)	(52.99)	(9.41)
Manuf. establishment density (1951)	5.90	5.46	2.08
	(9.46)	(8.60)	(2.63)
Population density (1951)	642.30	596.44	162.99
	(1025.90)	(918.83)	(325.32)
Agriculture share (%, 1951)	27.83	28.76	38.63
	(14.35)	(13.93)	(13.81)
High school education (%, 1951)	2.31	2.08	1.76
	(1.58)	(1.17)	(0.94)
Mean elevation	148.23	151.17	468.17
	(133.97)	(135.47)	(318.56)
Slope	381.77	382.39	725.14
	(412.46)	(416.94)	(468.80)
Coastal location	0.23	0.20	0.16
	(0.42)	(0.40)	(0.37)
Number of municipalities	326	312	2327

Notes: Means are computed separately for each group and standard deviations are in parentheses. Column (1) considers all IDA municipalities; Column (2) does the same but excludes IDA centers; Column (3) considers all other municipalities in the EIM area. Employment and establishment density computed as number of workers and establishments per km^2. We also show these separately for the manufacturing sector. "Population density" is the number of residents per km^2. "Agriculture share" computed as the number of agriculture workers per 100 residents aged at least 15. "High school education" is the share of residents aged at least 6 with high school education or more. "Mean elevation" measured in meters. "Slope" denotes the distance in meters between the highest and the lowest point in the municipality. "Coastal location" is a dummy equal to one for municipalities located by the sea.

Our analysis exploits the contiguity rule in a simple way. Let δ_m denote the geodesic distance between the centroid of a municipality m and the minimum border of the closest IDA. Negative values of δ_m are assigned to municipalities in the within-cutoff region, that is, the IDA center and its bordering neighbors. The binary indicator $W_m = \mathbb{1}[\delta_m \leq 0]$ identifies municipalities in the within-cutoff region. Let also IDA_m be a treatment indicator taking value of one if municipality m belongs to an IDA. To the extent that the probability of belonging to an IDA changes discontinuously at the minimum IDA border, the distance metric δ_m can be used as running variable in a fuzzy regression discontinuity (RD) setting where IDA_m is the treatment variable, W_m is the instrument and Y_m is the outcome:

$$IDA_m = \mu_{i(m)} + \vartheta \cdot W_m + \varphi(\delta_m) + u_m \tag{1a}$$

$$Y_m = \mu_{i(m)} + \pi \cdot W_m + \varphi(\delta_m) + v_m \tag{1b}$$

Equation 1a is the first-stage regression and Equation 1b is the reduced form. Here, $\varphi(\delta_m)$ is a linear RD polynomial and $\mu_{i(m)}$ denotes IDA regions comprising all municipalities within 25 km of each of the IDA centers (the limit for IDA inclusion), regardless of whether they belong to the IDA.

The peculiarities of this design pose restrictions on the bandwidth choice. Within the minimum IDA border, there are only 14 IDA centers and 137 contiguous municipalities. The small sample size requires picking a bandwidth wide enough to include all these municipalities, which is equivalent to 16 km. We then adopt a symmetric bandwidth of 16 km also outside of the minimum IDA border, although—as showed later—results are robust to choosing different bandwidths (including data-driven selection methods).[9]

This identification strategy rests on three main assumptions, which we here describe intuitively while leaving a more formal treatment to Appendix B. First, IDA status must discontinuously jump at the minimum IDA border—a first stage assumption. To illustrate this, Figure 3 Panel (b) plots the probability that a municipality m belongs to an IDA as a function of the distance to the minimum IDA border, $Pr(IDA_m = 1 \mid \delta_m)$.[10] There is a neat drop in IDA status at the cutoff, confirming a strong first stage. IDA status is very close to one within the RD cutoff and drops to about 50 percent right outside of it.[11]

Table 2 shows the estimation output of the first-stage Equation 1a. The drop in IDA status of Figure 3(b) is quantified at 39 percentage points (Column 1), and associated with lower EIM funding by €5,720 per capita (Column 2). This change in EIM expenses is almost fully driven by firm subsidies, although our data do not capture infrastructure expenses borne by the IDA's consortium (Section 2). This implies that we cannot disentangle the effects of the two main policy items—investment grants and infrastructure interventions.

The second assumption is that potential outcomes are continuous at the cutoff. This

[9]Admittedly, our RD design suffers from limited variation in the running variable within the cutoff (corresponding to the IDA centers and contiguous municipalities). We will show that results still hold when using a longitudinal design that does not rely on controlling for distance to the cutoff.

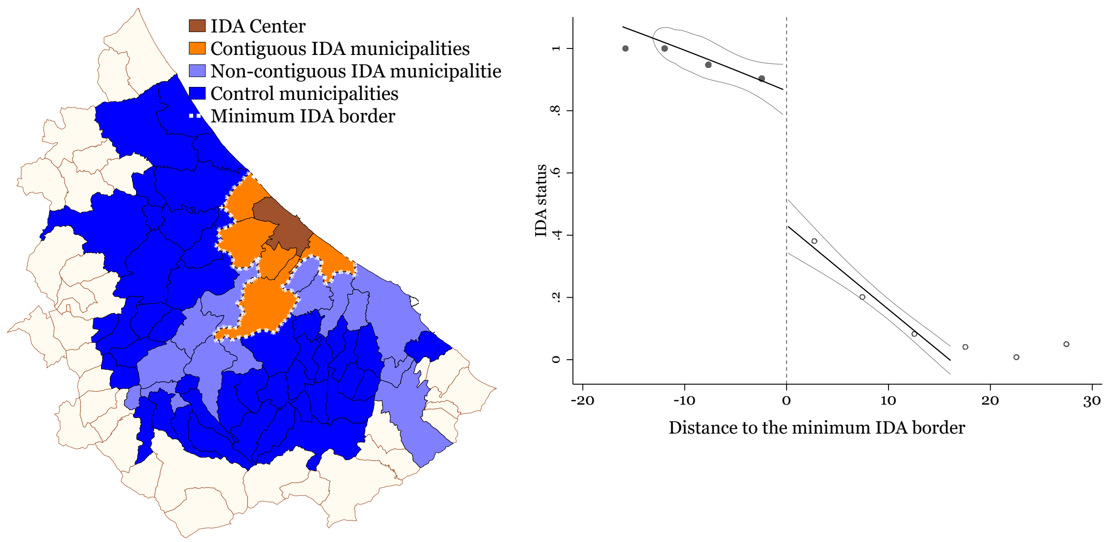
[10]Our analysis sample does not include two IDAs (Napoli and Caserta) due to the proximity of their centers (about 25 km). This reduces the sample within the minimum IDA border to 12 centers and 112 contiguous municipalities. Results will not change when including these two IDAs.

[11]The probability of belonging to an IDA is not exactly one within the cutoff, as very few (10) municipalities bordering IDA centers were not part of the IDA. The government admitted exceptions to the contiguity rule if "*a municipality of very large extension is contiguous to the main municipality* [i.e., the IDA center] *for a limited stretch of the perimeter*" (Ministerial Circular n. 21354/1959).

Figure 3. The Minimum IDA Border

(a) Illustration

(b) IDAs: First stage



Notes: Panel (a) illustrates our design for the Pescara IDA. The IDA center (the Pescara municipality) is in brown and the contiguous municipalities are in orange. Their outer boundary traces the minimum IDA border (dashed white line). Treated municipalities (those belonging to the Pescara IDA) are the center, the contiguous municipalities and the light blue municipalities outside of the minimum IDA border. The dark blue municipalities do not belong to the IDA. Panel (b) shows the jump in IDA status at the cutoff. The outcome is $Pr(IDA_m = 1 \mid \delta_m)$. Negative distance denotes municipalities within the minimum IDA border. See Footnote 11 for an explanation of the non-unitary treatment probability within the cutoff. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately at each side of the border using a symmetric 16-km bandwidth. The gray lines are 95 percent confidence intervals.

requires relevant factors other than IDA status not to jump at the minimum IDA border, thus enabling to causally attribute any observed change in outcomes to the IDA treatment. While the assumption is not testable, we argue that it is likely satisfied. The contiguity rule, which gives rise to the minimum IDA border, is an arbitrary choice of the government. While potential outcomes are related to the distance to a large city (the IDA center), there are few reasons to expect discontinuous jumps in this relationship. To confirm this, we look for discontinuities in lagged outcomes at the cutoff. Figure 4 shows RD plots for employment and firm density in 1951—a decade before IDAs were started—including a breakdown between manufacturing and services. Unsurprisingly, agglomeration in 1951 was larger 10-15 km within the cutoff, corresponding to the IDA centers. Yet there is no jump at the cutoff itself, as municipalities contiguous to the IDA center were very similar to those farther away from the center before the start of the policy.

Many additional checks, showed in Appendix B.1 and briefly summarized here, confirm balancing at the cutoff. There are no discontinuities in labor market and demographic variables (e.g., employment rate, population density, education, age and gender composition), geographical traits (e.g., extension and slope), or voting outcomes (e.g., votes for the incumbent government—suggesting that IDA inclusion was not driven by political

Table 2. Minimum IDA Border: First Stage Estimates

	IDA status (1)	EIM expenses (2)
RD Estimate	0.39	5.72
	(0.09)	(2.50)
Mean around the border	0.36	7.41
Standard deviation	0.48	13.54
Observations	587	563
R^2	0.46	0.11

Notes: Estimation output of the first stage Equation 1a using a 16-km symmetric bandwidth around the minimum IDA border. The specification controls for a linear polynomial in the distance to the border and for IDA region effects. Column (1): the outcome is IDA status, a binary indicator taking value of one if a municipality belongs to an IDA and zero otherwise. Column (2): the outcome are EIM expenses, measured as total expenses in IDA municipalities cumulated between 1950 and 1992, in thousand € (2011 prices) per 1951 resident, winsorized at 1 and 99 percent. Mean and standard deviation computed within the estimation sample. Standard errors clustered by IDA region in parentheses.

considerations).[12] The next paragraphs will describe complementary designs aiming to address concerns about unobserved, possibly time-varying confounders at the cutoff.

The third assumption requires that there is no municipality that would belong to an IDA if and only if it was not contiguous to the IDA center (no defiers). Under these standard assumptions, the fuzzy RD estimand (π/ϑ) identifies the local average treatment effect (LATE) for compliers. Appendix B.2 provides a more detailed discussion.

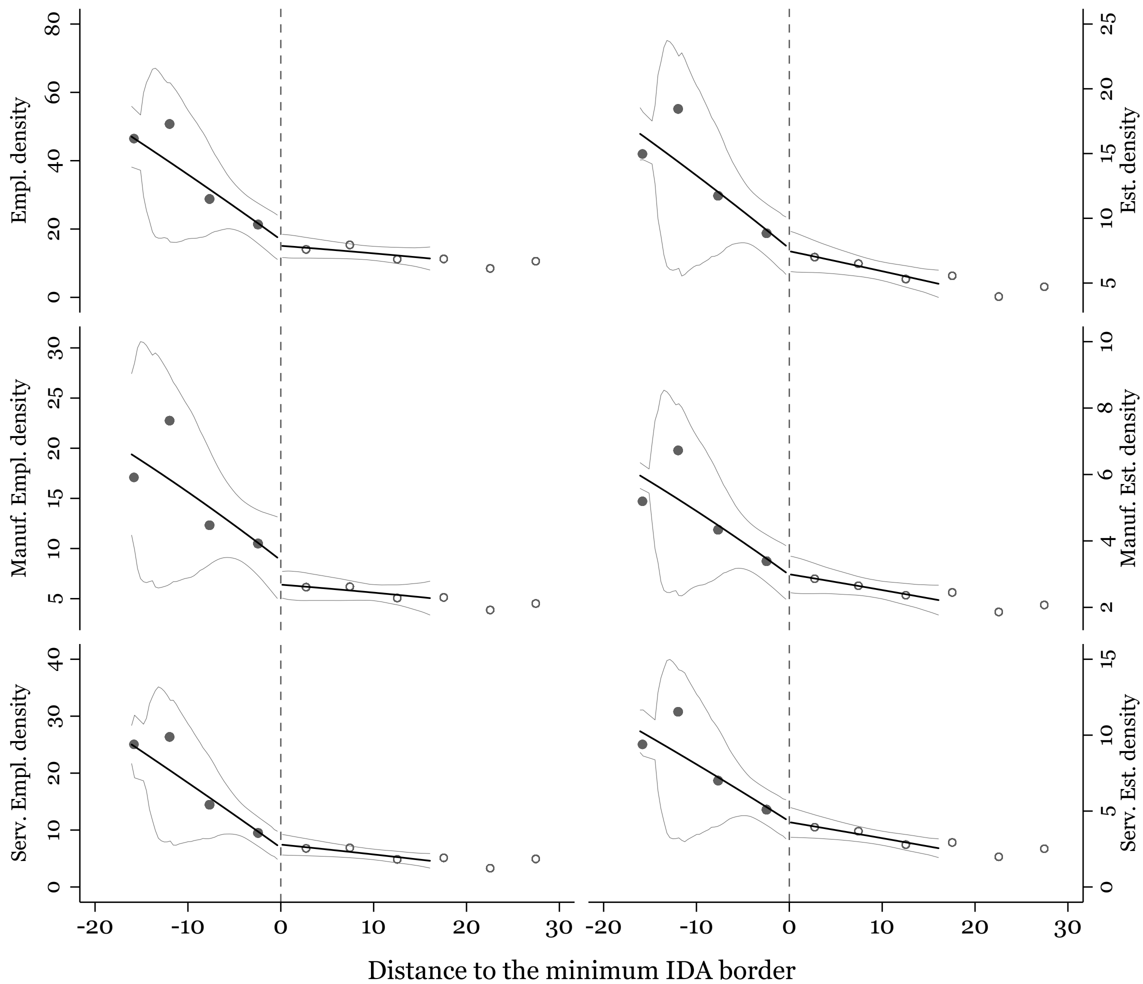
This approach does not exploit the longitudinal dimension of our data. In fact, we observe the main outcomes (employment and firm density) at ten points in time (1911, 1927, 1951, 1961, 1971, 1981, 1991, 1996, 2001 and 2011) over one century. We can then corroborate our design by accounting for unobserved, time-invariant municipality characteristics. The regression form is a dynamic specification of reduced-form Equation 1b:

$$Y_{m,t} = \mu_m + \sigma_t + \sum_{j \neq 1951} \rho_j \cdot \mathbb{1}[t = j] \cdot W_m + \epsilon_{m,t} \tag{2}$$

Here, $Y_{m,t}$ is the outcome for municipality m and census year t, μ_m are municipality fixed effects and σ_t are census year fixed effects. The specification tracks municipalities contiguous to IDA centers over time (we exclude the centers themselves) and compares them to municipalities up to 16 km away from the minimum IDA border, before and after the establishment of IDAs. The coefficients of interest ρ_j capture the difference in

[12] We also check for imbalances in government funding before the IDAs. First, there is no discontinuity in EIM infrastructure spending during the 1950s. Second, the intensity of allied bombing during World War II does not change at the cutoff, arguably implying small differences in Marshall Plan funding (Gagliarducci et al., 2020; Bianchi and Giorcelli, 2023).

Figure 4. Balancing at the Minimum IDA Border, 1951



Notes: "Empl. density" (left panel) and "Est. density" (right panel) are the number of workers and establishments per km^2, respectively. We show also plots separately for workers and firms in manufacturing and services. Negative distance denotes municipalities within the minimum IDA border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately at each side of the border using a symmetric 16-km bandwidth. The gray lines are 95 percent confidence intervals. Table B1.1 shows coefficient estimates.

outcomes between municipalities within and outside of the cutoff in census year j relative to the baseline difference in 1951, which is normalized to zero. Valid identification no longer requires continuity of potential outcomes at the cutoff, but hinges on the weaker assumption that outcomes in municipalities bordering IDA centers would have behaved similarly to municipalities right outside of the cutoff in the absence of the policy. An indirect test of this parallel trends assumption is provided by the coefficients ρ_{1911} and ρ_{1927}, which should be undistinguishable from zero.[13]

[13] We focus on reduced-form estimates where W_m is the independent variable, but results easily extend to a fuzzy design under realistic assumptions. See Millán-Quijano (2020) and Appendix B.2 for details.

Placebo centers. Our empirical design is not immune to threats. The estimated effects may incorporate (positive or negative) spillovers to control municipalities, which being very close to IDAs may themselves be affected by the policy. There may also be differential trends between municipalities contiguous to IDA centers and those farther away, due, say, to urban growth stemming from IDA centers. We propose an alternative design to address these concerns. Namely, we identify placebo centers—provincial capitals in the Center-North of Italy that would have been candidate IDA centers had they been part of the EIM region.[14] We run a triple differences specification that compares the longitudinal coefficients estimated around IDA centers (as per Equation 2) to the same coefficients obtained around placebo centers, thus subtracting any differential trend at the cutoff. Placebo centers are also used to directly estimate the spatial spillovers of the IDA policy to nearby untreated areas, by comparing the control group in the baseline design (municipalities just outside of the minimum IDA border) to its counterpart in the Center-North around municipalities contiguous to placebo centers. We run these specifications either considering all possible placebo centers (i.e., all provincial capitals in the Center-North) or, to improve comparability, matching each IDA center with a "twin" placebo center obtained using synthetic control methods (Abadie and Gardeazabal, 2003)—where municipalities around each placebo center are, in turn, weighted by its synthetic weights.[15] Appendix B.3 describes these designs more in detail.

The EIM border. In Section 8, we present results from a spatial RD design at the border separating the EIM jurisdiction from the rest of Italy. This empirical strategy, proposed in Albanese et al. (2024), is summarized in Appendix B.4. Comparing these results to those obtained for the IDAs will provide insights into the role of initial conditions in determining the effects of place-based intervention, as it will contrast high-potential target locations (the IDAs) to beneficiary regions with low initial agglomeration (around the EIM border).

5. Results

How has the IDA policy affected local employment? Viewed through the lens of a simple model of spatial equilibrium (Kline and Moretti, 2014b), a place-based policy that alters the cost of capital or local productivity across locations shifts the relative labor demand

[14] We exclude regions in the far North of Italy (see Appendix B.3). We search for placebo centers outside of the EIM area, rather than in the South, since nearly all large Southern cities were IDA centers, and the very few possible placebo-center candidates were themselves treated under the so-called "*Industrialization Nuclei*" program (Appendix A.1)—implying that there would not be enough placebo centers in the EIM area.

[15] For example, if IDA center i is matched with placebo centers 1 and 2 with weights w_{i1} and w_{i2}, then municipalities around IDA center i are matched with municipalities around placebo center 1 (which all receive weight w_{i1}) and with municipalities around placebo center 2 (which all receive weight w_{i2}).

curve up in the targeted area and raises employment. To test this prediction, we first provide graphical evidence by plotting employment density around the minimum IDA border, then show regression estimates to quantify the discontinuities.

Graphical evidence. Figure 5 shows RD plots for employment density around the minimum IDA border in each census year. There is no tangible difference in agglomeration at the cutoff not only at the onset of the EIM in 1951 (as showed in Figure 4) but also in the previous decades (1911 and 1927), which further supports the continuity assumption. Starting in the 1970s a positive discontinuity emerges at the cutoff, as agglomeration increased in municipalities bordering IDA centers relative to those immediately outside of the cutoff. The jump at the border remains visible at the end of subsidies in 1991 and, importantly, also in the following decades. We document a very similar pattern for firm density, as showed in Appendix Figure C1.[16]

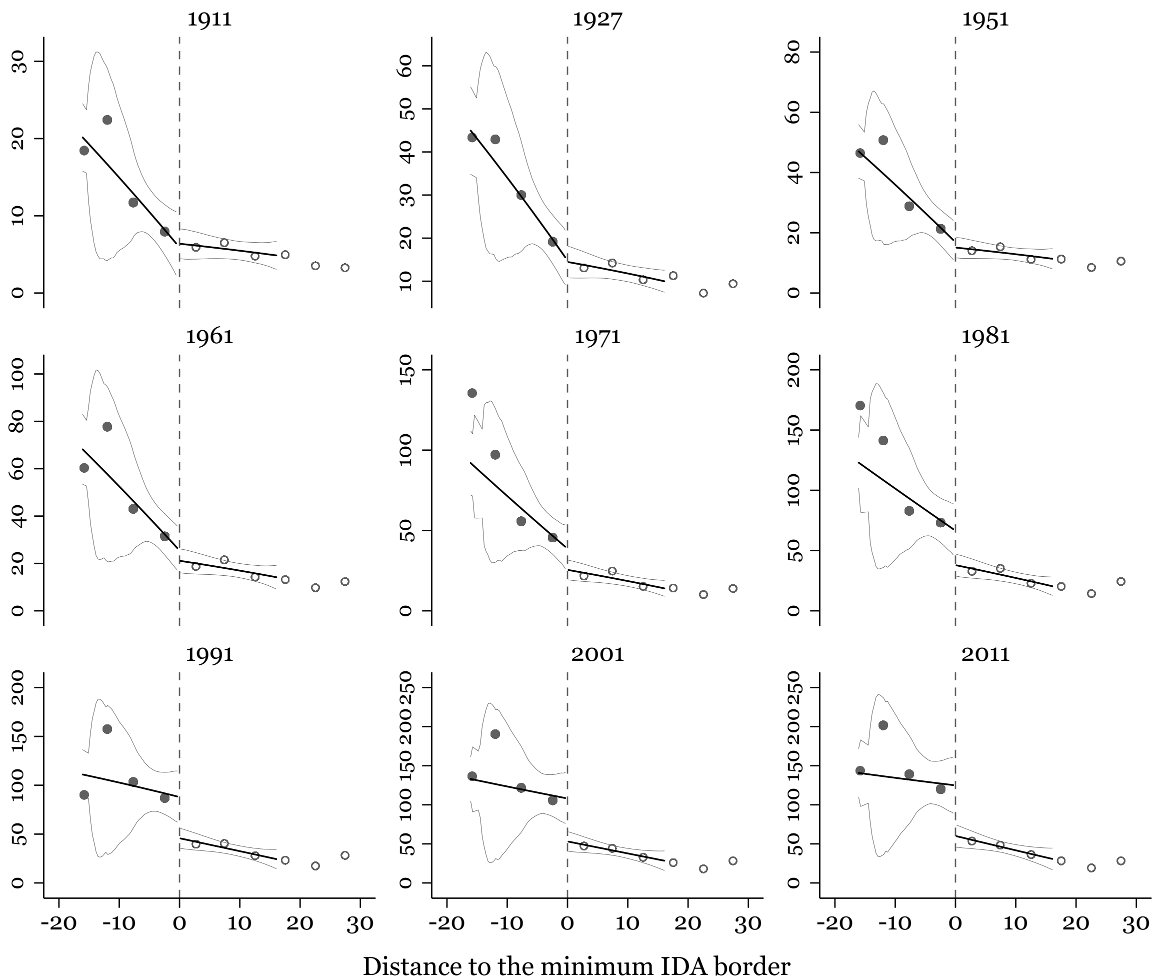
Baseline estimates. Table 3 shows the baseline regression estimates for employment density separately for 1991 (at the end of the intervention) and 2011 (the latest period we observe).[17] Column (1) reports the reduced-form estimates from the sharp RD design in Equation 1b. We quantify the discontinuity in 1991 at about 43 workers per km^2, or roughly half of a standard deviation in the estimation sample. By 2011, the RD coefficient rises to about 63 workers per km^2 (60 percent of a standard deviation). These effects are equivalent to 51 log points in 1991 and 55 log points in 2011 (Table C5) and are comparable in magnitude to those in von Ehrlich and Seidel (2018). Column (2) reports 2-SLS estimates for the LATE, which is estimated at 111 workers per km^2 in 1991 and 161 workers per km^2 in 2011. Column (3) replaces the binary treatment (IDA status) with a continuous one (EIM funding). A rise in subsidies of €1000 (2011 prices) per 1951 resident (about 13 percent of the mean subsidy, see Table 2) leads to 7.2 more workers per km^2 in 1991 and 10.3 more in 2011. We interpret these estimates with more caution in light of the weaker first stage.[18] Appendix Table C1 shows results for establishment density, confirming a significant and lasting impact of the policy also on local agglomeration of firms.

[16]The noisier confidence intervals in the inner bins (e.g., -20 km, -15 km) are due to the smaller sample size in these bins. We also notice a change in slope within the cutoff, with some employment shifting from the IDA center to the contiguous municipalities. This effect of the policy may be due to decreasing returns to scale in production in the IDA center, but cannot be quantified using our design.

[17]Although IDAs were phased out in the late 1970s, we consider 1991 as the end of the intervention as IDA municipalities continued to receive EIM transfers until the end of the EIM in 1992. Also, we show the effect in 1991 rather than in 1981 to preserve consistency with the results (showed later) from social security data, which are not available before 1990. That said, results for 1981 and 1991 are very similar.

[18]The design of Column (3) also imposes a stronger exclusion restriction, that the observed effect is driven only by EIM subsidies. In fact, we noticed earlier that we cannot measure infrastructure expenses from the IDA's consortium. Because these expenses also jump at the cutoff, this assumption is not satisfied and we may be overestimating the intensive margin effect.

Figure 5. Employment Density Over Time at the Minimum IDA Border



Notes: The outcome is employment density, measured as number of workers per km^2, for each census year. Negative distance denotes municipalities within the minimum IDA border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately at each side of the border using a symmetric 16-km bandwidth. The gray lines are 95 percent confidence intervals.

Robustness tests. The baseline estimates are robust to several checks, showed in Appendix C and summarized here. Tables C2-C3 report robustness tests to *i*) more flexible specifications of the RD control function; *ii*) excluding IDA centers from the sample; *iii*) controlling for distance to the IDA center; *iv*) excluding IDA region effects from the specification; *v*) including two IDAs that are omitted in the baseline analysis because of the short distance between the two centers; *vi*) allowing for spatial correlation in standard errors (Conley, 1999); and *vii*) conducting local randomization inference (Cattaneo et al., 2016). Performing these checks leaves the baseline results broadly unchanged, with positive and persistent effects at the cutoff. Figure C2 shows that the RD coefficient remains stable as we replicate the baseline estimation excluding one IDA region at a time, confirming that

Table 3. Employment Density: Baseline RD Estimates

	Reduced form	2-SLS	
		IDA status	EIM subsidies
	(1)	(2)	(3)
	Contemporaneous effect (1991)		
RD Estimate	43.31	110.82	7.23
	(19.08)	(43.03)	(3.26)
Mean around the border	47.62	47.62	46.63
Standard deviation	79.68	79.68	78.05
Observations	586	586	562
R^2	0.22		
KP F-stat		19.06	5.18
	Persistent effect (2011)		
RD Estimate	62.99	161.16	10.34
	(27.18)	(63.14)	(4.49)
Mean around the border	62.97	62.97	61.42
Standard deviation	108.15	108.15	105.18
Observations	586	586	562
R^2	0.24		
KP F-stat		19.06	5.18

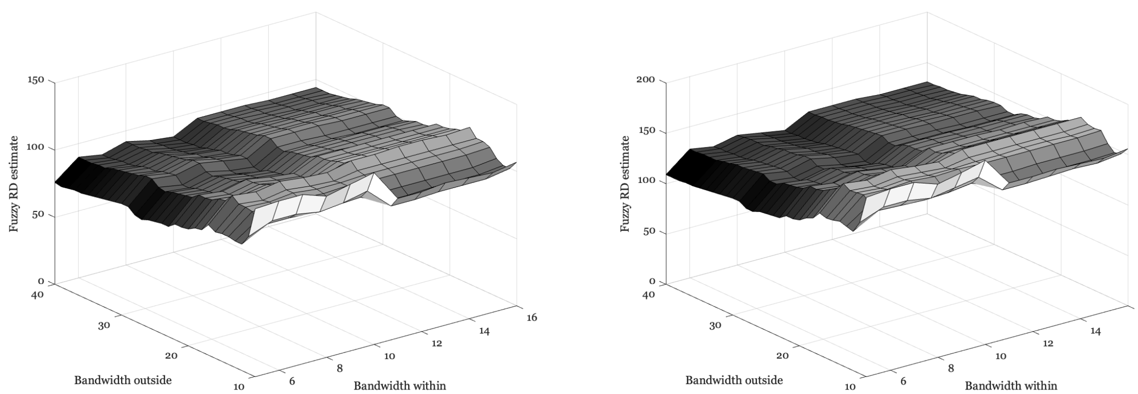
Notes: The outcome is employment density, measured as number of workers per km^2. Column (1) shows the estimation output of the reduced form Equation 1b, measuring the jump in outcome at the minimum IDA border. Column (2) reports the fuzzy RD estimates using a binary treatment (IDA status) and a binary instrument equal to one for municipalities within the cutoff—see Equations 1a and 1b. Column (3) replaces IDA status with total EIM funding (cumulated 1950 to 1992) per municipality resident in 1951 as treatment variable. All regressions are estimated over a 16-km symmetric bandwidth around the minimum IDA border and control for a linear polynomial in the distance to the border and IDA region effects. Mean and standard deviation computed within the estimation sample. Standard errors clustered by IDA region in parentheses.

results are not driven by a specific IDA. Last, Table C4 presents non-parametric estimates obtained following Calonico et al. (2014). We weight municipalities using a triangular kernel function and compute an MSE-optimal bandwidth that can differ within and outside the cutoff. This procedure delivers a narrow bandwidth within the cutoff (6-7 km), focusing only on the contiguous municipalities. The RD coefficient rises in magnitude but is less precisely estimated—most likely because of the smaller number of observations.

Bandwidth choice. How sensitive are results to the bandwidth choice? Figure 6 shows the LATE coefficient (Table 3 Column 2) obtained over different combinations of bandwidths within and outside the cutoff. This is a first assessment of whether the baseline estimates incorporate spatial spillovers: the positive effects discussed so far may reflect displacement of workers and firms from control areas right outside of the cutoff; if driven

Figure 6. Employment Density: Robustness to Bandwidth Choice

(a) 1991 (b) 2011



Notes: Fuzzy RD estimates using a binary treatment (IDA status) and a binary instrument equal to one for municipalities within the cutoff—see Equations 1a and 1b. The outcome is employment density, measured as number of workers per km^2. Regressions are estimated over varying bandwidths both inside and outside of the minimum IDA border and control for a linear polynomial in the distance to the border and IDA region effects. We present estimates in 1991 (Panel a) and 2011 (Panel b).

by such displacement, coefficients should *shrink* when using a broader control group farther away from the cutoff. Indeed, Figure 6 shows that effects decline as more and more municipalities are added to the sample outside of the border. Yet, the impact of the policy remains stable overall—suggesting that displacement effects, albeit present, are likely of limited magnitude. We address these issues more in detail in the next paragraphs.

Commuting, migration, participation. Our employment data is based on the municipality of work, hence results may reflect worker commuting around the cutoff. Table C5 shows however a similar effect on population density (based instead on the municipality of residence), suggesting that commuting is not a key driver—also confirmed in Table C6 Columns (1)-(2), which show no impact on commuting rates. A concrete possibility is that the policy led to migration into IDAs. Data available starting in 1991 show no significant effect on migration rates in 1991 and 2011 (Table C6 Column 3). Yet migration into IDAs might have occurred during the policy years. While we lack municipality-level historical migration data to directly test it, we will investigate migration into IDAs using placebo centers at the end of this section. Here, we notice that our large and persistent effects could hardly originate solely from displacement from untreated areas. Table C6 Columns (4)-(6) show indeed that the policy also led to the creation of new jobs, as the employment rate and labor market participation of residents rose and the unemployment rate decreased.[19]

[19]Our analysis refers to the private sector. We observe public sector employment only in 2011, and find no effect on the share of public employees (2-SLS point estimate: 1.12, standard error: 8.14).

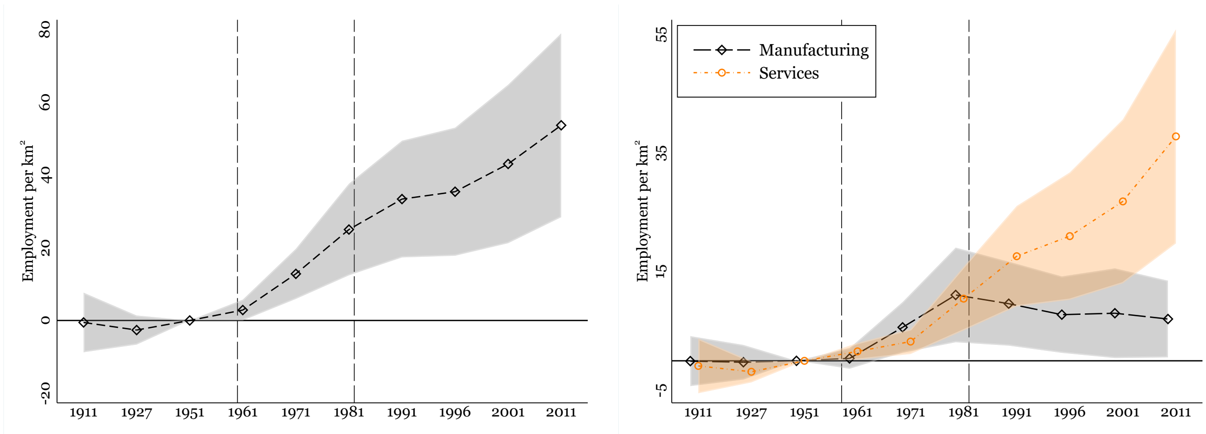
Longitudinal regressions. Figure 7 Panel (a) shows the estimated ρ_j coefficients from the longitudinal design in Equation 2, comparing over time municipalities bordering IDA centers to municipalities farther away (up to 16 km) from them. First, we find evidence of parallel trends, as there is no difference in employment density between treated and control municipalities in 1911 and 1927 relative to the difference in 1951 (which, as showed in Figure 5, is very close to zero itself). We then observe a steady increase in the coefficient during the policy years, reaching about 30 workers per km^2 at the end of the intervention. The effect continues to rise in the ensuing decades and is close to 50 workers per km^2 in 2011. Again, we find similar results for firm density—see Appendix Figure C3(a).

Manufacturing versus services. Where does such stark persistence originate? We replicate the longitudinal estimation separately for employment density in manufacturing and services and show coefficients in Figure 7(b). The rising agglomeration during the 1960s is driven largely by manufacturing employment (black diamonds) and, to a smaller extent, services (orange circles). The manufacturing surge levels off at the end of the policy and slowly declines afterwards. In contrast, the decades after the end of IDAs see a large increase in agglomeration in the services sector, which underpins the persistent effect of the policy. For firm density (Figure C3 Panel b), we find a small effect for manufacturing, suggesting that the rise in manufacturing employment during the policy years largely occurred at incumbent plants. For services establishments, instead, we document a very similar pattern as that found for employment—suggesting an effect on firm location decisions and, possibly, firm creation. Appendix Figures C4-C7 and Table C7 show the cross-sectional RD plots and RD estimates separately by manufacturing and services.

Placebo centers. We now test whether results hold with the alternative approach using placebo centers—provincial capitals in the Center-North of Italy that would have been candidate IDA centers had they been part of the EIM region (see Section 4). We estimate a triple differences specification (Equation B3.1) that compares over time the double difference between municipalities within and outside of the minimum IDA border to a placebo double difference between municipalities bordering placebo centers and their neighbors. This approach allows for differential pre-trends in Equation 2, due to, say, urban growth stemming from the IDA center and affecting contiguous municipalities differentially from areas farther away from the center—see Appendix B.3 for a discussion. We show results for worker and firm density in Appendix Figures C8 to C11, both when considering all placebo centers (i.e., all provincial capitals in the Center-North) as well as "synthetic" placebo centers obtained with a synthetic control approach matching each IDA center with

Figure 7. Employment Density: Longitudinal Estimates At the Minimum IDA Border

(a) Employment density (b) Manufacturing versus services



Notes: Coefficient estimates for Equation 2, comparing over time municipalities bordering IDA centers to municipalities up to 16 km away from them. The outcome is employment density, measured as number of workers per km^2. Panel (b) shows employment density separately for manufacturing (black diamonds) and services (orange circles). Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the IDAs.

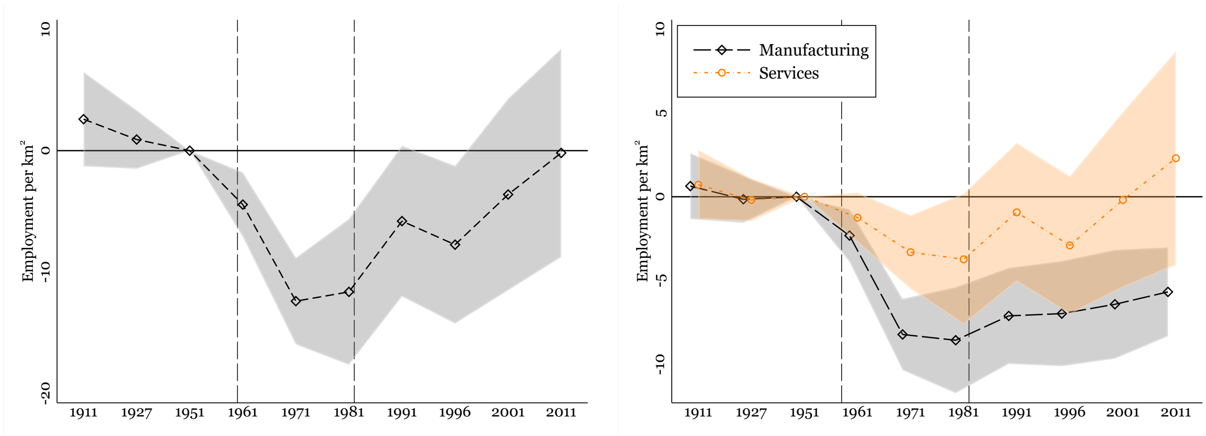
a statistical twin (Section 4 and Appendix B.3). Although less precisely estimated—likely because of the more demanding triple differences specification—the point estimates are very similar to the main findings for both worker and firm density. This, in turn, suggests that our baseline results are not biased by differential trends at the cutoff.

Estimating spatial spillovers. We then directly estimate spatial spillovers. We consider municipalities up to 16 km outside of the minimum IDA border (the control group in the baseline RD design) as treatment group. As new control group, we take their counterpart in the Center-North: municipalities up to 16 km outside of the "placebo" boundary traced by municipalities bordering placebo centers. Again, we repeat the exercise considering either all placebo centers or the matched synthetic controls. This set-up allows us to investigate possible displacement effects to areas right outside of the minimum IDA border. Figure 8 shows the results when considering all placebo centers as controls. Panel (a) documents a negative effect on employment density outside of the minimum IDA border while IDAs were in place, suggesting some displacement as a result of the policy. During the 1970s, these spillovers reached about 10 workers per km^2, vis-à-vis a baseline effect of 30 workers per km^2 in 1981 (Figure 7 Panel a). According to these estimates, roughly one third of the effect of IDAs while they were in place reflects an employment shift around the cutoff. Crucially, these effects tend to fade in the long term: by 2011, we observe little spillovers of the IDA policy. Looking at sectoral patterns in Figure 8(b), displacement effects are largely concentrated in manufacturing (black diamonds), where they also appear to be somewhat

Figure 8. Employment Density: Policy Spillovers to Nearby Control Areas

(a) Employment density

(b) Manufacturing versus services



Notes: Coefficient estimates for Equation B3.2, comparing over time municipalities up to 16 km outside of the minimum IDA border (treatment group) with municipalities up to 16 km away from municipalities bordering placebo centers (control group). The treatment group excludes IDA municipalities. The outcome is employment density, measured as number of workers per km^2. Panel (b) shows the outcome separately for manufacturing (black diamonds) and services (orange circles). Standard errors clustered at the municipality level. Shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the IDAs.

persistent as treated areas still feature lower manufacturing employment density in 2011; in the services sector (orange circles), instead, spillovers are barely noticeable during the policy years and even turn slightly positive in the long term.[20] We find directionally similar spillovers, but smaller in size, when using synthetic placebo centers (Figure C12). Results for firms (Figures C13-C14) show a similar pattern: during the policy years, untreated areas close to IDAs experienced displacement in manufacturing firm density, then compensated by positive spillovers in the services sector in the long run.

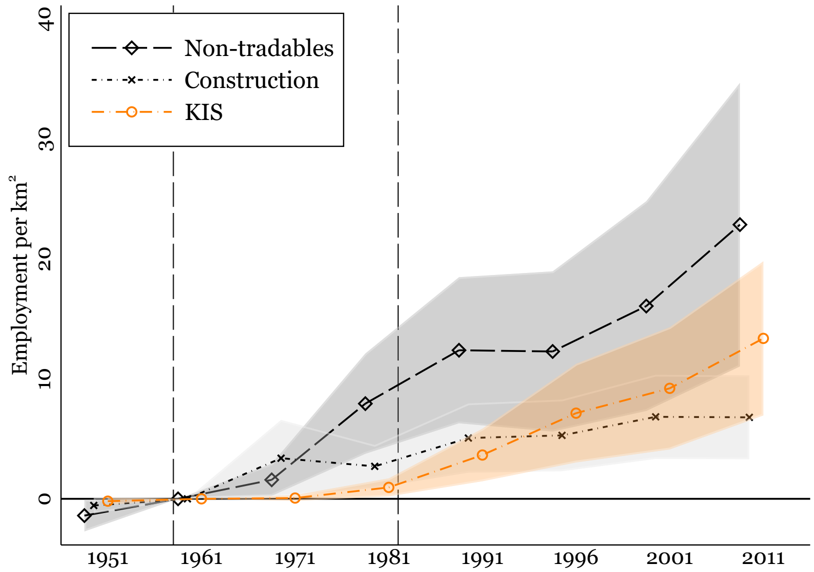
6. Mechanisms

Our results indicate persistent effects of PBIP and highlight clear sectoral patterns. We document an immediate response of manufacturing (the directly subsidized sector) and, to a lower extent, services, during the policy years. As the intervention ceases, the effect on manufacturing stabilizes but employment in services continues to grow. How did the rise in services—a sector which did not directly receive subsidies—take place? To answer, we begin by decomposing the effect on services.

Non-tradables versus KIS. We distinguish between non-tradables (e.g., retail, hospitality) and knowledge-intensive services (KIS, e.g., information technology, business ser-

[20]Consistent with our results, Gerritse et al. (2024) find short-lived and manufacturing-focused migration effects following China's Industrial Transfer Policy.

Figure 9. Employment Density: Decomposition Across Services



Notes: Coefficient estimates for Equation 2, comparing over time municipalities bordering IDA centers to municipalities up to 16 km away from them. The outcome is employment density, measured as number of workers per km^2. Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the IDAs. "Non-tradables": wholesale and retail trade, hotels and restaurants and other (black diamonds). "KIS" (knowledge-intensive services): communication, finance and insurance and services to firms (orange circles). The black crosses denote employment density in the construction sector. We cannot perform the breakdown within services for the 1911 and 1927 historical censuses.

vices) and run our longitudinal analysis (Equation 2) using employment density in each sub-sector as outcome. Figure 9 shows the results. Non-tradables (black diamonds) fully account for the increase in services employment while IDAs were in place. This suggests local multiplier effects: the policy-led stimulus to local manufacturing boosted demand for local goods and services, raising labor demand in the non-tradable sector (Moretti, 2010). Simple calculations using our estimates suggest that one additional manufacturing job per km^2 is associated with 0.95 more services jobs per km^2 at the end of the policy.[21] In line with local multipliers, Figure 9 also shows a rise in local construction (black crosses).

As to KIS (orange circles), we estimate close to null effects during the policy years—which is not surprising as KIS employment in the 1960s-70s was very small in our sample. With time, however, we document a steady increase of KIS, which by 2011 accounted for almost half of the total treatment effect on services employment in IDAs.[22] Results are qualitatively similar for firm density (Figure D1). Importantly, these sectoral patterns do

[21]This number is obtained by dividing the point estimate for services by that for manufacturing for the year 1981 in Figure 7. It is smaller than the long-term multiplier of 1.6 calculated for the United States in Moretti (2010). The smaller multiplier in our setting might be driven by different labor supply elasticity in Italy due, for example, to lower labor mobility.

[22]We also observe continued rise in non-tradable services, likely driven by both multiplier effects (from manufacturing or KIS) and by endogenous agglomeration in urban amenities (Leonardi and Moretti, 2022).

not simply reflect structural change in the suburbs of large cities: they also hold in the auxiliary triple differences design using placebo centers, which confirms an initial increase in non-tradable services in IDAs, followed by a "second-leg" rise in KIS (Figures D2-D3).

Our KIS classification is based on broad sector definitions in the industrial census data. We thus turn to social security data, available at much finer sectoral detail and allowing us to formally define KIS following the Eurostat classification (Appendix A.3). Estimating the cross-sectional RD design (Equations 1a-1b) using this dataset—we cannot conduct longitudinal analysis as the data start in 1990—confirms the above results, with IDA status leading to a larger long-run share of workers and firms in KIS (Table D1).

What led to the rise in KIS? Pecuniary externalities such as multiplier effects can account for the contemporaneous rise in non-tradables, but cannot by themselves explain a persistent response of skilled services. Assuming a multiplier of 1 also after 1981, higher manufacturing employment in treated areas after the end of the policy would account for 50 percent of the increase in services employment in 1991 and only 20 percent in 2011. To investigate the reasons for such enduring growth of the services sector after the end of the policy, we next focus on the *type* of manufacturing stimulated in IDAs.

The role of high-technology manufacturing. Did the policy affect the composition of manufacturing, and if so, did this play a role in the growth of KIS? Using again the social security data, we distinguish between high- and low-technology manufacturing industries based on the Eurostat classification and calculate the share of workers and firms in each group. We then estimate the cross-sectional RD design (Equations 1a-1b) using these shares as outcome, and find a larger incidence of high-technology manufacturing in IDAs at the end of the policy (Appendix Table D1).[23] The stimulus to high-technology industries might have contributed to the subsequent development of KIS in two ways. First, by establishing a local pool of specialized, high-skill workers—a thick labor market externality. Second, by creating demand for business services such as consulting, legal and information technology—a local demand multiplier.[24]

Both channels seem to be at play. To study the first one, we use employer-employee data to compute the share of workers in KIS firms hired each year from high-technology manufacturing firms.[25] Between 1990 (the first year the data are available) and 2011, the

[23]While EIM firm subsidies were, by law, higher for heavy (high-technology) industries, these criteria did not differ between firms in IDAs versus elsewhere. Still, in IDAs, we notice a larger share of subsidies to firms in heavy manufacturing industries (Figure A1.1).

[24]More high-technology industries also imply higher multipliers in non-tradables, as workers in the local tradable sector would command higher earnings and thus demand more local services (Moretti, 2010).

[25]The majority of KIS hires between 1990 and 2011 are from non-employment (mostly higher education). The share of KIS hires via job-to-job transitions is 30 percent in treated areas and 25 percent in control areas.

Table 4. (Log) Wages: Baseline RD estimates

	Total	By sector		Within services	
		Manufacturing	Services	KIS	Other serv.
	(1)	(2)	(3)	(4)	(5)
			Contemporaneous effect (1991)		
RD Estimate	0.13	0.18	0.13	0.26	0.11
	(0.06)	(0.10)	(0.07)	(0.17)	(0.07)
Mean around the border	7.11	7.09	7.13	7.13	7.12
Standard deviation	0.14	0.23	0.19	0.40	0.18
Observations	582	566	570	450	570
			Persistent effect (2011)		
RD Estimate	0.10	0.12	0.12	0.27	0.11
	(0.04)	(0.06)	(0.05)	(0.13)	(0.05)
Mean around the border	7.10	7.09	7.01	7.05	7.00
Standard deviation	0.12	0.19	0.17	0.32	0.18
Observations	586	569	585	490	585

Notes: Fuzzy RD estimates using a binary treatment (IDA status) and a binary instrument equal to one for municipalities within the cutoff—see Equations 1a and 1b. The outcome is the mean (log) monthly wage paid by the firm, averaged across firms in a municipality (see Appendix A.3). We compute it for all firms (Column 1) and then separately by sector (Columns 2-5). Knowledge-intensive services (KIS) defined following the Eurostat/OECD classification (Appendix A.3). All regressions are estimated over a 16-km symmetric bandwidth around the minimum IDA border and control for a linear polynomial in the distance to the border and IDA region effects. Mean and standard deviation computed within the estimation sample. Standard errors clustered by IDA region in parentheses.

share of KIS new hires from high-technology industries rose more rapidly in municipalities bordering IDA centers relative to control areas, bringing evidence in favor of this channel (Figure D4). Assessing the second one is harder. National input-output tables show that high-technology manufacturing industries' demand for skilled services is twice as large as that of low-technology industries (Figure D5). While we lack municipality/firm data on input-output linkages to directly assess this in our setting, we leverage granular sector information in the social security firm data. In Table D2, we zoom into the sub-sectors (within services) that were most stimulated by the policy and observe a higher incidence of business services such as human resources, computer programming, consulting, legal and other professional activities in IDAs.

Wages, education, and skills. The prevalence of KIS jobs should be reflected in higher wages and a more skilled workforce in IDAs. We explore this in Tables 4 and 5, reporting estimates from the cross-sectional RD design (Equations 1a-1b). Table 4 shows a positive effect on mean (log) wages of about 13 log points in 1991, which persists in 2011 at 10

Table 5. Human Capital and Skill Composition: Baseline RD estimates

	High school educ. (1)	Univ. degree (2)	Low-skill (3)	High-skill (4)
	Contemporaneous effect (1991)			
RD Estimate	11.04	5.42	-9.26	11.08
	(3.75)	(2.20)	(3.40)	(4.27)
Mean around the border	15.12	5.60	15.23	17.86
Standard deviation	5.60	3.57	7.81	6.93
Observations	587	587	587	587
	Persistent effect (2011)			
RD Estimate	10.58	9.02	-11.36	9.84
	(3.63)	(3.10)	(3.02)	(3.39)
Mean around the border	35.22	18.56	21.95	25.02
Standard deviation	6.93	5.90	8.10	6.51
Observations	587	587	587	587

Notes: Fuzzy RD estimates using a binary treatment (IDA status) and a binary instrument equal to one for municipalities within the cutoff—see Equations 1a and 1b. Column (1): "High school educ." is the share of people aged at least 6 with high school education or more. Column (2): "Univ. degree" is the share of the resident population aged 30-34 years old with a university degree. Column (3): "Low-skill" is the employment share of residents in low-skill jobs (unskilled occupations—Isco08 code 9). Column (4): "High-skill" is the employment share of residents in high-skill jobs (Legislators, Entrepreneurs, High Executives, Scientific and Highly Specialized Intellectual Professions, Technical Professions—Isco08 codes 1, 2 and 3). All regressions are estimated over a 16-km symmetric bandwidth around the minimum IDA border and control for a linear polynomial in the distance to the border and IDA region effects. Mean and standard deviation computed within the estimation sample. Standard errors clustered by IDA region in parentheses.

log points (Column 1). The wage effect is present in both manufacturing and services (Columns 2-3), and most pronounced in KIS at about 27 log points (Column 4). Table 5 considers instead educational attainments and skills among the resident population. We estimate a persistent effect of 10-11 percentage points on the share of high-school educated (Column 1), and of 5 percentage points on the share of young people with a university degree in 1991, which rises to 9 points in 2011 (Column 2). We also estimate a large positive effect—10-11 percentage points—on the share of high-skilled occupations (e.g., managers and professionals, Column 4), at the expenses of low-skilled ones (Column 3).

Firms. We briefly summarize results for other firm-level outcomes, reported in Appendix Tables D3-D4 and Figure D6. IDA status leads to firm distributions persistently more skewed towards large and high-paying firms. For manufacturing and KIS firms, we estimate positive long-run effects on labor productivity, investment and sales. Manufacturing firms also earn higher profits per worker. While there are no systematically different patterns in overall firm dynamics, we notice interesting heterogeneity across sectors: firm birth and death rates are affected positively in KIS, suggesting high business dynamism; the effects for manufacturing are instead negative, but imprecisely estimated.

Assessing persistence. Given our results, can we say more about the underlying economic mechanisms? Path-dependence in residential choices is likely a primary channel. As we show, many workers were attracted into IDAs by the availability of manufacturing jobs (Figure 8). Such one-off population shocks can have lasting consequences (Schumann, 2014). In our case, workers settling in IDAs likely raised new generations of people who eventually became employed in newly available services jobs, driving the observed effects.

While we cannot directly assess this channel with the data at hand, we can rule out that it is the only one at play. First, we show longitudinal estimates (Equation 2) using outcomes in logarithms. In case of a one-off level shift, any positive effect on log-employment would appear once and level out afterwards. Figure D7 shows instead rising effects—especially in services—indicating that the policy led to a divergence in *growth rates* between treated and control areas and not simply a one-off, path-dependent shift in local economic activity.

Second, we exploit placebo centers to assess the geographic scale of the effects and, in turn, infer whether they only reflect the above neighborhood-level channels linked to residential choices, or also broader labor market channels (Bartik, 2022). We run longitudinal regressions comparing, first, municipalities bordering IDA centers with those bordering placebo centers; then, we gradually enlarge both the treatment and control groups by including municipalities farther away from centers. To improve comparability, we weight control municipalities using synthetic weights (Appendix B.3 provides more detail on this exercise). While residential effects should feature prominently in estimates for the starting sample, coefficients estimated at higher levels of aggregation should capture broader market effects. Figure D8 shows the estimates. Coefficients are larger when using only municipalities bordering IDA centers and their placebo counterparts—a very local effect where the residential channel is likely at play. As we consider more extensive areas in our sample, estimates decrease in magnitude but remain positive and significant. This suggests that, while neighborhood-level channels explain our baseline results to a large extent, *part of* those effects also reflects additional, local labor market-level channels.

More precisely, local labor markets in host locations may have undergone a process of structural transformation following the policy, continuing to benefit from knowledge spillovers and a specialized labor pool developed while IDAs were in place. In other words, results are consistent, in principle, with the presence of agglomeration economies.[26]

[26]Following government intervention, the targeted areas witness an increase in economic density. In the presence of knowledge spillovers or thick market externalities, higher proximity between agents boosts local

Admittedly, our empirical design based on local spatial variation is not well suited to precisely identify such externalities, which should arise at higher levels of aggregation as showed in the previous exercise. Still, additional findings showed in Table D5 at least do not exclude the presence of agglomeration economies. First, we document long-term effects on local house prices, suggesting rising congestion in IDAs.[27] Local incomes are higher, too—although this seems to have come with higher local inequality as evidenced by the higher Gini coefficient. Second, sectoral specialization within manufacturing—measured with the Krugman Specialization Index (Krugman, 1992)—has *decreased* in IDAs, suggesting that the benefits of subsidies extended beyond the targeted industries and led to a diversified industrial structure. Last, we show no discontinuity in municipal government expenditure, EU structural funds, and other government transfers at the cutoff—ruling out another possible source of persistence linked to continued public investment in treated areas (von Ehrlich and Seidel, 2018). That said, we cannot rule out that other local policies and regulations (that we do not account for) explain, at least in part, our persistent effects.[28]

7. Cost-benefit analysis

While our findings highlight a positive impact of the policy, we have not yet considered its costs. We therefore use our estimates to inform a cost-benefit analysis of the IDA program. Appendix E provides more detail.

Cost per job. We begin by calculating the cost per job. While relatively straightforward, this measure provides an easy way to compare policies with each other. We first use the empirical estimates of Table 3, Column (3), suggesting that an increase in EIM funding of €1,000 per 1951 resident leads to 10.3 more workers per km^2 in 2011. For the average municipality in the estimation sample, these estimates translate in a cost per job of €17,989 or $25,048 (2011 prices), which rises to $37,571 assuming a deadweight loss of 50 percent.[29] Using the long-run longitudinal estimates (Figure 7 Panel a) delivers a similar cost per

productivity, generating a virtuous cycle lasting until local prices grow high enough. Government subsidies that internalize these externalities have an efficiency justification (Duranton and Puga, 2004; Moretti, 2011).

[27]While the intervention was not directly aimed at improving residential amenities in host locations, infrastructure works such as better transportation networks might also have made IDAs more desirable places to live, which may explain—on top of the labor demand increase—the observed rise in house prices.

[28]Another regional policy conducted after 1992—the *Area Contracts*—only involved one of the IDAs (Salerno) and brought relatively modest investments (€1.9 billion between 1998 and 2007).

[29]For a similar analysis see Freedman (2012). The magnitude of the deadweight loss largely depends on the effect of place-based policy on location decisions (Busso et al., 2013). While we estimate no migration effects in the long run, our results suggest that IDAs attracted immigrants while they were in place. We therefore assume a 50 percent deadweight loss as in Criscuolo et al. (2019) and Siegloch et al. (2022).

job of \$21,716 (\$32,575 including deadweight loss), which remains roughly stable when substituting in the estimates from the triple differences design. The cost per job of the IDA policy falls not far from the range of estimates for similar programs in the US (Busso et al., 2013), Germany (Siegloch et al., 2022), Japan (Lapoint and Sakabe, 2022) and the UK (Criscuolo et al., 2019), and is smaller than that estimated for Law n.488/1992—a subsidy program introduced in Italy after the EIM, which did not lead to large employment effects (Cerqua and Pellegrini, 2014; Cingano et al., 2022).

Cost-benefit analysis. We then conduct a broader cost-benefit analysis building on the method proposed in Busso et al. (2013) and applied in Chaurey (2017), Lu et al. (2019) and Lapoint and Sakabe (2022). In contrast to these studies, our extended time horizon allows us to evaluate the local benefits of the program long after its termination, and compare them with the costs. The benefits of the IDA policy accrue to local workers, firms and landlords in the form of wages, profits and rents, respectively. For each of these outcomes, we estimate long-term gains as the present discounted sum (1991 to 2011) of the yearly differences between their observed value and the counterfactual value obtained using our regression estimates. We estimate that IDAs generated a total gain of €86 billion between 1991 and 2011, with most benefits accruing to workers and, to a lower extent, firms. Total IDA costs can be computed in the ASET data and amount to €88 billion. The gains generated locally by IDAs after their termination thus roughly cover the costs of the program. In turn, this suggests net benefits assuming that the policy induced gains also while it was in place or after 2011.

We caveat that this analysis abstracts from possible general equilibrium effects of the policy. While spillovers to control municipalities close to IDAs have been showed to be short-lived and not substantial (Section 5), our design cannot assess crowding-out of workers and firms elsewhere in the country. These general equilibrium considerations fall beyond the scope of our paper, but are nevertheless relevant for cost-benefits assessments since the costs of the program were largely sustained by the central government. Cerrato and Filippucci (2024) tackle these aspects through a macro-structural model.

8. The role of initial conditions

The final part of our analysis explores how the long-run effects of PBIP depend on the characteristics of the targeted areas, with a specific focus on their initial conditions.

Heterogeneity. We first explore heterogeneous results across IDAs. We split the 12 IDA regions in our sample into two sub-groups based on whether a region is above or below the median value for variables capturing local geographic and economic characteristics (recall IDA regions comprise all municipalities within 25 km of each IDA center). We then estimate Equation 2 separately for IDAs above and below the median. As showed in Figure F1, the largest differential effects are found when splitting the sample of IDAs based on education levels in 1951. IDAs with larger initial human capital endowment were also those where the policy had a larger employment impact in the long term.[30] Still, some persistence in the effect of the policy remains visible across all heterogeneity cuts. Our set-up is admittedly not best suited to heterogeneity analysis because of the relatively small sample size and the RD design. To further investigate heterogeneous results, we conduct our analysis in other areas of Southern Italy, which also received EIM subsidies.

The EIM border. As summarized in Appendix B.4 and detailed in Albanese et al. (2024), the northern border separating the EIM region from the rest of Italy gives rise to a spatial RD design comparing areas south of the border, which received firm subsidies and infrastructure investments from the Cassa, to areas north of it. For sake of brevity, Figure 10 shows the most robust estimates from a longitudinal design comparing employment density in treated and control areas before and after the onset of the EIM in 1950 (Equation B4.2).[31] As showed in Panel (a), areas north and south of the border were on parallel trends before 1950. A positive effect emerges in the 1970s, though not statistically significant. The coefficient peaks at the end of the EIM in 1991 but eventually declines, showing no lasting impact of the intervention. Panel (b) breaks down the effect between manufacturing (black diamonds) and services (orange circles). Similarly to IDAs, manufacturing employment rises during the policy years but stabilizes as the incentives terminate. However, in stark contrast with the case of IDAs, services *do not* respond to subsidies.

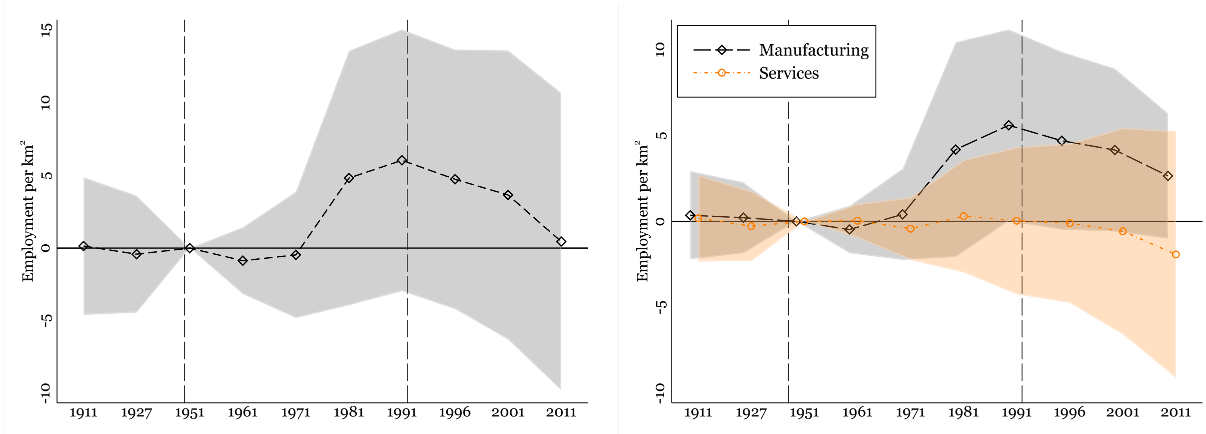
The key results presented in Section 6 do not hold at the EIM border (Appendix F). The share of workers and firms in KIS and high-technology manufacturing is unaffected. Wages are higher south of the border in 1991, but only in manufacturing and non-tradable services. By 2011, the wage effect has disappeared. We find no effect on local educational attainments, and even a small decline in the share of high-skill occupations. Last, we find no impact on local incomes and even negative long-run effects on house prices.

[30]These results resonate with Gagliardi et al. (2023), who find that the effects of deindustrialization on local employment vary greatly depending on the share of college-educated in the local workforce.

[31]Cross-sectional RD plots and RD estimates at the EIM border are in Appendix Figures F2 to F7 and Table F1. Figure F8 shows the longitudinal coefficients for firm density.

Figure 10. Employment Density at the EIM Border: Longitudinal Estimates

(a) Employment density | (b) Manufacturing versus services



Notes: Coefficient estimates for Equation B4.2, comparing over time municipalities south and north of the EIM border—see Appendix B.4. The outcome is employment density, measured as number of workers per km^2. Panel (b) shows employment density separately for manufacturing (black diamonds) and services (orange circles). Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the EIM.

Initial conditions. While government intervention led to broad and persistent results in IDAs, its effects at the EIM border were concentrated in the targeted manufacturing sector and dissipated shortly after the end of subsidies. These divergent findings may depend on different initial conditions. Table 6 provides suggestive evidence in this regard, comparing municipalities bordering IDA centers (Column 1) to municipalities south of the EIM border (Column 2). The two groups do not differ much in the amount of per capita funding from the Cassa. There are, however, substantial differences in preexisting (1951) agglomeration of workers and firms, which was two to three times larger in municipalities contiguous to IDA centers. This should not come as a surprise as these areas were, essentially, suburbs of large cities. Places south of the EIM border had instead much less favorable geography, a larger share of workers in agriculture and a less educated population before the policy. Put differently, IDAs were explicitly selected as hubs for future agglomeration and development of a skilled workforce. Instead, areas around the EIM border were more peripheral and, arguably, less suited to the formation of local clusters. Indeed, EIM firm subsidies at the border went mostly to low-technology industries such as textiles and food (Figure F10), as opposed to more advanced industries in the case of IDAs (Figure A1.1).

This exercise is necessarily suggestive, as we cannot rule out that other factors—such as the presence of consortia in IDAs—contributed to the stark differences observed between the two cases.[32] Nonetheless, the finding that the same place-based subsidies,

[32] Another possible explanation for these findings lies in the role of expectations. In models with multiple steady states, agents' expectations that a community will be in a developed equilibrium can become self-

Table 6. The IDAs Versus the EIM Border: Descriptive Statistics

	IDAs (1)	EIM border (2)
Firm subsidies	4.99	4.53
	(10.51)	(8.21)
Infrastructure spending	2.62	3.10
	(5.18)	(4.76)
Employment density (1951)	19.01	7.47
	(23.09)	(14.31)
Establishment density (1951)	8.33	3.43
	(8.55)	(5.11)
Manuf. employment density (1951)	9.47	3.10
	(13.76)	(6.19)
Manuf. establishment density (1951)	3.44	1.64
	(3.64)	(2.25)
Population density (1951)	307.76	111.81
	(318.29)	(104.39)
Agriculture share (%, 1951)	31.28	34.49
	(13.53)	(12.00)
High school education (%, 1951)	2.17	1.84
	(1.20)	(0.88)
Mean elevation	188.38	728.24
	(153.53)	(440.26)
Slope	417.26	947.85
	(460.47)	(572.53)
Seismicity	2.80	1.66
	(0.91)	(0.72)
Number of municipalities	95	168

Notes: Means are computed separately for each group and standard deviations are in parentheses. Column (1) restricts the sample to municipalities bordering IDA centers and Column (2) to municipalities 50 km south of the EIM border. The sample excludes municipalities 50 km south of the EIM border that belong to IDAs. "Firm subsidies" and "Infrastructure spending" measured in thousand € (2011 prices) per 1951 resident, winsorized at 1 and 99 percent. Employment and establishment density computed as number of workers and establishments per km^2. We also show these separately for the manufacturing sector. "Population density" is the number of residents per km^2. "Agriculture share" computed as the number of agriculture workers per 100 residents aged at least 15. "High school education" denotes the share of people aged at least 6 with high school education or more. "Mean elevation" measured in meters. "Slope" denotes the distance in meters between the highest and the lowest point in the municipality. "Seismicity" is a categorical variable ranging from 1 "High seismicity" to 4 "Very low seismicity".

implemented under the same policy, led to markedly different outcomes across targeted areas is both striking and novel. This evidence highlights that whether the local impact of PBIP is broad and persistent versus short-lived and limited to subsidized industries may depend, at least in part, on the preexisting conditions of host locations. Importantly,

fulfilling (Kline, 2010). The policymaker committed to establishing local hubs in IDAs, while there was no such explicit commitment for the areas around the EIM border.

this perspective helps reconcile our results with prior evidence on development policy in Southern Italy, which has so far documented only small and transitory economic benefits to these regions.

9. Conclusion

The shift away from manufacturing employment experienced by most industrialized countries has come at the cost of substantial increases in regional inequality. As place-based industrial policies (PBIPs) aimed at assisting "left-behind" industrial districts gain renewed popularity, many questions arise about their effectiveness and potential drawbacks. Can policies targeting the formation of industrial clusters promote economic development? Do they play any role in the transition of clusters out of industry and into knowledge-based local economies?

We tackle these questions by analyzing a PBIP conducted in Italy during the 1960s and the 1970s. Our findings illustrate that PBIPs can lead to continued agglomeration of workers and firms in targeted areas, persisting well after the end of the intervention. We show that these long-run effects are tightly intertwined with the response of the services sector, as the initial boost to manufacturing stabilizes when government incentives are phased out. In particular, the development of high-skill services jobs suggests technological adaptation in local communities. We stress that the policy-induced promotion of high-technology manufacturing has played a key role in this process, through both increased demand of business services and the establishment of a high-human capital local labor force. We speculate that these persistent effects reflect both neighborhood-level channels linked to path dependence in residential choices, as well as broader structural transformations in local labor markets.

As advocated in Rodrik and Stantcheva (2021) and Rodrik (2022), the lasting impact of industrial policy hinges on the creation of "good jobs" and "good jobs externalities". While our analysis of an historical program resonates with these views, we also provide suggestive evidence that preexisting local conditions in the targeted areas may be an important determinant of persistent effects. Taken together, our evidence has relevant implications for the future of industrial policy, but also warrants further investigation and provides ground for future research.

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A. Appendix A: Background and data

A.1. Appendix A1: The EIM subsidies

As described in Section 2, the two main policy items managed by the Cassa were infrastructure spending and, starting in the 1960s, firm investment grants.

Infrastructure spending. The policy goal during the first decade of the EIM was improving infrastructure in Southern Italy. The Cassa was in charge of planning and monitoring of initiatives in four domains (agriculture, drains and aqueducts, transport and tourism). Project proposals were transmitted by local bodies to the Cassa for investigation and approval. Upon approval, the Cassa launched a public tender to procure the execution. Often, both the formulation and execution of the initiatives were performed directly by the Cassa.

Firm grants. Starting in 1960, the focus of the EIM shifted towards industrial policy to stimulate investment in the South. The main policy item was firm investment grants. Grant applications were submitted by firms to special credit institutions in charge of evaluating the proposed investment (including estimated job creation). The applications were then forwarded to the Cassa, which decided on the outcome and the amount of the subsidy (we only observe successful applications in the data). The specific allocation criteria changed several times over the course of the EIM.[33] During the 1960s-70s, the key inputs for the subsidy rate were firm size, sector, and location. More precisely, small firms, firms in heavy industries, and firms located in IDAs could obtain a higher subsidy rate on their investment (up to 6.5 percentage points higher, separately for each of these three criteria). The maximum subsidy rate, originally set at 20 percent, has been periodically increased and reached 45 percent by 1971. Firms could apply for concessional loans, too. The sum of grants and loans conceded by the Cassa to a single firm could not exceed 85 percent of the total investment by the firm.

The IDAs. The establishment process for IDAs is described in Section 2. Here we clarify how investment grants differed for IDA firms compared to other firms in the EIM area. Firms in IDAs were entitled to larger subsidies in two ways. First, the subsidy rate was up to 6.5 percentage points higher for IDA firms than for other EIM firms, as mentioned above. Second, all IDA firms could access grants regardless of size, while there where limits to

[33] All relevant documents and laws (in Italian) are stored in the ASET digital library: https://aset.acs.beniculturali.it/aset-web/biblio.

Table A1.1. Cumulative EIM Expenses Per Decade

	Total expenses		Infrastructure spending		Firm subsidies	
	Amount	Per capita	Amount	Per capita	Amount	Per capita
1950-1959	5,309	236.4	5,290	235.5	19	0.8
1960-1969	29,990	1,335.2	8,607	383.2	21,382	952.0
1970-1979	79,439	3,536.9	26,368	1,174.0	53,071	2,362.9
1980-1989	37,270	1,659.4	16,781	747.2	20,489	912.3
1990-1992	13,494	600.8	3,635	161.8	9,859	439.0
Total	165,502	7,368.7	60,681	2701.7	104,821	4,667.0

Notes: EIM expenses (total and by expenditure item) by decade. Raw amounts in € million (2011 prices). Per capita amounts in € (2011 prices) per 1951 inhabitant in the EIM region. Amounts computed only from geo-coded interventions available in the ASET database.

both firm size (up to 500 workers, investment below €1.5 million) and municipality size (up to 75,000 people) for firms located elsewhere in the EIM region.[34] These size limits were removed in 1967. Subsidy rates were equalized between IDA and non-IDA firms in the late 1970s. Together with the IDAs, the government also introduced the so-called *Industrialization Nuclei* to favor "*minor concentration*" (see footnote 34). The Nuclei were less extensive areas (usually just one municipality) where a small number of firms could take advantage of local raw materials and a specialized workforce. The contiguity rule, which inspires our identification strategy, did not apply to the Nuclei. The 79 municipalities included in Nuclei are dropped from our analysis and estimation sample.

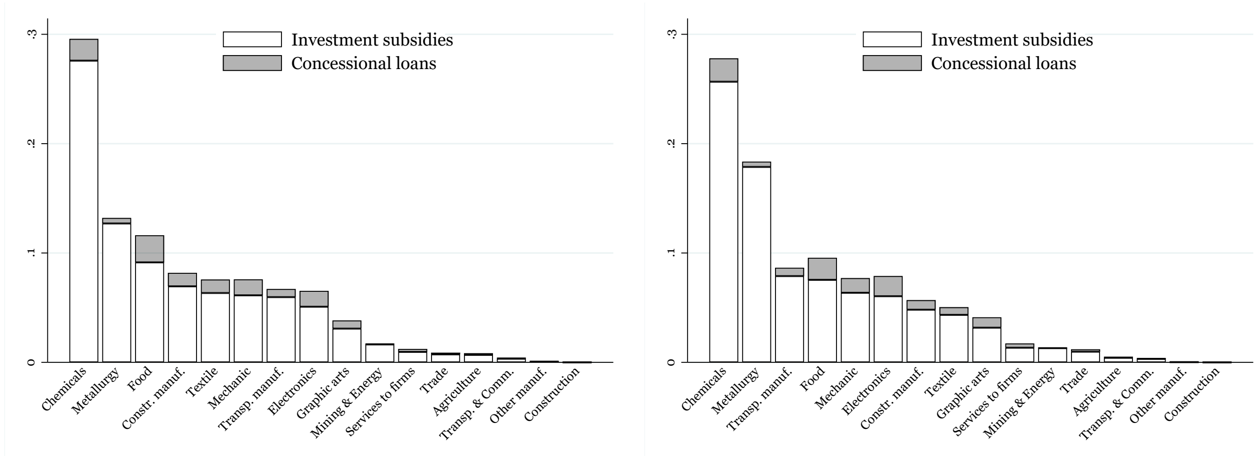
The ASET data. The ASET archives record information on the universe of transfers by the Cassa, separately by type of intervention: 76,445 infrastructure projects (49,579 public works and 26,866 agricultural improvements), 112,622 investment subsidies and 62,902 concessional loans to firms. We do not have information on subsidized firms, except for their sector. Each dataset reports the (current euro) amount, date and location of the intervention. We drop interventions for which information on date, amount or location is missing, along with those with negative amount or for which the date lies outside of the EIM lifespan (1950-1992). We also drop interventions whose location is not a single municipality but a province or a region. The amounts are converted to 2011 prices using the GDP deflator. Table A1.1 reports EIM expenses cumulated by decade and split between infrastructure spending and subsidies to firms, both in raw amounts and per 1951 resident.

[34] To provide more context, the Cassa was pursuing two policy goals: *i*) "*industrial concentration*", establishing large industrial clusters (the IDAs) or smaller ones ("*Industrialization Nuclei*", briefly described in this paragraph); and *ii*) "*industrial diffusion*", favoring industrial development in peripheral regions by supporting firms in municipalities with limited industrial activity.

Figure A1.1. EIM Transfers to Firms: Breakdown Across Industries

(a) Full EIM area

(b) IDAs



Notes: Breakdown of firm investment subsidies (white bars) and concessional loans (gray bars) across sectors based on the sector where the subsidized firm operates. Panel (a) includes incentives to firms in the full EIM area. Panel (b) considers IDA municipalities only.

Figure A1.1 breaks down firm grants and loans across sectors. Panel (a) shows that about 30 percent of total subsidies went to the chemical sector, while between 7 and 15 percent to other industries such as metallurgy, food and textile. Panel (b) focuses on IDAs, where chemicals remain the most subsidized sector at almost 30 percent, followed by other heavy industries such as metallurgy (20 percent) and transport manufacturing (10 percent). We notice that transfers to firms are almost entirely in the form of grants, while loans are more limited. Last, the share of firm subsidies in the services sector is negligible.

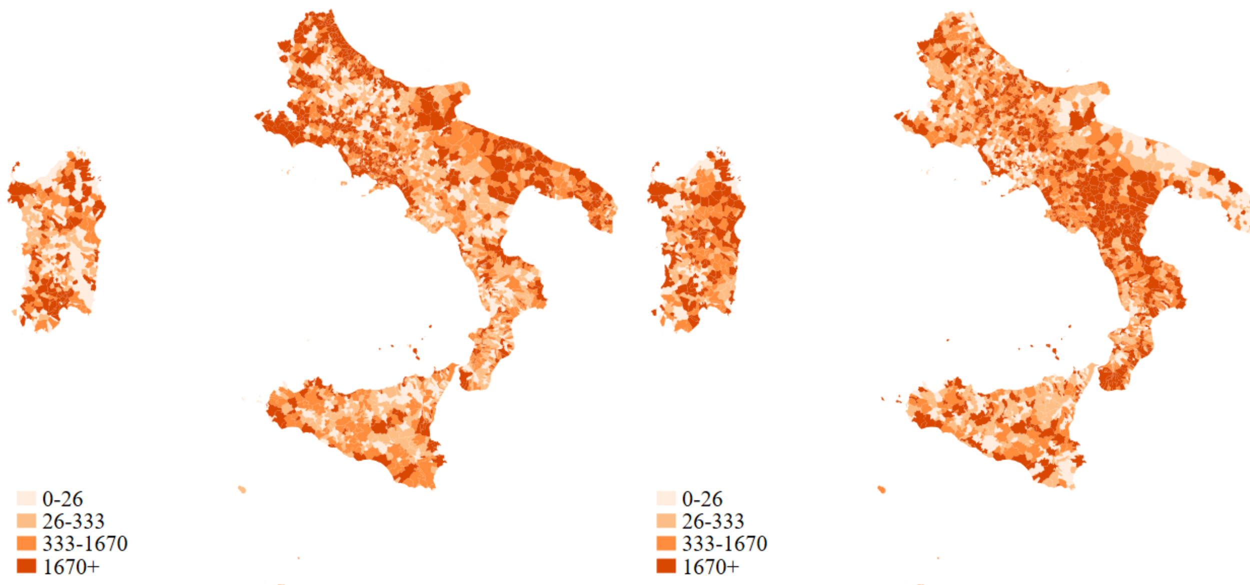
Figure A1.2 plots the distribution of EIM expenses across municipalities in the EIM area, separately by expenditure item. The EIM jurisdiction included ten regions: Abruzzo, Basilicata, Calabria, Campania, Lazio, Marche, Molise, Apulia, Sardinia and Sicily. The territories of all these regions, except for Lazio and Marche, traditionally define the Italian South (the EIM region also included some small islands of Tuscany, which we drop from the sample). We observe that firm subsidies are largely concentrated in the IDAs (Panel a), while infrastructure spending is most pronounced in the internal areas (Panel b).

A.2. Appendix A2: Industrial censuses

We collect data on the number of workers and establishments by sector across Italian municipalities from decennial industrial censuses between 1951 and 2011 (including an intermediate census in 1996), sourced from the Istat website. We complement the data by hand-digitizing the 1911 and 1927 industrial censuses, available only in pdf format in the Istat historical archives. We use 1991 administrative boundaries, and match the post-World War II censuses with the historical censuses using municipality names. To

Figure A1.2. Cumulative EIM Expenses Across Municipalities (1950-1992)

(a) Firm subsidies (b) Infrastructure expenses



Notes: Panel (a) shows EIM firm investment subsidies in € (2011 prices) per 1951 inhabitant, cumulated between 1950 and 1992. Panel (b) shows EIM infrastructure spending in € (2011 prices) per 1951 inhabitant, cumulated between 1950 and 1992.

correct for municipality name changes, annexations, and mergers we rely on a database reporting all administrative changes since Italy's unification in 1861 (`www.elesh.it`). We exclude municipalities in the 1911 and/or the 1927 census that are then split into two or more municipalities in the post-War censuses.

The data also report a sector breakdown between manufacturing (food, textile, wood, metallurgy, mechanic, mineral, chemical, rubber, plastic and others), construction, mining, energy and services (wholesale and retail trade, hotels and restaurants, transport, communications, finance and insurance, firm services and other services).[35] We exploit the within-manufacturing sectoral breakdown to compute a measure of sectoral concentration—the Krugman Specialization Index (Krugman, 1992):

$$KrugmanIndex_{m,t} = \sum \left| \frac{y^s_{m,t}}{y_{m,t}} - \frac{y^s_t}{y_t} \right| \tag{A2.1}$$

Where $y^s_{m,t}$ is the number of manufacturing workers in municipality m, census year t and sector s, $y_{m,t}$ is the number of manufacturing workers in municipality m and census year t, y^s_t is the number of manufacturing workers in the reference group in census year t and sector s and y_t is the number of manufacturing workers in the reference group in census

[35]The 1927 and 1911 censuses only separate between broad manufacturing and services. The 1911 Census of Factories and Industrial Enterprises only covered firms in manufacturing and "collective needs" services.

year t. The index provides a simple, time-varying measure of sectoral specialization in municipality m relative to a reference group, which we set here as all Italian regions except for the more developed regions of the North (Lombardy, Veneto and Piemonte) and the small regions close to the Alps (Valle d'Aosta, Friuli Venezia Giulia and Trentino Alto Adige)—areas with likely uncomparable industrial structure to that of the EIM regions.

A.3. Appendix A3: Administrative social security data

Firms. We collect data on the universe of firms in the Italian private sector from the archives of the Italian Social Security Institute (INPS) between 1990 and 2015, available at the Bank of Italy. For each firm, the data report the number of employees, the average monthly earnings, the 6-digit sector (based on Eurostat's NACE Rev. 2 groups) and the municipality. Using firm tax identifiers, we match this dataset with balance sheet information from the Cerved group, available for limited liability corporations since 1995. The Cerved data report detailed income statements including firm sales, value added, profits and investment. We narrow our focus to firms in the non-agricultural private sector and exclude NACE codes 1 to 3, 84 to 88 and 97 to 99, corresponding to agriculture, public sector and families as employers. This selection is standard for the Italian data, as these industries are only partially represented in the social security archives. The detailed sector information allows us to adopt Eurostat/OECD classifications to manufacturing and services—namely, we break down manufacturing into high- and medium-high-technology versus low- and medium-low-technology, and services into knowledge-intensive and other services.[36]

Workers. We obtain social security data consisting of the work and pay history (1990 to 2011) of a 7 percent random sample of private-sector workers, which we link to the firm data to construct a matched employer-employee dataset. For the period of analysis and for each worker-firm match, we observe all the information related to social security contributions on a yearly basis, including the annual gross earnings, the number of weeks and days worked, whether the schedule is part-time or full-time, or whether the contract is fixed-term or open-ended. We also observe some demographic characteristics such as gender, year of birth, and region of residence. The data allow to reconstruct all labor market transitions of the included workers, and can thus be used to compute hiring rates as discussed in Section 6. We define new hires in a given year t as workers experiencing non-employment to employment and firm-to-firm transitions between $t-1$ and t.

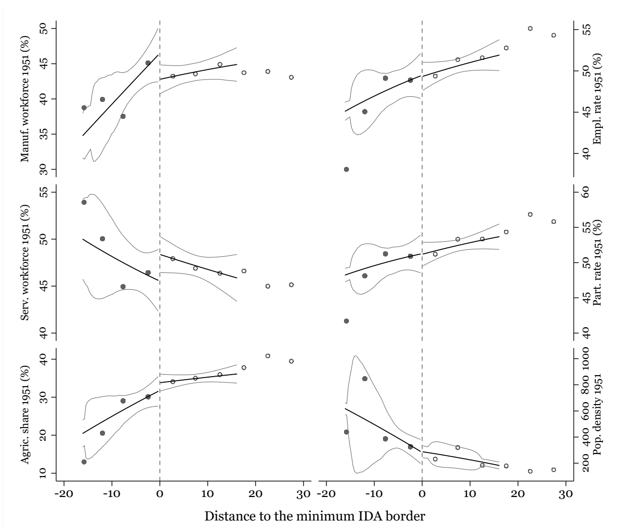
[36]Detailed industry classifications are available here https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:High-tech_classification_of_manufacturing_industries; and here https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Knowledge-intensive_services_(KIS).

B. Appendix B: Identification

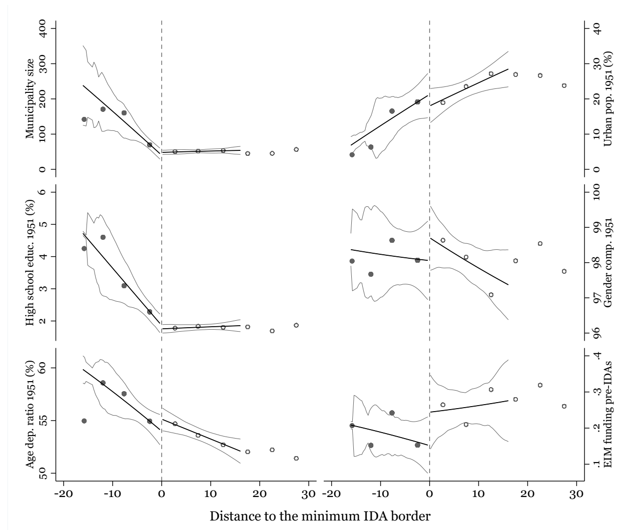
B.1. Appendix B1: Balancing at the minimum IDA border

Figure B1.1. Balancing at the Minimum IDA Border: Additional Variables

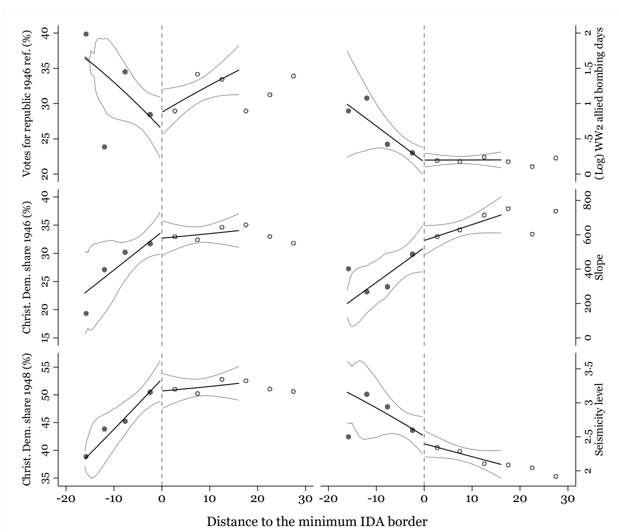
(a)



(b)



(c)



Notes: Panel (a): "Manuf. workforce" and "Serv. workforce" are the shares of manufacturing and services workers over the total number of workers in the 1951 industrial census, respectively. "Agric. share" computed as the number of agriculture workers per 100 residents aged at least 15. "Empl. rate" is the ratio of employed people to total residents aged 15 years and older. "Part. rate" is the ratio of the resident population participating in the labor market to the resident population of the same age group. "Pop. density" is measured as number of inhabitants per km2. Panel (b): "Municipality size" is the total area of the municipality in km2. "High school educ." denotes the share of people aged at least 6 with high school education or more. "Age dep. ratio" is the share of those aged below 14 and above 65 to those aged 15-64. "Urban pop." is the share of resident population living in cities. "Gender comp." is the ratio of male to female population. "EIM funding pre IDAs" is total EIM infrastructure spending per capita before 1960. Panel (c): "Votes for republic" is the votes share in favor of republic versus monarchy at the 1946 referendum. "Christ. Dem. share" is the votes share for Christian Democrats, showed separately for the 1946 and 1948 election. "WW2 allied bombing days" is the number of days of allied bombing during World War II (Gagliarducci et al., 2020). "Slope" is the difference in meters between the highest and lowest point of the municipality. "Seismicity level" is a categorical variable ranging from 1 "High seismicity" to 4 "Very low seismicity". Negative distance denotes municipalities within the minimum IDA border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately at each side of the border using a symmetric 16-km bandwidth. The gray lines are 95 percent confidence intervals. Appendix Table B1.1 shows the corresponding coefficient estimates.

Table B1.1. Balancing at the Minimum IDA Border: Coefficient Estimates

(a): Fig. 4	Empl. dens.	Manuf. empl.	Serv. empl.	Est. dens.	Manuf. est.	Serv. est.
RD Estimate	6.50	4.12	2.19	1.49	0.41	0.90
	(3.17)	(1.40)	(1.97)	(1.52)	(0.52)	(0.91)
Mean	15.75	7.01	7.24	7.03	2.87	3.95
S.D.	25.09	11.85	12.05	9.23	3.30	5.80
Observations	586	586	586	586	586	586
R^2	0.15	0.16	0.16	0.20	0.20	0.20

(b): Fig. B1.1(a)	Manuf. work.	Serv. work.	Agric. share	Empl. rate	Part. rate	Pop. dens.
RD Estimate	1.67	-2.16	-3.80	-0.70	-0.53	34.26
	(1.83)	(1.36)	(1.86)	(1.01)	(1.02)	(80.33)
Mean	43.76	47.01	33.73	50.21	52.10	267.44
S.D.	12.57	11.84	12.97	9.51	9.23	602.66
Observations	563	563	563	563	563	563
R^2	0.20	0.17	0.28	0.42	0.46	0.09

(c): Fig. B1.1(b)	Muni. size	High school	Age dep.	Urban pop.	Gender	Pre-IDA exp.
RD Estimate	24.33	0.57	-0.85	2.52	-0.58	-0.06
	(11.45)	(0.23)	(0.54)	(3.90)	(0.59)	(0.07)
Mean	59.67	1.97	54.05	21.95	98.05	0.24
S.D.	72.37	1.20	5.95	25.05	4.78	0.46
Observations	586	563	563	537	563	563
R^2	0.20	0.17	0.46	0.63	0.25	0.07

(d): Fig. B1.1(c)	Rep. 1946	CD 1946	CD 1948	WW2 Bomb.	Slope	Seism.
RD Estimate	1.03	-0.71	-0.68	0.13	-27.45	-0.03
	(2.14)	(2.67)	(2.49)	(0.13)	(57.73)	(0.04)
Mean	31.26	32.83	50.85	0.24	598.33	2.34
S.D.	17.43	15.09	15.73	0.63	515.50	1.03
Observations	550	545	545	587	587	513
R^2	0.32	0.12	0.18	0.20	0.26	0.85

Notes: Estimation output of Equation 1b using a 16-km symmetric bandwidth around the minimum IDA border. The specification controls for a linear polynomial in the distance from the border and IDA region effects. Mean and standard deviation (S.D.) computed within the estimation sample. Standard errors clustered by IDA region in parentheses. Each Panel in the table refers to a RD plot: Panel (a) refers to Figure 4, Panel (b) to Figure B1.1(a), Panel (c) to Figure B1.1(b) and Panel (d) to Figure B1.1(c). See Figure 4 and Figure B1.1 for details and descriptions of each outcome.

B.2. Appendix B2: Identification details

Main identification. Here, we describe more formally the identification strategy of the paper. The outer boundaries of the municipalities contiguous to the IDA center trace a "minimum" IDA border $\mathcal{I}$ that separates two regions within ($\mathbb{W}$) and outside ($\mathbb{O}$) of this boundary. Let the centroid of municipality m be denoted by the latitude-longitude pair $\ell_m = (l_{x,m}, l_{y,m})$. Let also $\delta_m \equiv d(\ell_m, \mathcal{I})$ denote the geodesic distance between municipality m's centroid and the minimum border of the closest IDA, with negative values of δ_m assigned to municipalities in the within region $\mathbb{W}$ (i.e., the IDA center and its contiguous municipalities). The binary instrument $W_m = \mathbb{1}[\ell_m \in \mathbb{W}] = \mathbb{1}[\delta_m \leq 0]$ identifies these municipalities. Let also IDA_m be a treatment indicator equal to one for municipalities belonging to an IDA. This identification strategy rests on three main assumptions:

A1. Relevance. *The minimum IDA border induces a discontinuous jump in treatment status* IDA_m: $\lim_{\delta_m \to 0^+} Pr(IDA_m = 1 \mid \delta_m) < \lim_{\delta_m \to 0^-} Pr(IDA_m = 1 \mid \delta_m)$.

A2. Continuity. *Mean potential outcomes* $E[Y_m(0) \mid \delta_m]$ *and* $E[Y_m(1) \mid \delta_m]$ *are continuous at* $\delta_m = 0$.

Where $Y_m(0)$ and $Y_m(1)$ denote potential outcomes under control and treatment status, such that $Y_m = Y_m(0) + IDA_m \cdot (Y_m(1) - Y_m(0))$.

A3. Local monotonicity (no defiers). *There exists a neighborhood* $\mathbb{S}$ *of the cutoff where no municipality is such that:* $IDA_m(\delta_m) = 1 - W_m$

Where $IDA_m(\delta_m)$ denotes potential treatment selection as a function of the running variable. Three municipality types are therefore allowed in the proximity of the cutoff: always-takers ($IDA_m(\delta_m) = 1$), never-takers ($IDA_m(\delta_m) = 0$) and compliers ($IDA_m(\delta_m) = W_m$). Under Assumptions A1, A2 and A3, the fuzzy RD estimand $\beta = \pi/\vartheta$ identifies the local average treatment effect (LATE) for compliers at the cutoff (Hahn et al., 2001).

(Fuzzy) Difference in discontinuities. We discuss identification for the longitudinal design introduced at the end of Section 4, drawing on the difference-in-discontinuities literature (Grembi et al., 2016; Millán-Quijano, 2020). Let the time indicator $P = \mathbb{1}[year \geq 1960]$ denote the census years after the introduction of the IDAs. Let us also introduce two treatments W_m^p and IDA_m^p where the superscript $p \in \{0, 1\}$ denotes the period. In particular:

$$W_m^p = \begin{cases} \text{if } \delta_m > 0: \ 0 & \forall p \\ \text{if } \delta_m \leq 0: \ 1 & \forall p \end{cases}$$

$$IDA_m^p = \begin{cases} \text{if } p = 0: \ 0 \\ \text{if } p = 1: \ \lim_{\delta_m \to 0^+} Pr(IDA_m = 1 \mid \delta_m) < \lim_{\delta_m \to 0^-} Pr(IDA_m = 1 \mid \delta_m) \end{cases}$$

In words, W_m^p denotes whether a municipality borders a provincial capital (an IDA center) and depends solely on the running variable δ_m and not on the time period. IDA_m^p denotes IDA status and is equal to zero for all municipalities at $p = 0$. After the introduction of the policy, imperfect compliance is such that IDA status jumps discontinuously (but not sharply) at the cutoff (Assumption A1). Define potential outcomes $Y_m^p(i, w)$ with $IDA_m^p = i \in \{0, 1\}$ and $W_m^p = w \in \{0, 1\}$, such that the observed outcome $Y_m^p = Y_m^p(1, 1) \cdot IDA_m^p \cdot W_m^p + Y_m^p(1, 0) \cdot IDA_m^p \cdot (1 - W_m^p) + Y_m^p(0, 1) \cdot (1 - IDA_m^p) \cdot W_m^p + Y_m^p(0, 0) \cdot (1 - IDA_m^p) \cdot (1 - W_m^p)$.

This longitudinal set-up is more robust than the previous cross-sectional design in that it allows bordering a large city (the IDA center) to affect the outcome independently of IDA status (the treatment of interest). To show this, we posit a new continuity assumption implying that, once accounting for IDA treatment and for contiguity to an IDA center, no other relevant factors jump at the minimum IDA border.

A2b. Continuity. *Mean potential outcomes $E[Y_m^p(i, w) \mid \delta_m]$ are continuous at $\delta_m = 0$ for $p = 0, 1$, $i = 0, 1$ and $w = 0, 1$.*

Using the standard fuzzy RD proofs (Hahn et al., 2001) and Assumption A2b, one can show that the following holds at time $p = 1$ (when the IDAs are in place):

$$\begin{aligned} \lim_{\delta_m \to 0^-} E[Y_m^1 \mid \delta_m] - \lim_{\delta_m \to 0^+} E[Y_m^1 \mid \delta_m] = \; & E[Y_m^1(1, 1) - Y_m^1(0, 0) \mid \theta = \theta_C, \ \delta_m = 0] \cdot Pr(\theta = \theta_C \mid \delta_m = 0) + \\ & E[Y_m^1(1, 1) - Y_m^1(1, 0) \mid \theta = \theta_A, \ \delta_m = 0] \cdot Pr(\theta = \theta_A \mid \delta_m = 0) + \\ & E[Y_m^1(0, 1) - Y_m^1(0, 0) \mid \theta = \theta_N, \ \delta_m = 0] \cdot Pr(\theta = \theta_N \mid \delta_m = 0) \end{aligned}$$

Where θ denotes municipality types, so that $\theta = \theta_A$ if $IDA_m(\delta_m) = 1$ (always-takers), $\theta = \theta_N$ if $IDA_m(\delta_m) = 0$ (never-takers) and $\theta = \theta_C$ if $IDA_m(\delta_m) = W_m$ (compliers). The cross-sectional reduced-form estimator identifies not only the treatment effect of interest (that of IDA status, on the first row), but also a "contiguity treatment"—expressed as a weighted average of the effect for IDA always-takers and never-takers, on the second and third row above. To identify the impact of IDA status, the confounding effect due to contiguity to IDA centers has to be canceled out. To do so, one can exploit the discontinuity at $p = 0$ when IDAs had not yet been introduced, implying that any difference in outcomes at $p = 0$ is driven by the contiguity treatment. Let us assume:

A4. Parallel trends. *The effect of contiguity at* $\delta_m = 0$ *does not change over time:* $Y_m^1(\cdot, 1) - Y_m^1(\cdot, 0) = Y_m^0(\cdot, 1) - Y_m^0(\cdot, 0)$.

Assumption A4 imposes that the contiguity effect is time-constant and therefore cancels out when taking first differences.[37] In turn, the (fuzzy) estimand:

$$\rho = \frac{(\lim_{\delta_m \to 0^-} E[Y_m^1 \mid \delta_m] - \lim_{\delta_m \to 0^+} E[Y_m^1 \mid \delta_m]) - (\lim_{\delta_m \to 0^-} E[Y_m^0 \mid \delta_m] - \lim_{\delta_m \to 0^+} E[Y_m^0 \mid \delta_m])}{\lim_{\delta_m \to 0^-} Pr(IDA_m = 1 \mid \delta_m) - \lim_{\delta_m \to 0^+} Pr(IDA_m = 1 \mid \delta_m)}$$

identifies again the LATE for compliers at the cutoff.

B.3. Appendix B3: Placebo centers

This complementary design exploits provincial capitals in the Center-North of Italy, which would have likely been IDA centers had they been part of the EIM region. We refer to these as "placebo centers", illustrated in black in Figure B3.1. For comparability purposes, we exclude the industrialized regions in the North of Italy (Lombardy, Veneto and Piemonte), and smaller regions close to the Alps—see also Appendix A.2. We leverage this source of variation in several ways.

Triple differences. In a first approach, we estimate a model pooling together i) municipalities bordering IDA centers; ii) municipalities bordering placebo centers; and iii) municipalities up to 16 km away from the first two groups. The resulting sample comprises 1478 municipalities; of these, 622 are in the EIM area (those bordering IDA centers and those further away from them) and are used in the baseline analysis (Section 4 and Appendix B.2). Let W_m be an indicator denoting municipalities bordering either IDA centers or placebo centers. Let also T_m be an indicator denoting municipalities in the EIM area (those around IDA centers) and let $P = \mathbb{1}[year \geq 1960]$ be the time indicator defined above. The observed outcome can be defined as a function of potential outcomes $Y_m = Y_m(1) \cdot T_m \cdot W_m \cdot P + Y_m(0) \cdot (1 - T_m \cdot W_m \cdot P)$. The causal effect of interest is now $E[Y_m(1) - Y_m(0) \mid T_m = 1,\ W_m = 1,\ P = 1]$. The fully saturated model is:

$$Y_m = \beta_0 + \beta_1 \cdot T_m + \beta_2 \cdot W_m + \beta_3 \cdot P + \beta_4 \cdot T_m \cdot W_m + \beta_5 \cdot T_m \cdot P + \beta_6 \cdot W_m \cdot P + \rho \cdot T_m \cdot W_m \cdot P + \epsilon_m$$

The triple DiD coefficient ρ identifies:

[37]The "invariant participation" assumption introduced in Millán-Quijano (2020) is redundant in our case as the probability of bordering the IDA center is constant over time and jumps sharply from zero to one at the cutoff.

$$
\begin{aligned}
\rho = &\{(E[Y_m \mid T_m = 1,\ W_m = 1,\ P = 1] - E[Y_m \mid T_m = 1, W_m = 0,\ P = 1]) \\
&- (E[Y_m \mid T_m = 1,\ W_m = 1,\ P = 0] - E[Y_m \mid T_m = 1, W_m = 0,\ P = 0])\} \\
&- \{(E[Y_m \mid T_m = 0,\ W_m = 1,\ P = 1] - E[Y_m \mid T_m = 0, W_m = 0,\ P = 1]) \\
&- (E[Y_m \mid T_m = 0,\ W_m = 1,\ P = 0] - E[Y_m \mid T_m = 0, W_m = 0,\ P = 0])\} \\
&= E[Y_m(1) - Y_m(0) \mid T_m = 1,\ W_m = 1,\ P = 1] \\
&+ \{(E[Y_m(0) \mid T_m = 1, W_m = 1,\ P = 1] - E[Y_m(0) \mid T_m = 1, W_m = 0,\ P = 1]) \\
&- (E[Y_m(0) \mid T_m = 1,\ W_m = 1,\ P = 0] - E[Y_m(0) \mid T_m = 1, W_m = 0,\ P = 0])\} \\
&- \{(E[Y_m(0) \mid T_m = 0,\ W_m = 1,\ P = 1] - E[Y_m(0) \mid T_m = 0, W_m = 0,\ P = 1]) \\
&- (E[Y_m(0) \mid T_m = 0,\ W_m = 1,\ P = 0] - E[Y_m(0) \mid T_m = 0, W_m = 0,\ P = 0])\}
\end{aligned}
$$

Causal identification now requires an even weaker assumption than A4, namely:

B3.1. Parallel trends. *Any differential time trends in the control outcome between contiguous and not contiguous municipalities must be the same around IDA centers and around placebo centers:*

$$
\begin{aligned}
&(E[Y_m(0) \mid T_m = 1, W_m = 1,\ P = 1] - E[Y_m(0) \mid T_m = 1, W_m = 0,\ P = 1]) \\
&- (E[Y_m(0) \mid T_m = 1,\ W_m = 1,\ P = 0] - E[Y_m(0) \mid T_m = 1, W_m = 0,\ P = 0]) \\
&= (E[Y_m(0) \mid T_m = 0,\ W_m = 1,\ P = 1] - E[Y_m(0) \mid T_m = 0, W_m = 0,\ P = 1]) \\
&- (E[Y_m(0) \mid T_m = 0,\ W_m = 1,\ P = 0] - E[Y_m(0) \mid T_m = 0, W_m = 0,\ P = 0])
\end{aligned}
$$

By allowing for differential pre-trends, this approach imposes less restrictive assumptions than the longitudinal design comparing municipalities within and outside of the minimum IDA border. Identification now requires that any differential trend in the control outcome is the same across the two groups, so that it would cancel out when taking the triple difference—in other words, this design allows any contiguity effects to be time-varying. We estimate the following dynamic triple differences specification:

$$
Y_{m,t} = \mu_m + \sum_{j \neq 1951} \gamma_j \cdot \mathbb{1}[t = j] \cdot W_m + \sum_{j \neq 1951} \eta_j \cdot \mathbb{1}[t = j] \cdot T_m + \sum_{j \neq 1951} \rho_j \cdot \mathbb{1}[t = j] \cdot W_m \cdot T_m + \epsilon_{m,t} \tag{B3.1}
$$

Where $Y_{m,t}$ is the outcome of interest for municipality m and census year t and μ_m are municipality fixed effects. The coefficients ρ_j capture the difference between two differences in census year j relative to the baseline difference in 1951: (i) the baseline difference in outcomes between municipalities bordering IDA centers and those right outside of

Figure B3.1. IDA Centers and Placebo Centers

Notes: IDA centers are in brown and placebo centers in black. Placebo centers are provincial capitals in the Center-North of Italy. The dashed blue line is the EIM border separating the EIM jurisdiction from the rest of Italy—see also Appendix B.4. Regions in white are excluded from the analysis for comparability purposes.

the minimum IDA border (i.e., that estimated by Equation 2); and (ii) the difference in outcomes between municipalities bordering placebo centers and those farther away from them. If Assumption B3.1 holds, the event study coefficients before the introduction of IDAs ρ_{1911} and ρ_{1927} should be undistinguishable from zero.

Testing for displacement. Placebo centers can also be exploited to investigate possible spillover effects of the IDA policy to nearby areas. Namely, we consider municipalities up to 16 km outside of the minimum IDA border (the control group in the baseline design, which now becomes our treatment group), and compare them with their counterpart around placebo centers: municipalities up to 16 km outside of the "placebo" boundary traced by municipalities contiguous to placebo centers. We compare these two groups before and after the institution of IDAs in a simple event study design, where T_m is a treatment indicator denoting municipalities in the EIM area—in this case, those outside of the minimum IDA border. Notice that, in order to identify spillover effects, the treatment group of this design excludes municipalities outside of the minimum IDA border that were part of the IDA (the always-takers, e.g., those in light blue in Figure 3 Panel a).

In practice, we estimate the following dynamic specification:

$$Y_{m,t} = \mu_m + \sigma_t + \sum_{j \neq 1951} \rho_j \cdot \mathbb{1}[t = j] \cdot T_m + \epsilon_{m,t} \tag{B3.2}$$

Where $Y_{m,t}$ is the outcome of interest for municipality m and census year t, μ_m are municipality fixed effects and σ_t are census year effects. Under parallel trends, the coefficients of interest ρ_j identify any differential effect on municipalities outside of the minimum IDA border compared to their counterparts in the Center-North following the establishment of IDAs. The ρ_{1911} and ρ_{1927} coefficients provide a test of the parallel trends assumption.

We notice that the triple differences design described earlier automatically accounts for these spillover effects. Re-arranging the expression for the ρ parameter in the fully saturated model, we obtain the following—where the "within" difference captures the effect on municipalities bordering IDA centers versus municipalities bordering placebo centers, while the "outside" difference estimates spillovers of the policy to nearby areas:

$$\begin{aligned}
\rho = & \underbrace{\begin{aligned}\{(&E[Y_m \mid T_m = 1,\ W_m = 1,\ P = 1] - E[Y_m \mid T_m = 1, W_m = 1,\ P = 0]) \\ -(&E[Y_m \mid T_m = 0,\ W_m = 1,\ P = 1] - E[Y_m \mid T_m = 0, W_m = 1,\ P = 0])\}\end{aligned}}_{\text{"Within" effect}} \\
& - \\
& \underbrace{\begin{aligned}\{(&E[Y_m \mid T_m = 1,\ W_m = 0,\ P = 1] - E[Y_m \mid T_m = 1, W_m = 0,\ P = 0]) \\ -(&E[Y_m \mid T_m = 0,\ W_m = 0,\ P = 1] - E[Y_m \mid T_m = 0, W_m = 0,\ P = 0])\}\end{aligned}}_{\text{"Outside" (spillover) effect}}
\end{aligned}$$

Synthetic control approach. The analysis based on placebo centers has so far considered *all* of them (i.e., all provincial capitals in the Center-North) as a comparison group for IDA centers. To account for observed differences between the two groups and improve comparability, we augment our placebo centers design by means of a synthetic control approach (Abadie and Gardeazabal, 2003; Abadie et al., 2010). Specifically, for each IDA center, we construct a synthetic placebo center as a weighted combination of all placebo centers showed in black in Figure B3.1. The synthetic control is calibrated to match the IDA center on the following pre-treatment characteristics: employment density in 1911, 1927, and 1951, the share of employment and establishments in manufacturing in the same years, the share of residents with a high school diploma in 1951, the agriculture share of employment in 1951, and slope. Formally, for each IDA center i, we select weights w_{ij} over placebo centers $j \in \mathcal{J}$ to minimize the distance between the IDA center and the synthetic control center on the vector of matching variables, subject to $w_{ij} \geq 0$ and $\sum_{j \in \mathcal{J}} w_{ij} = 1$.

The set of weights obtained for placebo centers from the synthetic control algorithm are then applied to municipalities around each placebo center, allowing us to construct a synthetic control group for municipalities around each IDA center. For example, if IDA center i is matched with placebo centers 1 and 2 with weights w_{i1} and w_{i2}, respectively, then municipalities around IDA center i will be matched with municipalities around placebo center 1 (which will all receive weight w_{i1}) and with municipalities around placebo center 2 (which will all receive weight w_{i2}). This enables us to estimate a triple differences model akin to Equation B3.1, where we compare the double difference between municipalities within and outside of the minimum IDA border with the placebo double difference obtained around synthetic placebo centers, by weighting Equation B3.1 by the synthetic control weights.

We adopt this framework also in a simple longitudinal design meant to estimate treatment effects at different levels of aggregation. Namely, we compare municipalities bordering IDA centers (our baseline treatment group) with municipalities bordering placebo centers weighted by their respective synthetic weights (i.e., the weight of the placebo center they are contiguous to). Then, we progressively expand the set of treated and control municipalities up to 15 km away from IDA centers and placebo centers—where control municipalities are again weighted using the synthetic weights of their associated placebo center. In the previous example where IDA center i is matched with placebo centers 1 and 2 with weights w_{i1} and w_{i2}, the first regression will compare over time municipalities bordering IDA center i with those bordering placebo center 1 (which will all receive weight w_{i1}) and with those bordering placebo center 2 (which will all receive weight w_{i2}); the second regression will compare over time municipalities up to 3 km away from IDA center i with those up to 3 km away from placebo center 1 (which will all receive weight w_{i1}) and with those up to 3 km away from placebo center 2 (which will all receive weight w_{i2}); and so on until 15 km away from centers. In practice, we estimate a design akin to Equation B3.2, where T_m denotes municipalities in the EIM area (those around IDA centers), over varying samples including, first, only municipalities bordering IDA centers and those bordering placebo centers, and then extending both groups away from centers. The key difference is that, now, we weight our regressions using synthetic weights. This design allows to assess the geographic scale of the estimated policy effects, and the extent to which neighborhood-level versus labor market-level mechanisms are driving our results—see the discussion in Section 6.

B.4. Appendix B4: The EIM border

Our last identification strategy exploits the discontinuity at the northern boundary of the EIM jurisdiction. When the EIM began in 1950, the policymaker had to separate the area of intervention from the rest of Italy, splitting the country in two halves. This border was set above the traditional boundaries of the Southern Italian regions and extended into Central Italy (Figure B4.1 Panel a). The border was set in 1950 and the EIM area remained since unchanged until the termination of the policy in 1992. Figure B4.1(b) plots Cassa's expenses around the border, clearly showing a stark jump equivalent to roughly 15,000 euros per capita. Albanese et al. (2024) provide more details on the EIM border and its suitability as a RD cutoff. Inspection of the parliamentary discussions that led to the drawing of the border reveals that this choice was informed by technical details related to the execution of infrastructure projects, without much consideration of the economic conditions of those areas. In addition, the border does not systematically coincide with regional boundaries, nor does it matter for other policies realized before, during or after the EIM. Balancing tests in Albanese et al. (2024) reveal no large discontinuity in pre-determined municipality characteristics at the border.

We specify a sharp RD design that uses distance to the border ι_m as running variable and $B_m = \mathbb{1}[\iota_m \geq 0]$ as treatment indicator, where positive distance denotes treated municipalities south of the border:

$$Y_m = \lambda_b + \kappa \cdot B_m + \varphi(\iota_m) + \epsilon_m \tag{B4.1}$$

Here, Y_m is the outcome of interest, λ_b are border-segment fixed effects denoting the segment of the border closest to municipality m and $\varphi(\iota_m)$ is a linear polynomial in distance to the EIM border. We use a baseline bandwidth of 50 km north and south of the border, which we obtain as a simple average of MSE-optimal bandwidths derived following Calonico et al. (2014) using employment density across sectors and census years as outcome. Standard errors allow for arbitrary correlation across space following Conley (1999).

We also specify the following dynamic version of Equation B4.1:

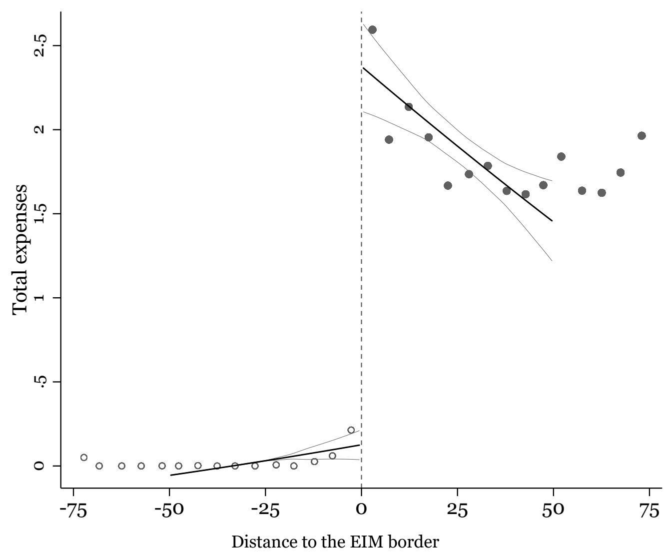
$$Y_{m,t} = \mu_m + \sigma_t + \sum_{j \neq 1951} \rho_j \cdot \mathbb{1}[t = j] \cdot B_m + \epsilon_{m,t} \tag{B4.2}$$

Where notation is as in Equation 2 and, as above, B_m is a treatment indicator denoting municipalities south of the EIM border. We use a 50-km symmetric bandwidth around the border and cluster standard errors by municipality.

Figure B4.1. The EIM Border

(a) The border

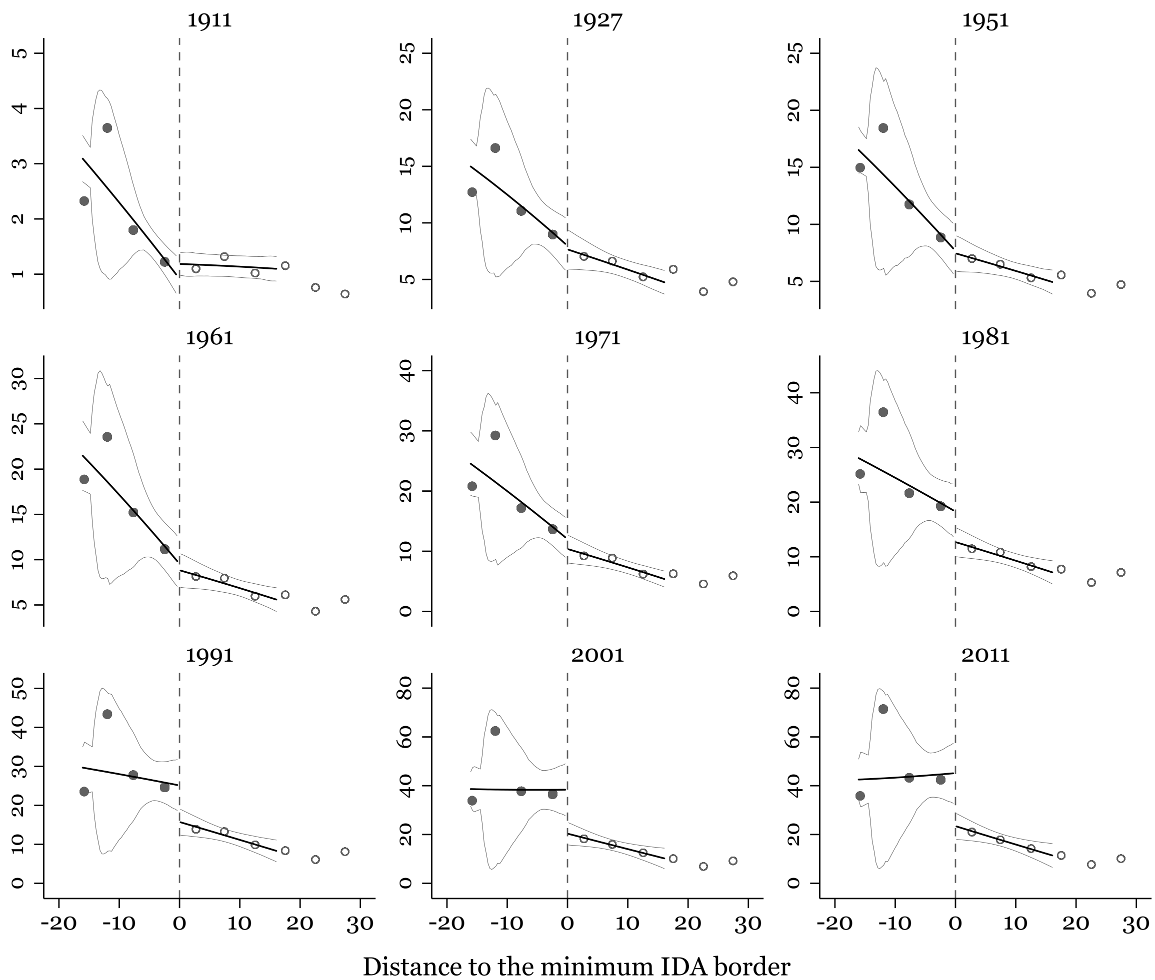
(b) Total EIM expenses



Notes: Panel (a) shows the EIM border as the dashed blue line. The yellow area south of the border belongs to the EIM jurisdiction. Panel (b) shows (log) total EIM expenses in thousand € (2011 prices) per 1951 resident, cumulated between 1950 and 1992. Negative distance denotes municipalities north of the EIM border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately north and south of the border using a 50-km symmetric bandwidth. The gray lines are 95 percent confidence intervals. The slightly positive amounts north of the border denote infrastructure spending in some small islands of Tuscany and grants to firms located in neighborhoods of four municipalities in Lazio.

C. Appendix C: Results

Figure C1. Establishment Density Over Time at the Minimum IDA Border



Notes: The outcome is establishment density, measured as number of establishments per km^2, for each census year. Negative distance denotes municipalities within the minimum IDA border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately at each side of the border using a symmetric 16-km bandwidth. The gray lines are 95 percent confidence intervals.

Table C1. Establishment Density: Baseline RD Estimates

	Reduced form	2-SLS	
		IDA status	EIM subsidies
	(1)	(2)	(3)
	Contemporaneous effect (1991)		
RD Estimate	9.18	23.50	1.60
	(4.82)	(11.01)	(0.81)
Mean around the border	15.08	15.08	14.82
Standard deviation	21.98	21.98	21.53
Observations	586	586	562
R^2	0.23		
KP F-stat		19.06	5.18
	Persistent effect (2011)		
RD Estimate	19.83	50.73	3.43
	(8.97)	(20.58)	(1.63)
Mean around the border	23.10	23.10	22.63
Standard deviation	37.88	37.88	36.87
Observations	586	586	562
R^2	0.25		
KP F-stat		19.06	5.18

Notes: The outcome is establishment density, measured as number of establishments per km^2. Column (1) shows the estimation output of the reduced form Equation 1b, measuring the jump in outcome at the minimum IDA border. Column (2) reports the fuzzy RD estimates using a binary treatment (IDA status) and a binary instrument equal to one for municipalities within the cutoff—see Equations 1a and 1b. Column (3) replaces IDA status with total EIM funding (cumulated 1950 to 1992) per municipality resident in 1951 as treatment variable. All regressions are estimated over a 16-km symmetric bandwidth around the minimum IDA border and control for a linear polynomial in the distance to the border and IDA region effects. Mean and standard deviation computed within the estimation sample. Standard errors clustered by IDA region in parentheses.

Table C2. Employment Density: Robustness Tests

	2^{nd} ord. (1)	3^{rd} ord. (2)	Excl. cent. (3)	Dist. to cent. (4)	No IDA eff. (5)	All IDAs (6)	Conley* (7)
				Contemporaneous effect (1991)			
RD Estimate	82.35	92.91	81.44	111.98	107.72	157.95	43.31
	(38.96)	(40.20)	(41.01)	(43.71)	(40.82)	(68.70)	(12.00)
Mean around the border	47.62	47.62	42.39	47.62	47.62	70.49	47.62
Standard deviation	79.68	79.68	66.86	79.68	79.68	111.57	79.68
Observations	586	586	574	586	586	775	586
KP F-stat	26.03	12.69	18.52	18.60	22.58	15.42	–
				Persistent effect (2011)			
RD Estimate	123.04	140.17	126.85	162.57	157.70	202.25	62.99
	(61.84)	(67.47)	(60.08)	(63.91)	(59.35)	(83.97)	(16.81)
Mean around the border	62.97	62.97	56.39	62.97	62.97	96.25	62.97
Standard deviation	108.15	108.15	93.55	108.15	108.15	149.60	108.15
Observations	586	586	574	586	586	775	586
KP F-stat	26.03	12.69	18.52	18.60	22.58	15.42	–

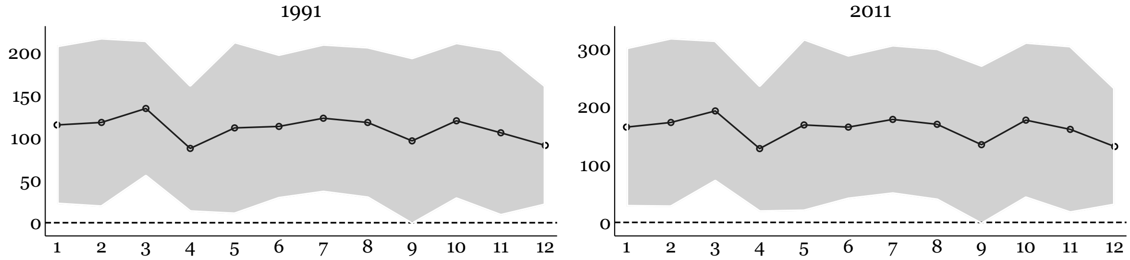
Notes: Fuzzy RD estimates using a binary treatment (IDA status) and a binary instrument equal to one for municipalities within the cutoff—see Equations 1a and 1b. The only exception is Column (7), which shows reduced-form estimates from Equation 1b. Mean and standard deviation computed within the estimation sample. The outcome is employment density, measured as number of workers per km^2. All regressions are estimated over a 16-km symmetric bandwidth around the minimum IDA border and control for a linear polynomial in the distance to the border and IDA region effects, unless noted otherwise. Standard errors clustered by IDA region in parentheses, except for Column (7). Columns (1) and (2) specify $\varphi(\delta_m)$ as a quadratic and cubic polynomial, respectively. Column (3) excludes IDA centers from the estimation sample. Column (4) controls linearly for the distance to the IDA center. Column (5) excludes IDA region effects from the baseline specification. In Column (6), the estimation includes also the Napoli and Caserta IDAs (excluded from the baseline analysis because of the small distance between the two IDA centers). *Column (7) calculates standard errors allowing for spatial correlation (Conley, 1999), showing reduced-form estimates from Equation 1b.

Table C3. Employment and Firm Density: Randomization Inference

	Employment per km^2		Establishments per km^2	
	1991	2011	1991	2011
ITT	47.06	73.62	13.21	27.57
Finite sample P-value	0.00	0.00	0.01	0.01
Asymptotic P-value	0.01	0.01	0.01	0.01
Window	2.06	2.06	2.06	2.06

Notes: Estimation output for the fuzzy RD design—see Equations 1a and 1b—using local randomization inference as proposed in Cattaneo et al. (2016), with 1,000 replications, uniform kernel and without specifying a polynomial for the outcome transformation model—see the *rdrandinf* command in Cattaneo et al. (2016). The window-selection procedure is built on balance tests for RD under local randomization—see the *rdwinselect* command in Cattaneo et al. (2016). The P-values refer to the sharp null hypothesis of no treatment effect at the cutoff.

Figure C2. Employment Density: Exclude One Individual IDA at a Time



Notes: Fuzzy RD estimates using a binary treatment (IDA status) and a binary instrument equal to one for municipalities within the cutoff—see Equations 1a and 1b. The outcome is employment density, measured as number of workers per km^2. Estimates are obtained excluding one IDA region at a time and presented both in 1991 (left panel) and 2011 (right panel). Each point on the horizontal axis denotes a specification where one of the IDA regions is removed from the sample. Dashed areas represent 95 percent confidence intervals. All regressions are estimated over a 16-km symmetric bandwidth around the minimum IDA border and control for a linear polynomial in the distance to the border and IDA region effects. Standard errors clustered by IDA region.

Table C4. Employment Density: Non-Parametric Fuzzy RD Estimates

	Contemporaneous effect (1991)		Persistent effect (2011)	
	Conventional	Robust	Conventional	Robust
RD Estimate	106.87	143.59	178.46	234.04
	(66.06)	(89.24)	(105.19)	(139.36)
Bandwidth within	5.94	5.94	6.42	6.42
Bandwidth outside	22.00	22.00	20.74	20.74
Mean around the border	40.84	40.84	54.36	54.36
Standard deviation	68.63	68.63	95.10	95.10
Observations	708	708	680	680

Notes: Fuzzy RD estimates obtained using the non-parametric estimation and robust bias-corrected inference method proposed by Calonico et al. (2014). The optimal bandwidth is computed by minimizing the Mean Squared Error separately left and right of the cutoff. Observations are weighted using a triangular kernel. The outcome is employment density, measured as number of workers per km^2. Mean and standard deviation computed within the estimation sample. The specification controls for IDA region effects and standard errors are clustered by IDA region.

Table C5. (Log) Employment and Population Density: RD Estimates

	(Log) Employment density		(Log) Population density	
	Red. Form	2-SLS	Red. Form	2-SLS
	(1)	(2)	(3)	(4)
	Contemporaneous effect (1991)			
RD Estimate	0.51	1.30	0.41	1.06
	(0.21)	(0.49)	(0.16)	(0.37)
Mean around the border	3.00	3.00	5.16	5.16
Standard deviation	1.30	1.30	1.13	1.13
Observations	586	586	587	587
	Persistent effect (2011)			
RD Estimate	0.55	1.41	0.39	1.00
	(0.22)	(0.52)	(0.16)	(0.37)
Mean around the border	3.16	3.16	5.20	5.20
Standard deviation	1.44	1.44	1.21	1.21
Observations	586	586	587	587

Notes: The outcome is the natural logarithm of employment (Columns 1-2) and population (Columns 3-4) density, measured as number of workers and residents per km^2, respectively. We show both the estimation output of the reduced form Equation 1b (Columns 1 and 3), measuring the jump in outcome at the minimum IDA border, and 2-SLS fuzzy RD estimates (Columns 2 and 4) using a binary treatment (IDA status) and a binary instrument equal to one for municipalities within the cutoff—see Equations 1a and 1b. Here, we show also reduced-form estimates for coefficient comparison with von Ehrlich and Seidel (2018). All regressions are estimated over a 16-km symmetric bandwidth around the minimum IDA border and control for a linear polynomial in the distance to the border and IDA region effects. Mean and standard deviation computed within the estimation sample. Standard errors clustered by IDA region in parentheses.

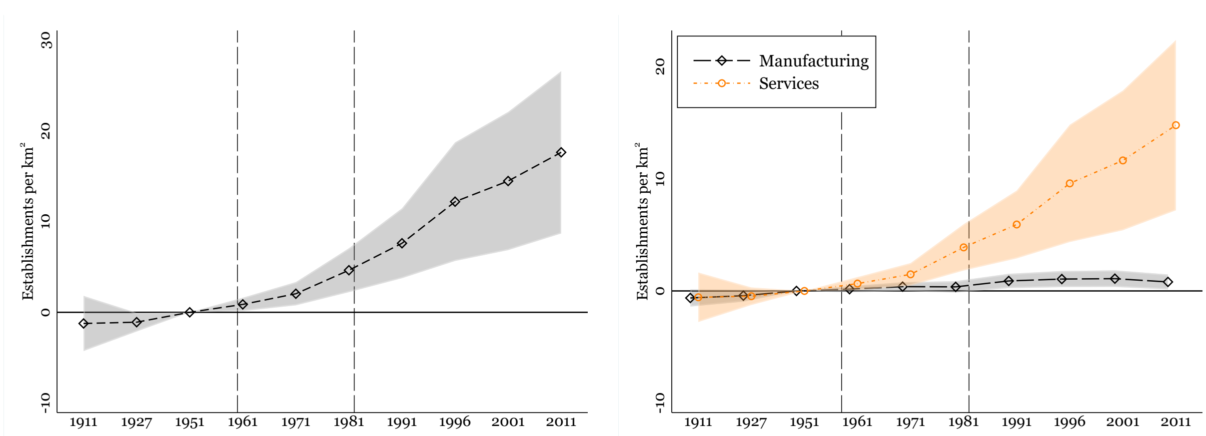
Table C6. Migration, Employment and Participation Rates: RD Estimates

	Mobil. (1)	Mobil. work (2)	Net migr. (3)	Empl. rate (4)	Part. rate (5)	Unem. rate (6)
			Contemporaneous effect (1991)			
RD Estimate	5.35	69.44	0.02	3.97	3.40	-3.56
	(2.96)	(38.37)	(0.09)	(1.69)	(1.17)	(2.17)
Mean around the border	19.35	108.48	-0.02	33.88	47.21	28.33
Standard deviation	8.48	92.48	0.31	5.68	4.51	9.32
Observations	587	587	587	587	587	587
			Persistent effect (2011)			
RD Estimate	4.19	62.07	-0.30	1.90	3.09	1.51
	(3.06)	(46.61)	(0.24)	(1.31)	(1.32)	(1.75)
Mean around the border	25.75	155.80	-0.04	38.33	46.13	16.97
Standard deviation	9.52	115.50	0.63	4.66	4.50	5.18
Observations	587	587	587	587	587	587

Notes: Fuzzy RD estimates using a binary treatment (IDA status) and a binary instrument equal to one for municipalities within the cutoff—see Equations 1a and 1b. "Mobil.": share of resident population who travel daily for work or study outside the municipality to the resident population aged up to 64. "Mobil. work": share of resident population commuting daily for work outside the municipality to resident population commuting daily for work within the municipality. "Net migr.": net inflow of immigrants into the municipality as a share of resident population. "Empl. rate": ratio of employed people to total residents aged 15 years and older. "Part. rate": ratio of the resident working population to the resident population of the same age group. "Unem. rate": ratio of the resident population 15 years and older seeking employment to resident population 15 years and older in employment. All regressions are estimated over a 16-km symmetric bandwidth around the minimum IDA border and control for a linear polynomial in the distance to the border and IDA region effects. Mean and standard deviation computed within the estimation sample. Standard errors clustered by IDA region in parentheses.

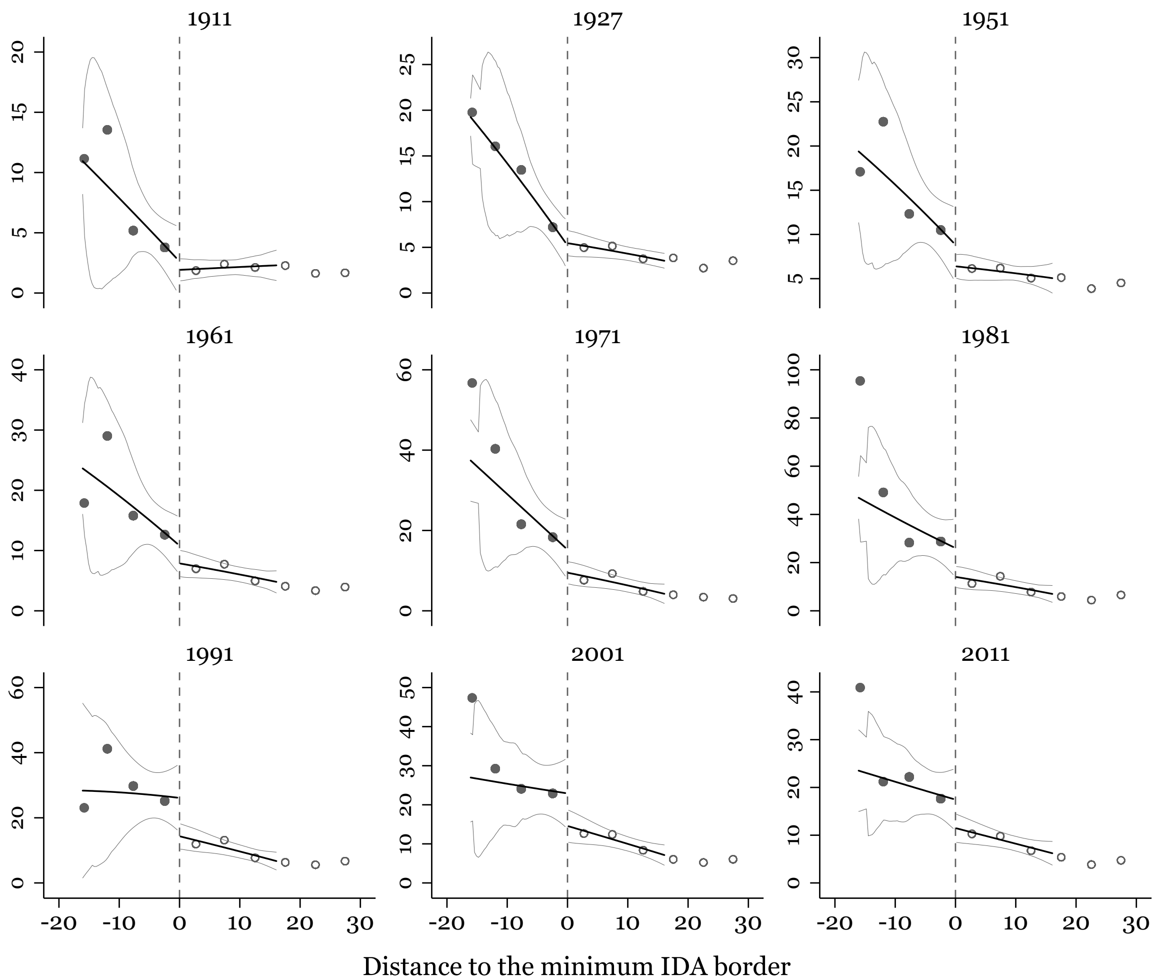
Figure C3. Establishment Density: Longitudinal Estimates at the Minimum IDA Border

(a) Establishment density (b) Manufacturing versus services



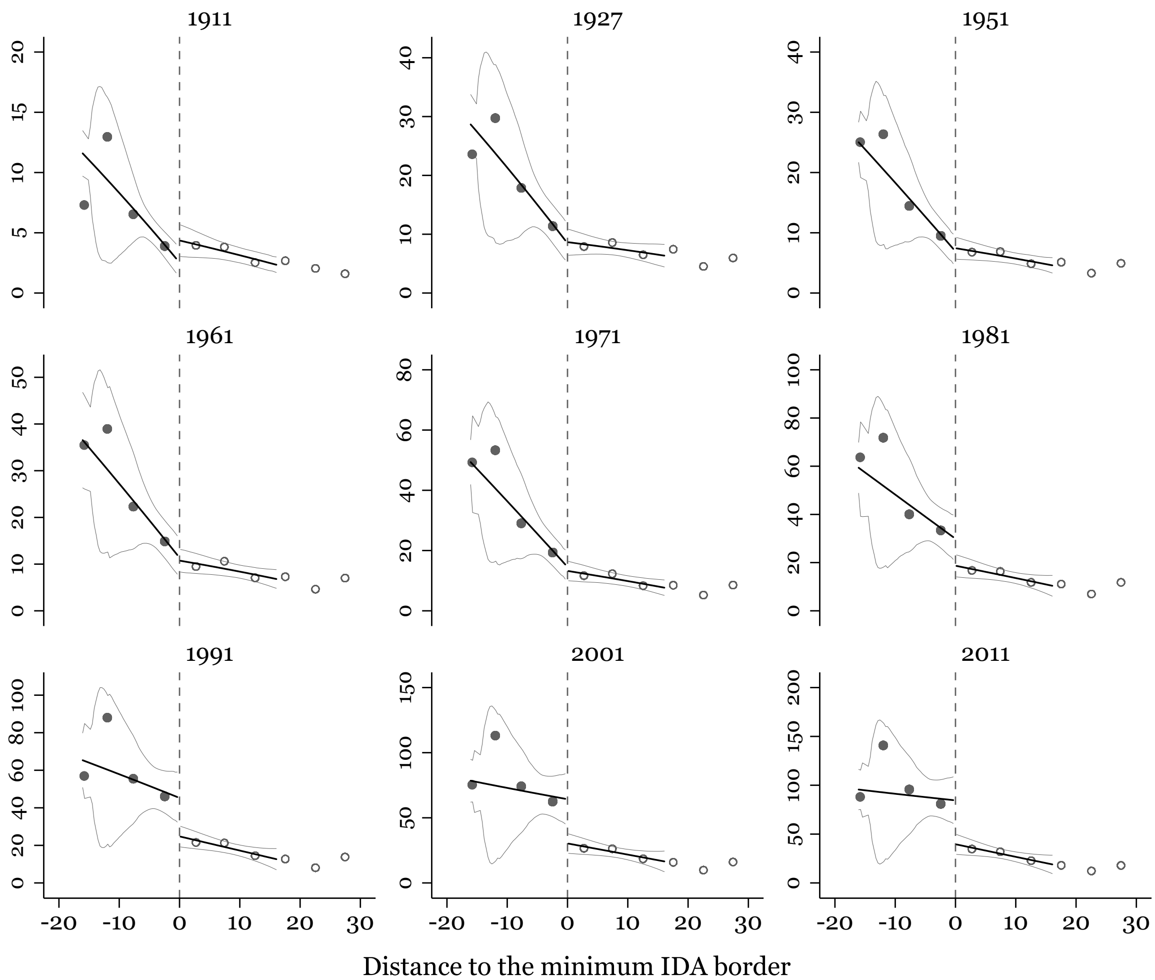
Notes: Coefficient estimates for Equation 2, comparing over time municipalities bordering IDA centers to municipalities up to 16 km away from them. The outcome is establishment density, measured as number of establishments per km^2. Panel (b) shows establishment density separately for manufacturing (black diamonds) and services (orange circles). Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the IDAs.

Figure C4. Manufacturing Employment Density Over Time at the Minimum IDA Border



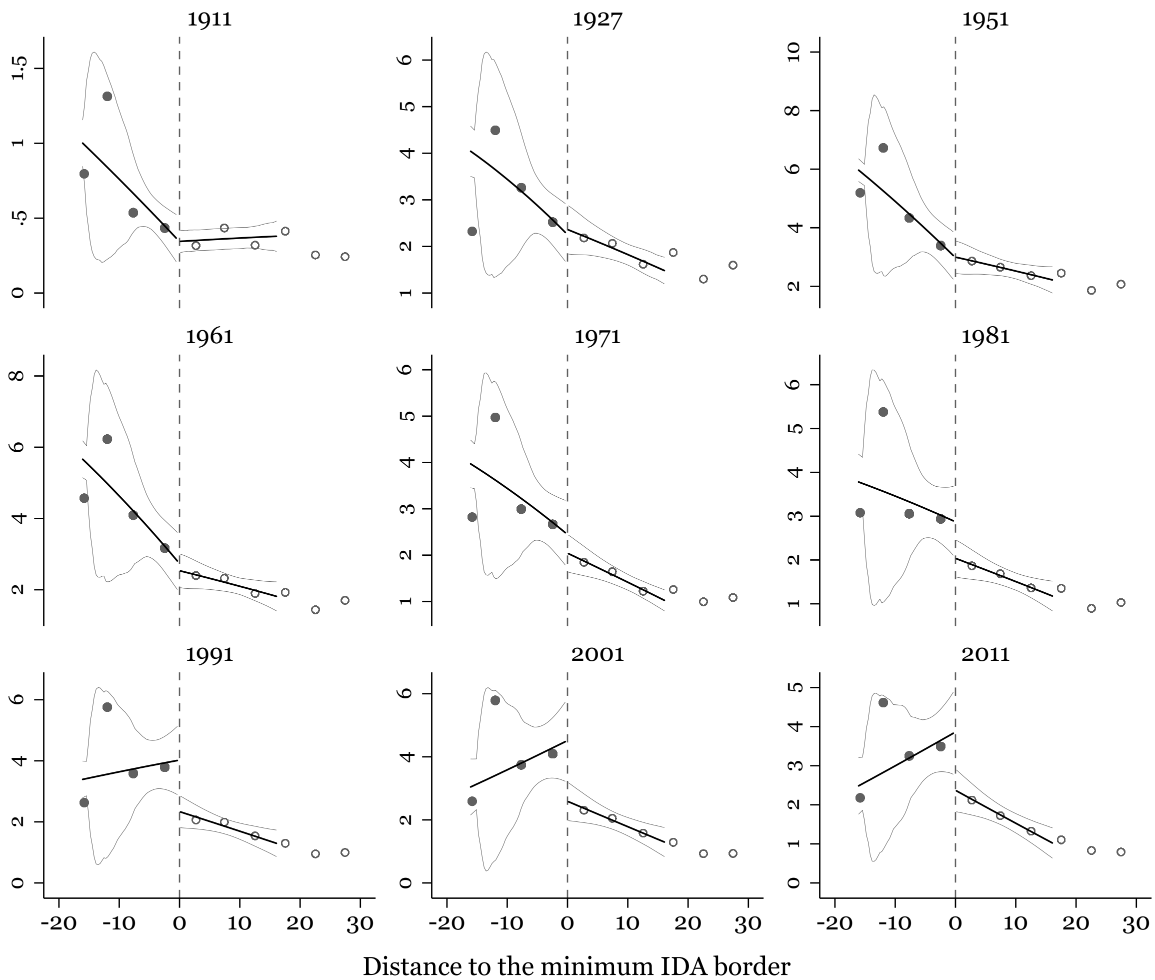
Notes: The outcome is manufacturing employment density, measured as number of manufacturing workers per km^2, for each census year. Negative distance denotes municipalities within the minimum IDA border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately at each side of the border using a symmetric 16-km bandwidth. The gray lines are 95 percent confidence intervals.

Figure C5. Services Employment Density Over Time at the Minimum IDA Border



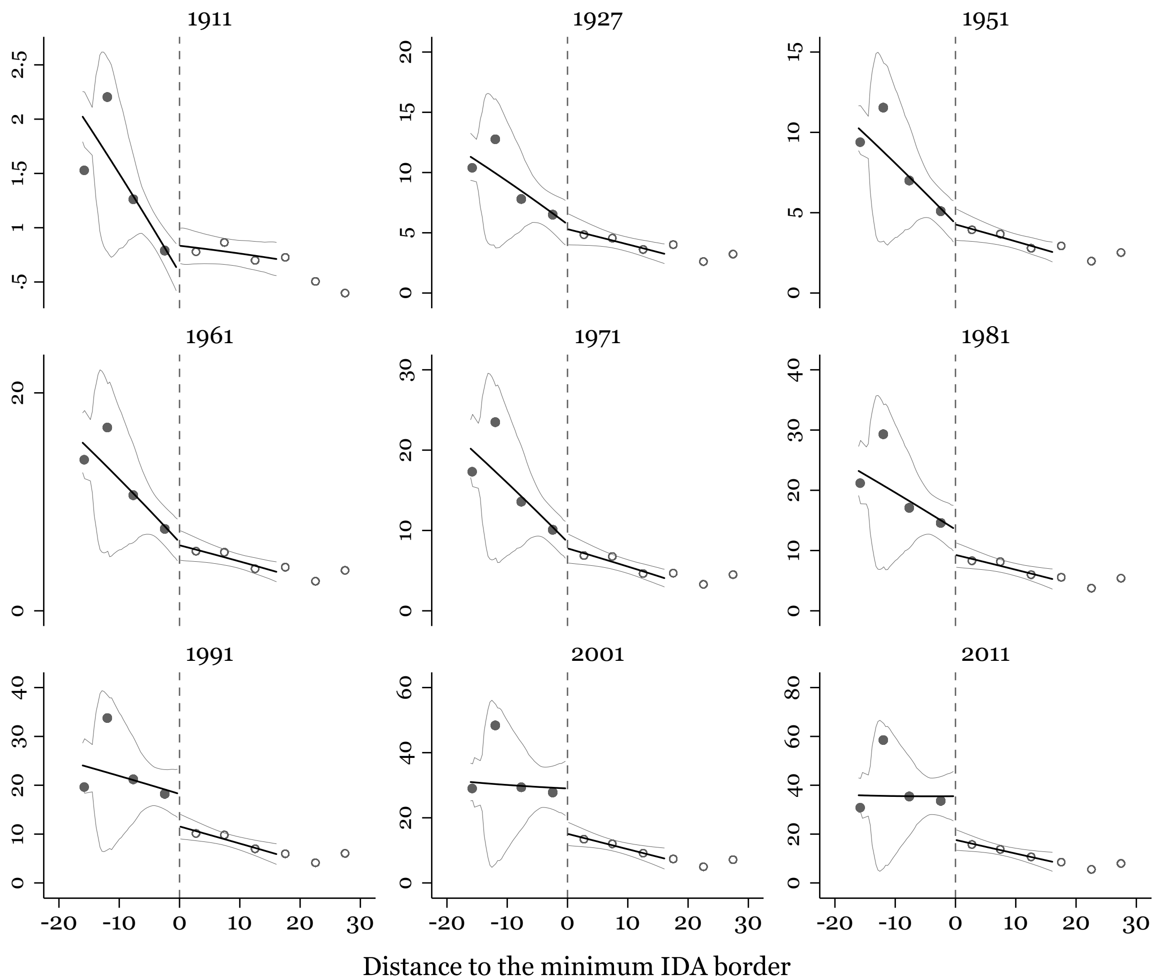
Notes: The outcome is services employment density, measured as number of services workers per km^2, for each census year. Negative distance denotes municipalities within the minimum IDA border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately at each side of the border using a symmetric 16-km bandwidth. The gray lines are 95 percent confidence intervals.

Figure C6. Manufacturing Establishment Density Over Time at the Minimum IDA Border



Notes: The outcome is manufacturing establishment density, measured as number of manufacturing establishments per km^2, for each census year. Negative distance denotes municipalities within the minimum IDA border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately at each side of the border using a symmetric 16-km bandwidth. The gray lines are 95 percent confidence intervals.

Figure C7. Services Establishment Density Over Time at the Minimum IDA Border



Notes: The outcome is services establishment density, measured as number of services establishments per km^2, for each census year. Negative distance denotes municipalities within the minimum IDA border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately at each side of the border using a symmetric 16-km bandwidth. The gray lines are 95 percent confidence intervals.

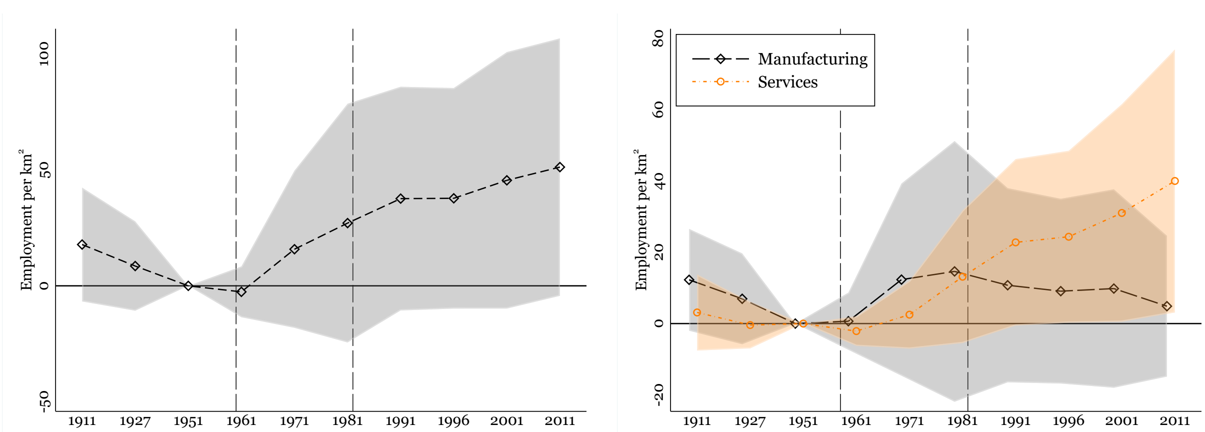
Table C7. Employment and Firm Density, Manufacturing and Services: RD estimates

	Employment density		Establishment density	
	Manufacturing	Services	Manufacturing	Services
	(1)	(2)	(3)	(4)
	Contemporaneous effect (1991)			
RD Estimate	28.27	57.40	3.69	17.76
	(14.08)	(23.17)	(1.61)	(8.32)
Mean around the border	14.06	25.45	2.26	11.10
Standard deviation	26.80	43.14	3.30	16.90
Observations	586	586	586	586
	Persistent effect (2011)			
RD Estimate	14.99	112.61	2.75	43.22
	(9.68)	(45.43)	(1.51)	(17.35)
Mean around the border	11.01	41.52	2.08	17.87
Standard deviation	18.74	75.44	3.08	30.85
Observations	586	586	586	586

Notes: Fuzzy RD estimates using a binary treatment (IDA status) and a binary instrument equal to one for municipalities within the cutoff—see Equations 1a and 1b. The outcomes are employment (Columns (1-2) and establishment (Columns 3-4) density, measured as number of workers and establishments per km^2, respectively, in manufacturing (Columns 1 and 3) and services (Columns 2 and 4). All regressions are estimated over a 16-km symmetric bandwidth around the minimum IDA border and control for a linear polynomial in the distance to the border and IDA region effects. Mean and standard deviation computed within the estimation sample. Standard errors clustered by IDA region in parentheses.

Figure C8. Employment Density: Triple Differences Estimates

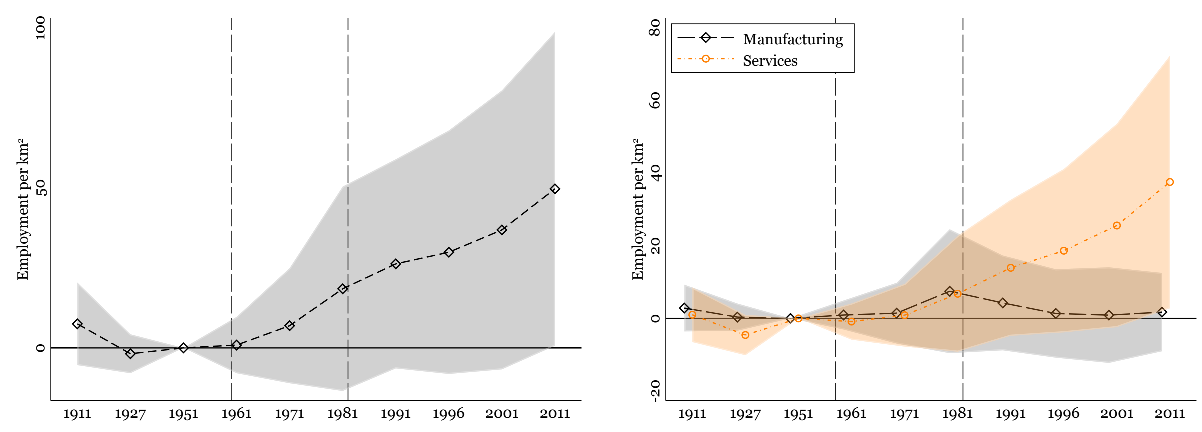
(a) Employment density (b) Manufacturing versus services



Notes: Coefficient estimates for Equation B3.1, comparing over time the double difference between municipalities within and outside of the minimum IDA border to a placebo double difference between municipalities bordering placebo centers and those further away. See Appendix B.3 for details. The outcome is employment density, measured as number of workers per km^2. Panel (b) shows employment density separately for manufacturing (black diamonds) and services (orange circles). Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the IDAs.

Figure C9. Employment Density: Triple Differences, Synthetic Placebo Centers

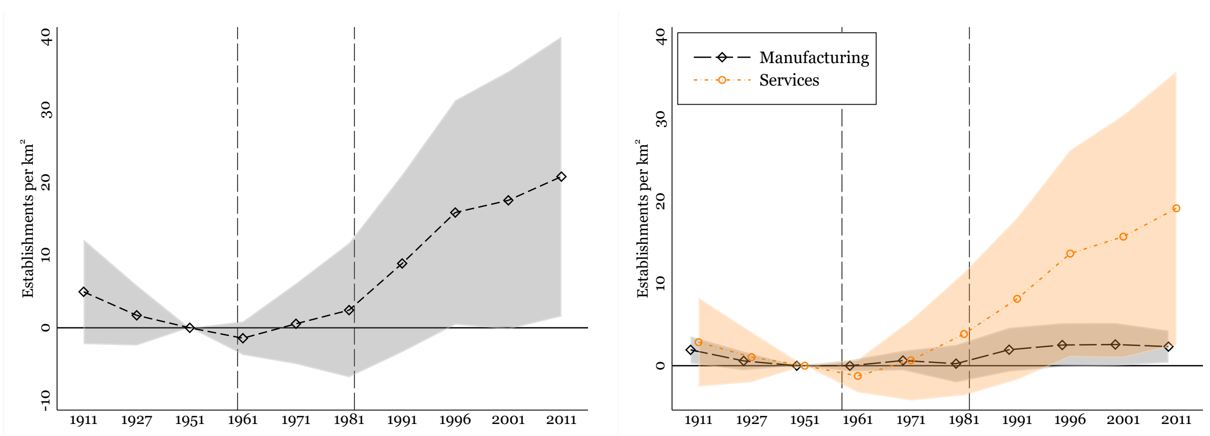
(a) Employment density (b) Manufacturing versus services



Notes: Coefficient estimates for Equation B3.1, comparing over time the double difference between municipalities within and outside of the minimum IDA border to a placebo double difference between municipalities bordering placebo centers and those further away. Municipalities around placebo centers are weighted using synthetic control weights. See Appendix B.3 for details. The outcome is employment density, measured as number of workers per km^2. Panel (b) shows employment density separately for manufacturing (black diamonds) and services (orange circles). Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the IDAs.

Figure C10. Establishment Density: Triple Differences Estimates

(a) Establishment density (b) Manufacturing versus services

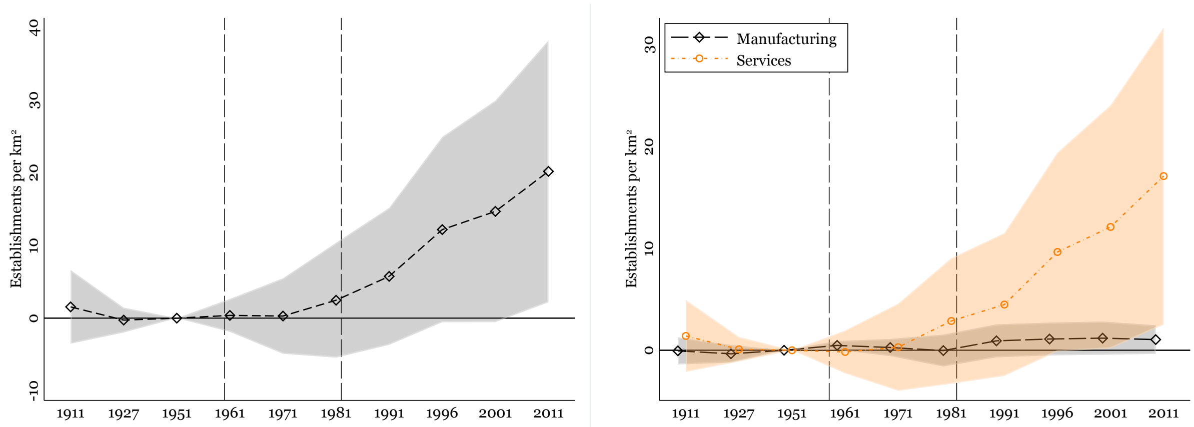


Notes: Coefficient estimates for Equation B3.1, comparing over time the double difference between municipalities within and outside of the minimum IDA border to a placebo double difference between municipalities bordering placebo centers and those further away. See Appendix B.3 for details. The outcome is establishment density, measured as number of establishments per km^2. Panel (b) shows establishment density separately for manufacturing (black diamonds) and services (orange circles). Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the IDAs.

Figure C11. Establishment Density: Triple Differences, Synthetic Placebo Centers

(a) Establishment density

(b) Manufacturing versus services

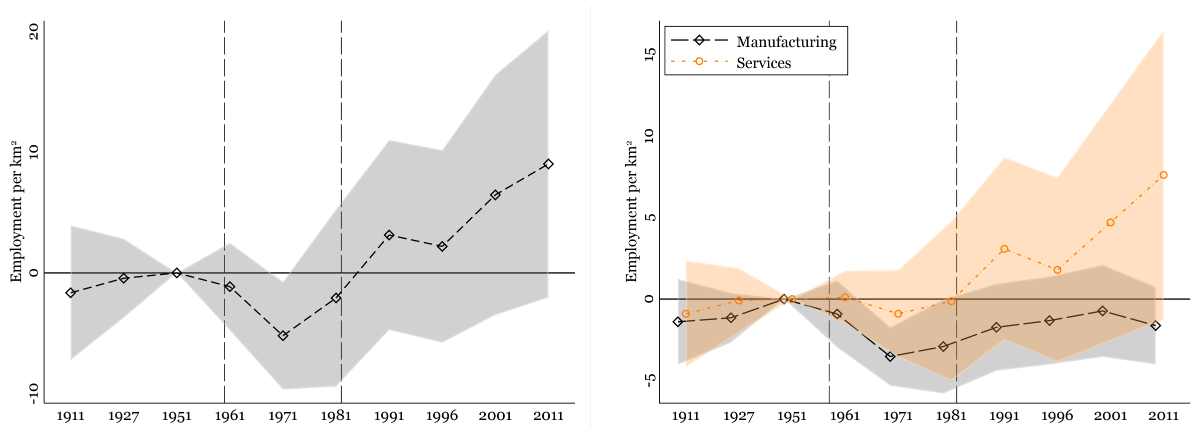


Notes: Coefficient estimates for Equation B3.1, comparing over time the double difference between municipalities within and outside of the minimum IDA border to a placebo double difference between municipalities bordering placebo centers and those further away. Municipalities around placebo centers are weighted using synthetic control weights. See Appendix B.3 for details. The outcome is establishment density, measured as number of establishments per km^2. Panel (b) shows establishment density separately for manufacturing (black diamonds) and services (orange circles). Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the IDAs.

Figure C12. Employment Density: Policy Spillovers, Synthetic Placebo Centers

(a) Employment density

(b) Manufacturing versus services

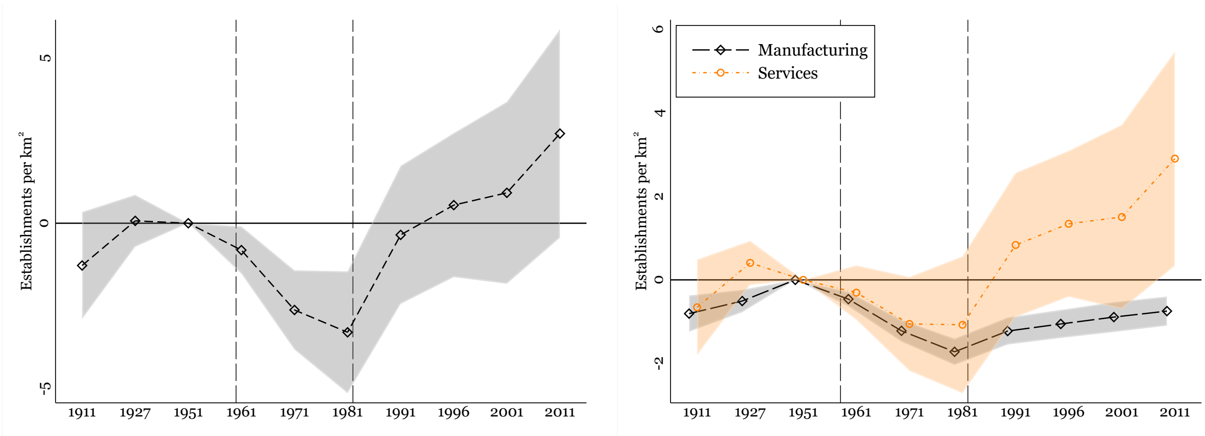


Notes: Coefficient estimates for Equation B3.2, comparing over time municipalities up to 16 km outside of the minimum IDA border (treatment group) with municipalities up to 16 km away from municipalities bordering placebo centers (control group). The treatment group excludes IDA municipalities. Municipalities around placebo centers are weighted using synthetic control weights. See Appendix B.3 for details. The outcome is employment density, measured as number of workers per km^2. Panel (b) shows employment density separately for manufacturing (black diamonds) and services (orange circles). Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the IDAs.

Figure C13. Establishment Density: Policy Spillovers to Nearby Control Areas

(a) Establishment density

(b) Manufacturing versus services

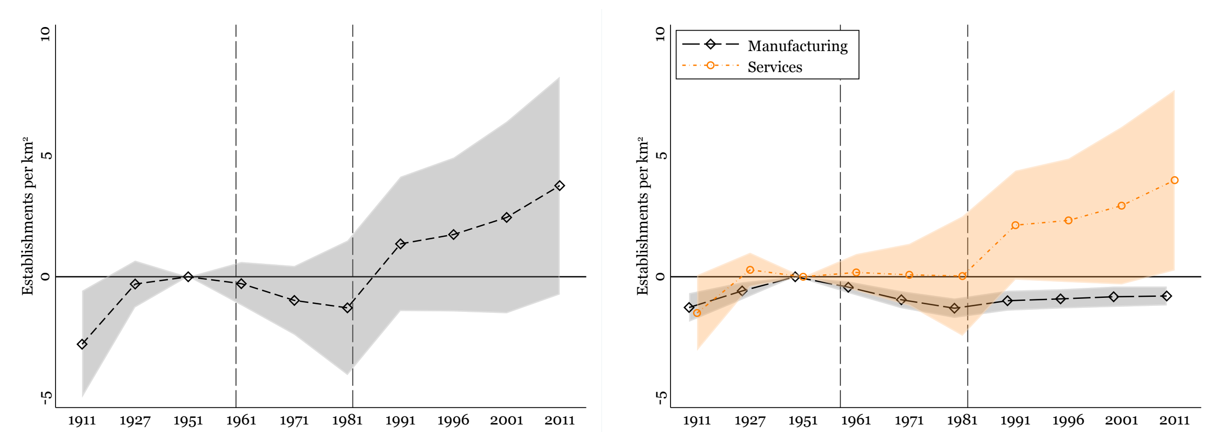


Notes: Coefficient estimates for Equation B3.2, comparing over time municipalities up to 16 km outside of the minimum IDA border (treatment group) with municipalities up to 16 km away from municipalities bordering placebo centers (control group). The treatment group excludes IDA municipalities. The outcome is establishment density, measured as number of establishments per km^2. Panel (b) shows establishment density separately for manufacturing (black diamonds) and services (orange circles). Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the IDAs.

Figure C14. Establishment Density: Policy Spillovers, Synthetic Placebo Centers

(a) Establishment density

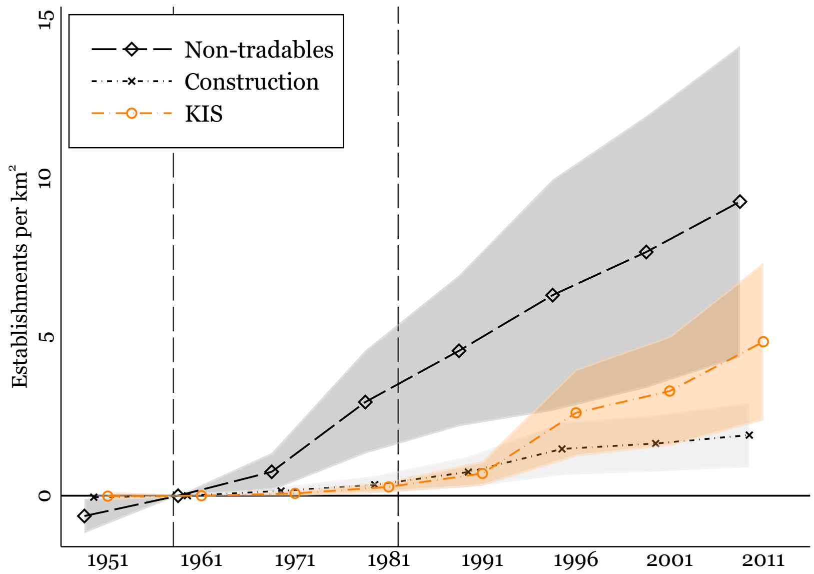
(b) Manufacturing versus services



Notes: Coefficient estimates for Equation B3.2, comparing over time municipalities up to 16 km outside of the minimum IDA border (treatment group) with municipalities up to 16 km away from municipalities bordering placebo centers (control group). The treatment group excludes IDA municipalities. Municipalities around placebo centers are weighted using synthetic control weights. See Appendix B.3 for details. The outcome is establishment density, measured as number of establishments per km^2. Panel (b) shows establishment density separately for manufacturing (black diamonds) and services (orange circles). Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the IDAs.

D. Appendix D: Mechanisms

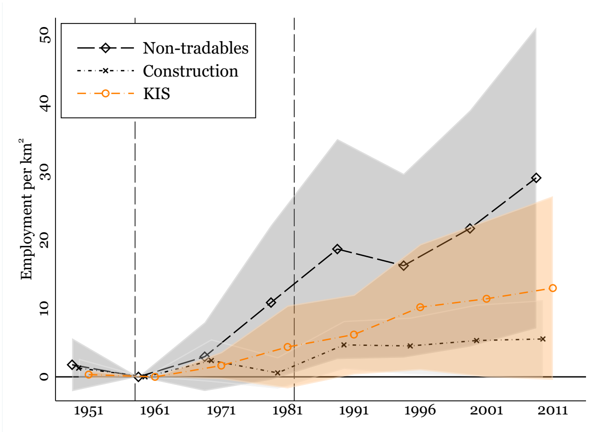
Figure D1. Establishment Density: Decomposition Across Services



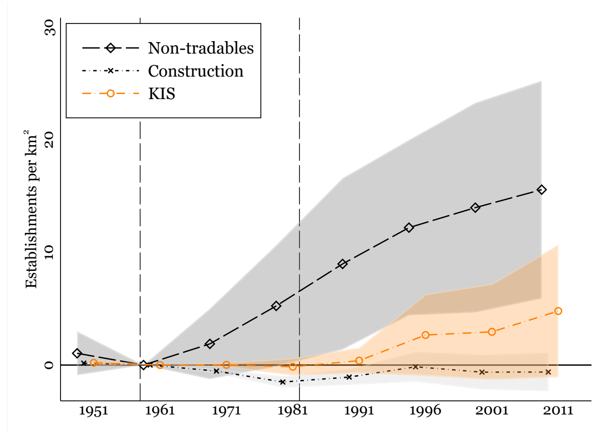
Notes: Coefficient estimates for Equation 2, comparing over time municipalities bordering IDA centers to municipalities up to 16 km away from them. The outcome is establishment density, measured as number of establishments per km^2. Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the IDAs. "Non-tradables": wholesale and retail trade, hotels and restaurants and other (black diamonds). "KIS" (knowledge-intensive services): communication, finance and insurance and services to firms (orange circles). The black crosses denote establishment density in the construction sector. We cannot perform the breakdown within services for the 1911 and 1927 historical censuses.

Figure D2. Decomposition Across Services: Triple Differences

(a) Employment density



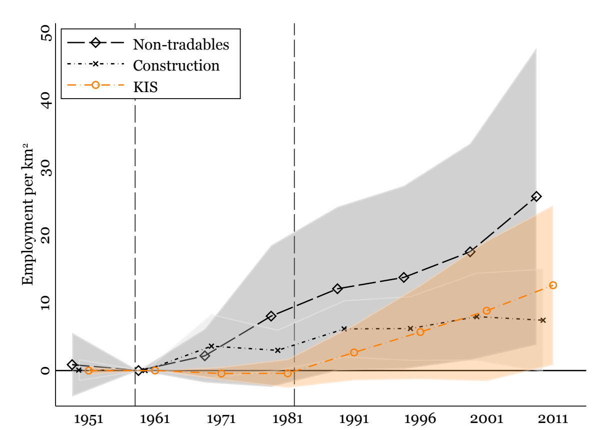
(b) Establishment density



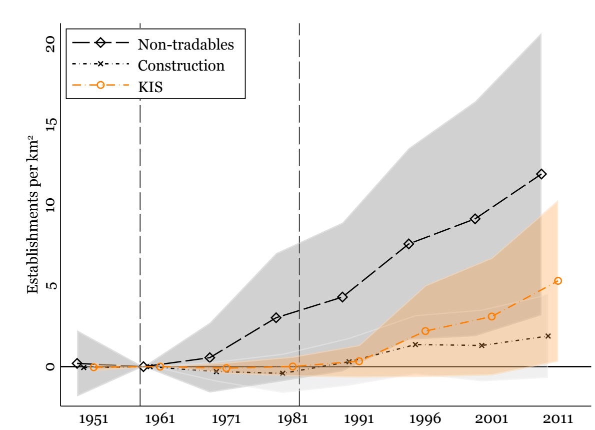
Notes: Coefficient estimates for Equation B3.1, comparing over time the double difference between municipalities within and outside of the minimum IDA border to a placebo double difference between municipalities bordering placebo centers and those further away. See Appendix B.3 for details. The outcomes are employment and establishment density, measured as number of workers (Panel a) and establishments (Panel b) per km^2, respectively. Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the IDAs. "Non-tradables": wholesale and retail trade, hotels and restaurants and other (black diamonds). "KIS" (knowledge-intensive services): communication, finance and insurance and services to firms (orange circles). The black crosses denote employment (Panel a) and establishment (Panel b) density in the construction sector. We cannot perform the breakdown within services for the 1911 and 1927 historical censuses.

Figure D3. Decomposition Across Services: Triple Differences, Synthetic Placebo Centers

(a) Employment density



(b) Establishment density



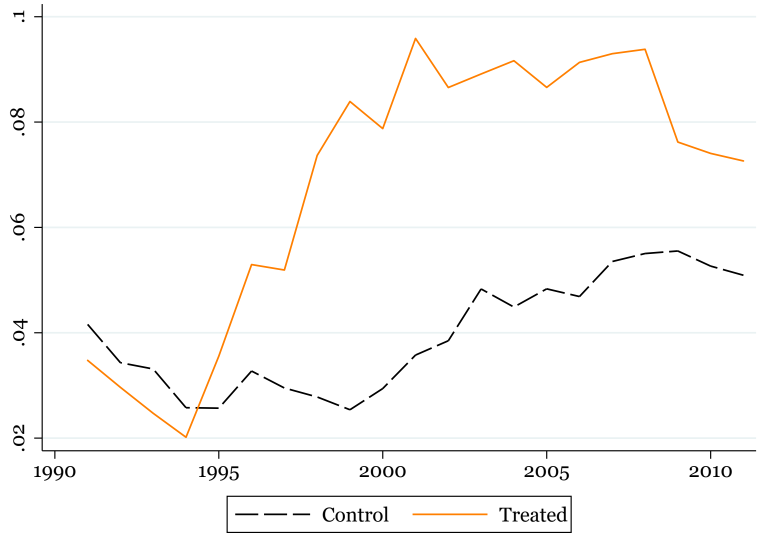
Notes: Coefficient estimates for Equation B3.1, comparing over time the double difference between municipalities within and outside of the minimum IDA border to a placebo double difference between municipalities bordering placebo centers and those further away. Municipalities around placebo centers are weighted using synthetic control weights. See Appendix B.3 for details. The outcomes are employment and establishment density, measured as number of workers (Panel a) and establishments (Panel b) per km^2, respectively. Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the IDAs. "Non-tradables": wholesale and retail trade, hotels and restaurants and other (black diamonds). "KIS" (knowledge-intensive services): communication, finance and insurance and services to firms (orange circles). The black crosses denote employment (Panel a) and establishment (Panel b) density in the construction sector. We cannot perform the breakdown within services for the 1911 and 1927 historical censuses.

Table D1. Employment and Firm Shares Within Services and Manufacturing: RD Estimates, Social Security Data

	Within services				Within manufacturing			
	Employment		Firms		Employment		Firms	
	KIS	Other serv.	KIS	Other serv.	High-tech	Low-tech	High-tech	Low-tech
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Contemporaneous effect (1991)							
RD Estimate	0.08	-0.08	0.06	-0.06	0.27	-0.27	0.15	-0.15
	(0.06)	(0.06)	(0.03)	(0.03)	(0.09)	(0.09)	(0.05)	(0.05)
Mean	0.17	0.83	0.11	0.89	0.16	0.84	0.14	0.86
S.D.	0.19	0.19	0.10	0.10	0.21	0.21	0.14	0.14
Obs.	570	570	570	570	566	566	566	566
	Persistent effect (2011)							
RD Estimate	0.08	-0.08	0.06	-0.06	0.19	-0.19	0.14	-0.14
	(0.04)	(0.04)	(0.02)	(0.02)	(0.08)	(0.08)	(0.05)	(0.05)
Mean	0.10	0.90	0.10	0.90	0.25	0.75	0.20	0.80
S.D.	0.10	0.10	0.06	0.06	0.24	0.24	0.16	0.16
Obs.	585	585	585	585	569	569	569	569

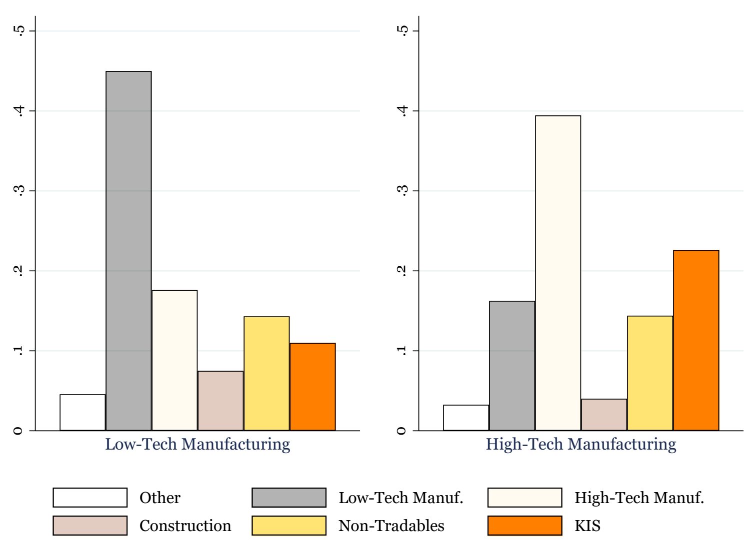
Notes: Fuzzy RD estimates using a binary treatment (IDA status) and a binary instrument equal to one for municipalities within the cutoff—see Equations 1a and 1b. Columns (1)-(4): the outcomes are the share of employment and establishments in KIS (Columns 1 and 3) and other services (Column 2 and 4), separately for workers (Columns 1 and 2) and firms (Columns (3 and 4). The shares are obtained from social security data on the universe of Italian firms in the private sector and the KIS classification is obtained from Eurostat/OECD. See Appendix A.3 for details. Columns (5)-(8): the outcomes are the share of employment (Columns 5 and 6) and firms (Columns 7 and 8) across manufacturing sub-sectors, grouped by technological intensity (high-technology in Columns 5 and 7, low technology in Columns 6 and 8). The shares are obtained from social security data on the universe of Italian firms and the technology classification is obtained from Eurostat/OECD. See Appendix A.3 for details. All regressions are estimated over a 16-km symmetric bandwidth around the minimum IDA border and control for a linear polynomial in the distance to the border and IDA region effects. Mean and standard deviation computed within the estimation sample. Standard errors clustered by IDA region in parentheses.

Figure D4. Share of New Hires in KIS Firms From High-Technology Manufacturing Firms



Notes: The graph shows the share of cumulative yearly job-to-job new hires in KIS firms coming from high-technology manufacturing firms, separately for municipalities bordering IDA centers (Treated, solid line) and municipalities up to 16 km away from them (Control, dashed line), since 1991. The KIS (knowledge-intensive services) classification and the manufacturing technology intensity classification are obtained from Eurostat/OECD (Appendix A.3). The shares are computed for municipalities included in the baseline estimation sample.

Figure D5. Share of Inputs in Low- and High-Technology Manufacturing, 2020



Notes: The chart shows the breakdown of inputs demanded at the Italian national level by low-technology (left) and high-technology (right) manufacturing industries, respectively, for 2020. Each bar is computed as the average across industries. The KIS classification and the manufacturing technology intensity classification are obtained from Eurostat/OECD (Appendix A.3).

Table D2. Employment and Firm Shares Within Services: RD Estimates, Social Security Data, Granular Industry Breakdown (Year 2011)

	RD Estimate	S.E.	Mean	S.D.
	a) Employment shares			
Other human resources provision	3.17	(1.76)	0.31	3.82
Maintenance and repair of motor vehicles	2.49	(0.66)	4.31	7.14
Computer programming, consultancy and related activities	1.60	(0.66)	0.91	2.53
Other specialized wholesale	1.43	(0.84)	1.93	3.48
Reinsurance	0.72	(0.41)	0.39	1.55
Sports activities	0.69	(0.38)	0.31	1.79
Management consultancy activities	0.49	(0.21)	0.34	1.05
Legal activities	0.30	(0.16)	0.45	0.80
Renting and operating of own or leased real estate	0.07	(0.04)	0.05	0.24
Other telecommunications activities	0.07	(0.04)	0.03	0.18
Passenger air transport	0.03	(0.01)	0.00	0.04
Fund management activities	0.01	(0.01)	0.00	0.03
Wholesale and retail trade and repair of motor vehicles	-0.01	(0.01)	0.00	0.02
Retail sale in non-specialized stores	-0.13	(0.08)	0.03	0.18
Wholesale of agricultural raw materials and live animals	-1.24	(0.77)	0.85	5.30
Retail sale of food, beverages and tobacco	-2.91	(1.06)	3.28	4.82
	b) Firm shares			
Reinsurance	0.79	(0.49)	0.66	1.80
Management consultancy activities	0.68	(0.30)	0.44	1.01
Data processing, hosting and related activities; web portals	0.66	(0.41)	0.52	1.29
Sports activities	0.64	(0.36)	0.39	1.61
Legal activities	0.55	(0.28)	0.75	1.13
Other professional, scientific and technical activities n.e.c.	0.47	(0.19)	0.33	0.99
Support activities for transportation	0.44	(0.17)	0.73	1.47
Buying and selling of own real estate	0.41	(0.20)	0.15	0.63
Retail trade not in stores, stalls or markets	0.26	(0.09)	0.16	0.52
Other postal and courier activities	0.14	(0.08)	0.06	0.24
Wholesale of information and communication equipment	0.11	(0.06)	0.12	0.39
Market research and public opinion polling	0.11	(0.06)	0.04	0.21
Fund management activities	0.03	(0.01)	0.01	0.06
Translation and interpretation activities	0.01	(0.00)	0.00	0.01
Wholesale and retail trade and repair of motor vehicles	-0.04	(0.02)	0.01	0.05
Retail sale in non-specialized stores	-0.21	(0.11)	0.05	0.26
Beverage serving activities	-3.16	(1.83)	9.77	7.36
Retail sale of food, beverages and tobacco	-4.15	(1.19)	5.38	4.57

Notes: Fuzzy RD estimates using a binary treatment (IDA status) and a binary instrument equal to one for municipalities within the cutoff—see Equations 1a and 1b. Regressions run for employment shares (Panel a) and firm shares (Panel b) within services using 3-digit sector shares, in 2011. We only show estimates with p-value<0.11. Each outcome is in percentage units. All regressions are estimated over a 16-km symmetric bandwidth around the minimum IDA border and control for a linear polynomial in the distance to the border and IDA region effects. Mean and standard deviation computed within the estimation sample. Standard errors clustered by IDA region in parentheses.

Table D3. Firm Size and Wage Distribution: RD Estimates

	Firm size			Firm wage		
	T1	T2	T3	T1	T2	T3
	(1)	(2)	(3)	(4)	(5)	(6)
	Contemporaneous effect (1991)					
RD Estimate	-0.02	-0.04	0.06	-0.10	0.04	0.06
	(0.03)	(0.03)	(0.04)	(0.03)	(0.02)	(0.04)
Mean around the border	0.42	0.32	0.26	0.39	0.31	0.30
Standard deviation	0.13	0.10	0.11	0.14	0.10	0.12
Observations	582	582	582	582	582	582
	Persistent effect (2011)					
RD Estimate	-0.05	-0.02	0.07	-0.04	-0.01	0.05
	(0.03)	(0.02)	(0.03)	(0.02)	(0.01)	(0.02)
Mean around the border	0.43	0.33	0.24	0.35	0.33	0.32
Standard deviation	0.09	0.07	0.09	0.10	0.07	0.10
Observations	586	586	586	586	586	586

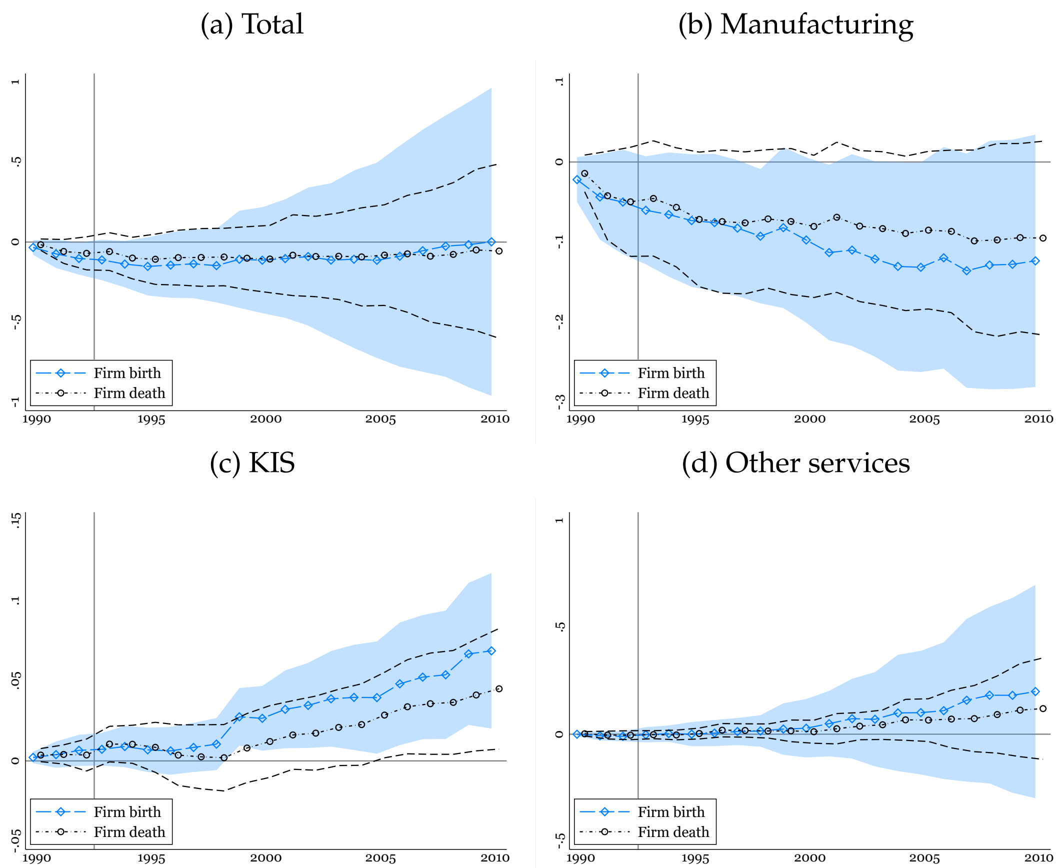
Notes: Fuzzy RD estimates using a binary treatment (IDA status) and a binary instrument equal to one for municipalities within the cutoff—see Equations 1a and 1b. Outcomes are computed as the share of firms in each tertile of the distribution of firm size (Columns 1-3) and in the distribution of firm wage paid (Columns 4-6). Tertiles are derived on the universe of the Italian firms each year. See Appendix A.3 for details. All regressions are estimated over a 16-km symmetric bandwidth around the minimum IDA border and control for a linear polynomial in the distance to the border and IDA region effects. Mean and standard deviation computed within the estimation sample. Standard errors clustered by IDA region in parentheses.

Table D4. Balance Sheet Outcomes, 2011: RD Estimates

	Total	By sector		Within services	
		Manufacturing	Services	KIS	Other serv.
	(1)	(2)	(3)	(4)	(5)
			Log Value added / Worker		
RD Estimate	0.52	1.54	0.04	1.43	-0.16
	(0.31)	(0.53)	(0.31)	(0.64)	(0.33)
Mean around the border	4.49	4.31	4.24	4.00	4.23
Standard deviation	0.88	1.07	0.90	1.12	0.91
Observations	577	507	545	369	543
			Log Investment / Worker		
RD Estimate	0.31	1.02	0.48	1.98	0.34
	(0.25)	(0.43)	(0.35)	(0.99)	(0.36)
Mean around the border	2.87	2.68	2.60	2.04	2.59
Standard deviation	1.14	1.41	1.25	1.56	1.27
Observations	582	516	553	369	552
			Log Sales / Worker		
RD Estimate	0.42	1.35	0.04	1.40	-0.05
	(0.35)	(0.55)	(0.38)	(0.72)	(0.42)
Mean around the border	6.07	5.78	6.00	5.00	6.04
Standard deviation	0.92	1.20	0.99	1.19	1.00
Observations	582	519	558	378	556
			Log Profits / Worker		
RD Estimate	1.04	2.23	0.82	-0.66	0.84
	(0.49)	(0.82)	(0.62)	(1.02)	(0.68)
Mean around the border	2.21	2.26	2.01	2.07	2.03
Standard deviation	1.42	1.63	1.49	1.69	1.47
Observations	361	285	316	240	307

Notes: Fuzzy RD estimates using a binary treatment (IDA status) and a binary instrument equal to one for municipalities within the cutoff—see Equations 1a and 1b. All outcomes are as of 2011 and expressed in natural logarithm, scaled by total firm workforce. See Appendix A.3 for details. We compute outcomes for all firms (Column 1) and then separately by sector (Columns 2-5). Knowledge-intensive services (KIS) defined following the Eurostat/OECD classification (Appendix A.3). All regressions are estimated over a 16-km symmetric bandwidth around the minimum IDA border and control for a linear polynomial in the distance to the border and IDA region effects. Mean and standard deviation computed within the estimation sample. Standard errors clustered by IDA region in parentheses. The coverage of the income statements data from Cerved is low in the 1990s (less than 20 percent of the universe of firms). We therefore only show the more informative long-term (2011) effects.

Figure D6. Firm Dynamics: RD Estimates

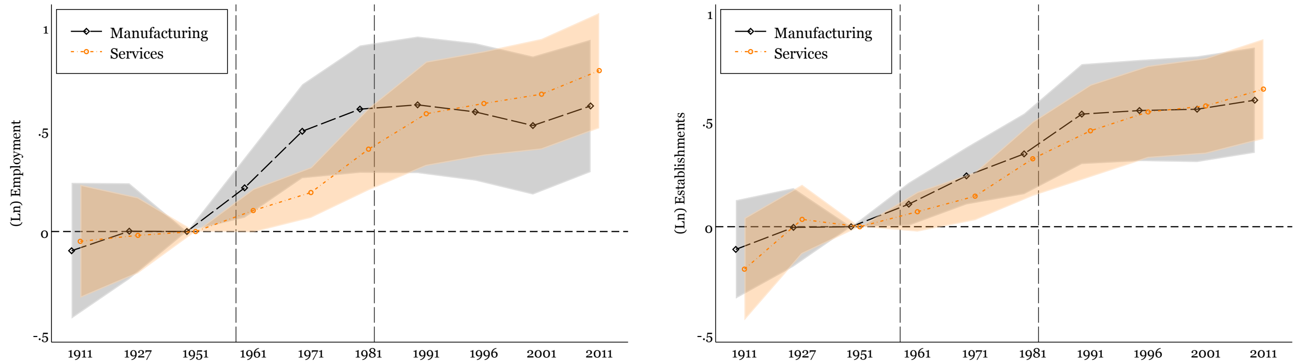


Notes: Year-by-year fuzzy RD estimates using a binary treatment (IDA status) and a binary instrument equal to one for municipalities within the cutoff—see Equations 1a and 1b. The shaded areas denote 95 percent confidence intervals. The vertical line marks the end of the EIM. The outcomes are firm birth rates (blue diamonds) and firm death rates (black circles), computed as the cumulative number of firm births and deaths every year since 1990, respectively, as a share of the total number of firms in the municipality in 1990. See Appendix A.3 for details. We compute outcomes for all firms (Panel a) and then separately by sector (Panels b-d). Knowledge-intensive services (KIS) defined following the Eurostat/OECD classification (Appendix A.3). All regressions are estimated over a 16-km symmetric bandwidth around the minimum IDA border and control for a linear polynomial in the distance to the border and IDA region effects.

Figure D7. Log Employment and Establishments: Longitudinal Estimates

(a) Log Employment

(b) Log Establishments

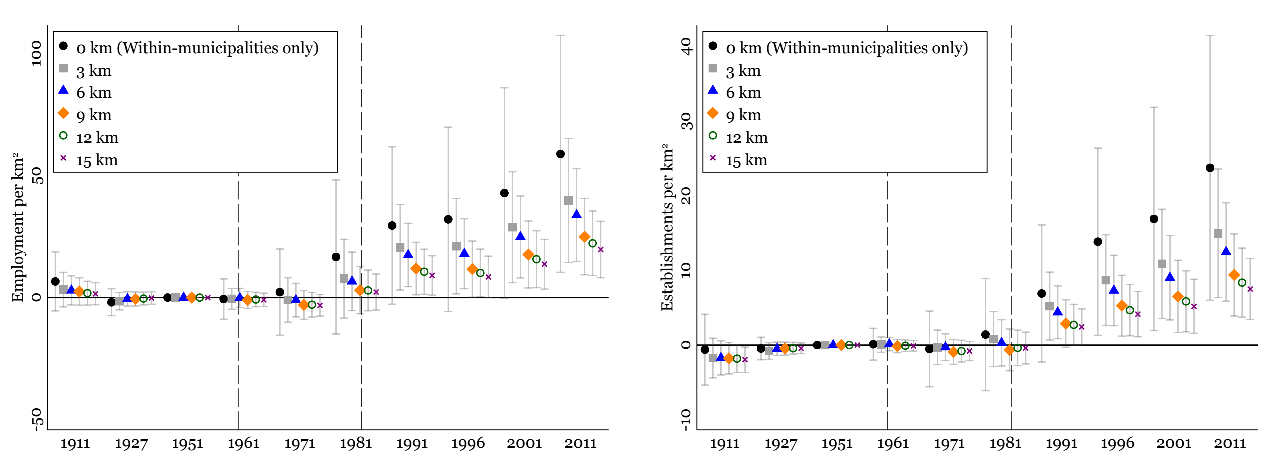


Notes: Coefficient estimates for Equation 2, comparing over time municipalities bordering IDA centers to municipalities up to 16 km away from them. The outcomes are the number of workers (Panel a) and establishments (Panel b), separately for manufacturing (black diamonds) and services (orange circles), in natural logarithm. Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the IDAs.

Figure D8. Employment and Firm Density: Longitudinal Estimates at Different Geographic Scales

(a) Employment density

(b) Establishments density



Notes: The chart shows longitudinal estimates resulting from the estimation of Equation B3.2 on varying treatment and control samples. The black dot "0 km" shows coefficients when comparing municipalities bordering IDA centers with municipalities bordering placebo centers weighted by their respective synthetic weights. Then, we progressively expand the set of treated and control municipalities up to 15 km away from their IDA and placebo center (where control municipalities are again weighted using synthetic weights). See Appendix B.3 for details. The outcomes are employment and establishment density, measured as number of workers (Panel a) and establishments (Panel b) per km^2, respectively. Standard errors clustered at the municipality level. The gray lines denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the IDAs.

Table D5. Other Outcomes and Expenditures: RD Estimates

	(1)	(2)	(3)	(4)	(5)
Panel a)	House prices	Rents	Tax income	Krugman Ind.	Gini coeff.
RD Estimate	543.97	2.01	0.33	-0.20	0.03
	(214.44)	(0.88)	(0.09)	(0.10)	(0.01)
Mean around the border	1087.09	3.94	8.95	0.97	0.38
Standard deviation	580.83	1.97	0.23	0.32	0.03
Observations	574	537	587	586	587
Panel b)	Total	Admin.	Educ.	Viabil.	Territ.
RD Estimate	-0.10	-0.06	-0.25	-0.11	-0.02
	(0.12)	(0.14)	(0.14)	(0.21)	(0.16)
Mean around the border	9.43	8.18	6.84	7.21	8.09
Standard deviation	0.41	0.39	0.43	0.65	0.58
Observations	587	587	587	587	587
Panel c)	Social	Just. & pol.	Cult. & sport	L. 488/1992	EU Funds
RD Estimate	0.11	0.21	-0.19	0.91	0.15
	(0.16)	(0.20)	(0.22)	(1.24)	(0.30)
Mean around the border	6.90	6.15	6.37	4.45	6.46
Standard deviation	0.54	0.41	0.75	4.34	1.24
Observations	587	587	587	587	544

Notes: Fuzzy RD estimates using a binary treatment (IDA status) and a binary instrument equal to one for municipalities within the cutoff—see Equations 1a and 1b. Panel (a): "House prices" and "Rents" are residential real estate prices and rents as of Q1-2011, measured in € / squared meter. "Tax income" denote (log) tax income in € / capita in 2010. "Krugman Ind." is the Krugman Specialization Index for manufacturing in 2011 (see Appendix A.2). "Gini coeff." is the Gini coefficient as of 2011. Panel (b) and Columns (1)-(3) of Panel (c): outcomes are cumulative municipality expenditures between 2000 and 2011, sourced from municipality balance sheets. All items include both current and capital expenditure. "Admin." measures spending in administrative services; "Educ." in education and childcare services; "Viabil." in viability, urban planning and infrastructure; "Territ." in environmental services (e.g., waste collection and recycling); "Social" in social services; "Just. & pol." in justice and local police; "Cult. & sport" in cultural and recreational services. Panel (c) Column (4): "L. 488/1992" measures the total funds obtained through Law 488/1992 (firm subsidies introduced right after the end of the EIM). Panel (c) Column (5): "EU Funds" are total funds received through the EU Structural Funds program between 2007 and 2013. All variables in Panels (b) and (c) are expressed in natural logarithm of the per capita amount in € (using the 2001 population). All regressions are estimated over a 16-km symmetric bandwidth around the minimum IDA border and control for a linear polynomial in the distance to the border and IDA region effects. Mean and standard deviation computed within the estimation sample. Standard errors clustered by IDA region in parentheses.

E. Appendix E: Cost-benefit analysis

This Appendix provides more details on the calculations described in Section 7.

Cost per job. To obtain a first measure of cost per job, we use the estimates of Table 3 Column (3). We estimate that an increase in EIM funding of €1000 (2011 prices) per 1951 resident leads to 10.3 more workers per km^2 in 2011. For municipalities in the estimation sample, the average 1951 population is 11,328.91 inhabitants and the average extension is 60.88 km^2. This implies that, for the average municipality, total EIM funding of €11,328,910 leads to 630 more jobs—an estimated cost per job of €17,989, or $25,048 (average exchange rate 1.3924 in 2011). The estimate rises to $37,571 assuming a deadweight loss of 50 percent. As alternative, we use the more robust longitudinal estimates to inform our calculations of the cost per job. We do so by taking the last point estimate from the event study regressions in *i*) the baseline dynamic specification (Figure 7(a): 53.64 workers per km^2), and *ii*) the triple differences (Figure C8(a): 51.20 workers per km^2).[38] For each of the two designs, we take the average extension of municipalities in the estimation sample (57.43 and 53.16 km^2, respectively) and obtain the total number of jobs created in the average municipality by multiplying the coefficients by the average area: 3080 for design *i*) and 2722 for design *ii*).

To compute the costs, both designs *i*) and *ii*) require an estimate of the jump in EIM funding at the minimum IDA border, which is provided in Table 2 Column (2). To retain consistency with the longitudinal designs, we re-estimate the discontinuity in EIM funding on a sample that excludes IDA centers. This yields an effect of €5,797 per 1951 resident, very similar to the €5,720 jump reported in Table 2 Column (2) for the full sample. We then multiply these average cost measures by the average 1951 population in the estimation sample (8287.16 and 7650.64) to obtain total EIM funding in the average municipality: €48,040,678 for design *i*) and €44,350,743 for design *ii*). Putting everything together, we estimate a cost per job of €15,596 ($21,716) for design *i*) and €16,294 ($22,687) for design *ii*). Assuming a 50 percent deadweight loss, the final estimates of the cost per job are similar to the baseline ones: $32,575 for design *i*) and $34,031 for design *ii*).

Cost-benefit analysis. We now describe a cost-benefit analysis based on our estimates, which builds on the study of US Empowerment Zones in Busso et al. (2013). The goal is to estimate the local gains entailed by IDAs and compare them with the total costs of the

[38] The point estimates from the triple differences design using synthetic placebo centers are very similar, see Figure C9.

policy to assess its cost-effectiveness. In our exercise, we focus exclusively on the benefits generated by the policy *after* its termination. We also caveat that this analysis focuses on gains generated locally and therefore abstracts from important general equilibrium effects, which are analyzed in Cerrato and Filippucci (2024) through a macro-structural model.

We break down total surplus into three components: wage gains for workers, corporate profits for firms, and rental gains for landlords.[39] For each of these components, we compute the flow each year between 1991 and 2011. Specifically:

1. Wage bill: we use firm-level information on average monthly wages, available for the universe of Italian firms in the Bank of Italy-INPS social security archives. These are multiplied by twelve to obtain annual values and then by the firm's total employment each year to compute the total wage bill.

2. Corporate profits: income statements from Cerved are available only for incorporated firms. In addition, the Cerved data start in 1995 and coverage is not very large until the 2000s. For these reasons, we impute firm profits for all incorporated firms using the fitted value of a regression of firm profits on total wages and employment, controlling for year and province dummies. This procedure sets to zero profits of all non-incorporated firms, thus underestimating total profits in a municipality.[40]

3. Housing rents: we have data on house prices and rents only for 2004 and 2011. We use information on rental prices in € /squared meter in a municipality, which we then multiply by the total building area in the municipality to obtain the flow.[41] We compute annual flows in 2004 and 2011, which we then linearly interpolate for the other years.

We then compute the effect of the policy on each of these outcomes in the post-IDA years ($\hat{\pi}_j$, Table E1). For the wage bill and firm profits, we run a cross-sectional specification of Equation 1b at the minimum IDA border on the pooled sample of years between 1991 and 2011, controlling for year effects. This produces a unique (reduced-form) estimate of the effect of IDAs after their termination. Estimating the coefficient year by year and then

[39]None of these variables are available during the policy years, which leads us to study long-run gains. We also cannot distinguish between benefits for IDA residents and non-resident commuters, as done in Busso et al. (2013). That said, our focus on long-run benefits makes this distinction less meaningful as we have documented no migration and commuting after the end of IDAs.

[40]Firms in the Cerved data cover just about 30 percent of the total number of firms in Italy. These are however the largest firms and likely account for the lion's share of aggregate profits.

[41]We approximate the building area of a municipality as 1.3 percent of total area. This estimate is produced by the Italian Tax Office, which calculates a total gross floor area of dwellings of roughly four billion squared meters (1.3 percent of Italy's surface). This share is likely much larger in our setting as we focus on urban centers, hence the estimated rental gains are a lower bound of the true value.

averaging the effect across years delivers almost identical results. For housing rents, we estimate Equation 1b separately for 2004 and 2011 and then compute the average of the two coefficients.

These estimates are used to calculate the counterfactual flow for each outcome j and year y as $counterfactual_{jy} = observed_{jy}/(1 + \hat{\pi}_j)$. The net benefit is then the difference between the observed and counterfactual amount. These net benefits are then aggregated over time using a discount rate of 10 percent to obtain the present discounted value of the IDA benefits. This rate, chosen to mirror the one-year rate on Italian treasury bonds in the early 1990s, is admittedly high. The estimated net benefits would increase with smaller discount rates of, say, 3 percent (Lu et al., 2019) or 5-7 percent (Lapoint and Sakabe, 2022). Table E2 shows the final calculations. The benefits generated by IDAs between 1991 and 2011 are estimated at €196 billion, 60 percent of which in the form of higher wage bill. The share of firm profits is smaller at 38 percent, and that of housing rents is almost negligible. The present discounted value of the total IDA benefits hovers just below €86 billion. Compared with total funding in IDA municipalities of €88 billion, this implies that the gains generated in the two decades after the end of the policy are enough to cover the total costs.

This analysis comes with some caveats. On the one hand, the total costs of the IDA policy are likely larger than €88 billion as they also include expenses from IDAs' consortia, which are not reported in the ASET data and cannot therefore be included in the calculations. On the other hand, however, our estimates of the program's gains are quite conservative. As noted, the true gains in firm profits and housing rents are underestimated since i) we only consider profits of incorporated firms and ii) we make very conservative assumptions on the building area of a municipality. In addition, we do not account for the gains in housing valuations, which are another important effect of the policy as showed in Table D5. In logarithmic terms, we estimate a positive effect of 18 percent on house prices in 2011. This results in further €10 billion accruing to landlords, which do not feature in our baseline calculations. All considered, our conclusion that the local gains of IDAs in the two decades after their termination at least compensate for the total costs of the policy seems fairly robust. In turn, this suggests that the program entailed a net surplus assuming that it also generated some benefits while it was in place.

Table E1. RD Coefficient Estimates ($\hat{\pi}_j$) for the Cost-Benefit Analysis

	(Log) Wage bill	(Log) Firm profits	(Log) Rents 2004	(Log) Rents 2011
	(1)	(2)	(3)	(4)
RD Estimate	0.70	0.97	0.18	0.19
	(0.33)	(0.37)	(0.05)	(0.06)
Observations	12,282	8,573	535	537

Notes: For wages and profits (Columns 1-2), we estimate the reduced-form Equation 1b on the pooled sample 1991-2011 and include year effects. For rents (Columns 3-4), we run Equation 1b separately for 2004 and 2011. In both cases, we use a 16-km symmetric bandwidth around the minimum IDA border. The specification controls for a linear polynomial in the distance from the border and IDA region effects. Standard errors clustered by IDA region in parentheses.

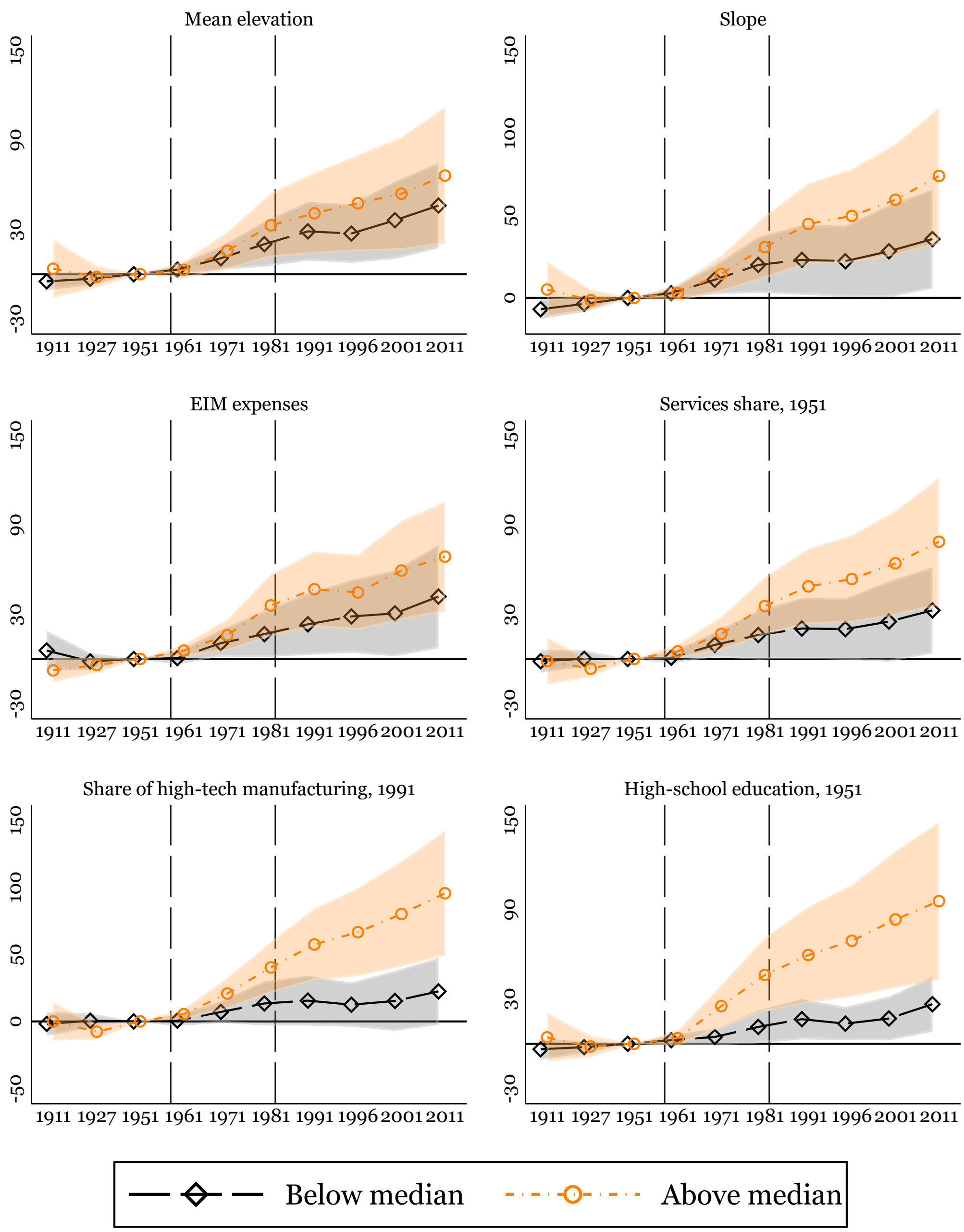
Table E2. Estimated Benefits of the IDA Policy

	Observed (€bn)	$\hat{\pi}_j$	Counterfactual (€bn)	Benefit (€bn)	PDV benefits (€bn)
	(1)	(2)	(3)	(4)	(5)
Wage bill	237.16	0.70	118.07	119.09	52.06
Firm profits	118.68	0.97	44.80	73.88	32.66
Housing rents	20.63	0.19	17.12	3.50	1.21
Total	376.46		179.99	196.47	85.93

Notes: All amounts are cumulated between 1991 and 2011 and measured in billion € (2011 prices). Counterfactual amount (Column 3) obtained as $counterfactual_j = observed_j/(1+\hat{\pi}_j)$. We transform the coefficient using $(e^{\hat{\pi}_j}-1)$. The benefit (Column 4) is calculated as the difference between observed (Column 1) and counterfactual (Column 3) amount. The presented discounted value (PDV, Column 5) is calculated using a 10% discount rate. The effect of the policy $\hat{\pi}_j$ (Column 2) is estimated using the reduced-form specification in Equation 1b—see Table E1 . For firm profits, the actual flows refer only to incorporated firms in the Cerved data.

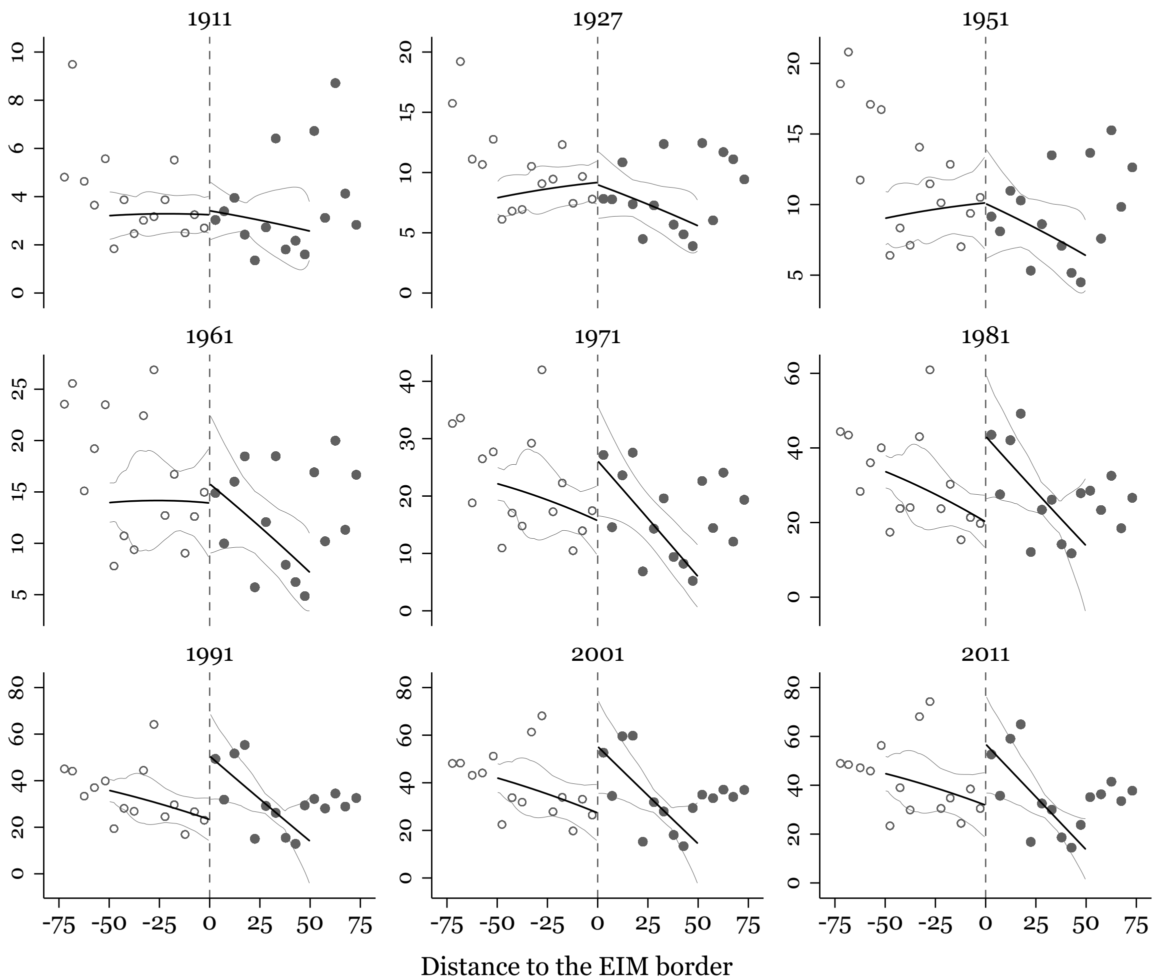
F. Appendix F: The EIM Border

Figure F1. Employment Density: Longitudinal Estimates, Heterogeneity Based on IDA Characteristics



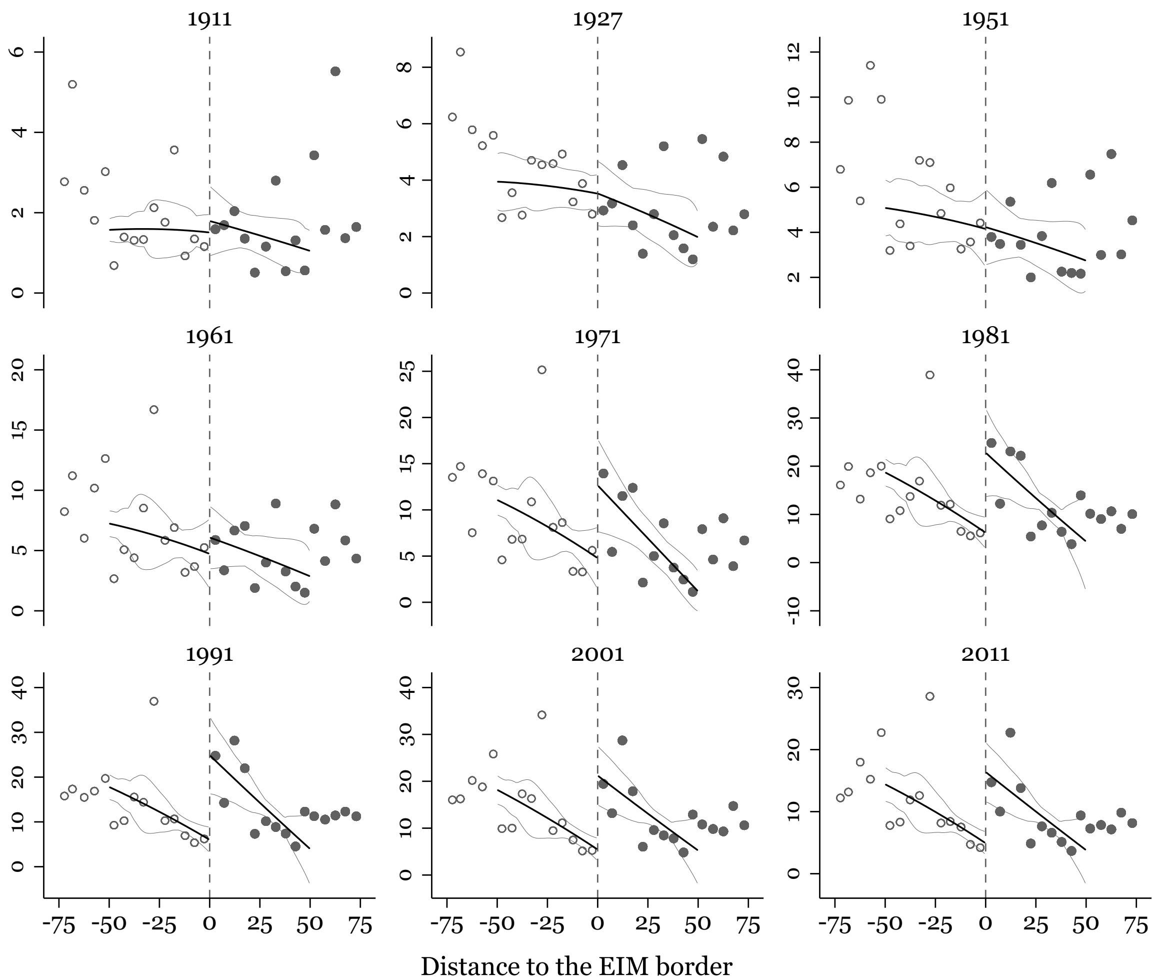
Notes: Coefficient estimates for Equation 2, comparing over time municipalities bordering IDA centers to municipalities up to 16 km away from them. The outcome is employment density, measured as number of workers per km^2. For each of the six variables, we compute the mean within each IDA region using only municipalities bordering the IDA center. We then compute the median value across all IDA regions and conduct analysis separately for IDA regions above (orange circles) and below (black diamonds) the median. IDA regions comprise all municipalities within 25 km of IDA centers (regardless of whether they belong to the IDA). EIM expenses measured in euros (2011 prices) per 1951 inhabitant, cumulated between 1950 and 1992. Share of high-technology manufacturing computed according to the Eurostat/OECD classification (Appendix A.3). Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals.

Figure F2. Employment Density Over Time at the EIM Border



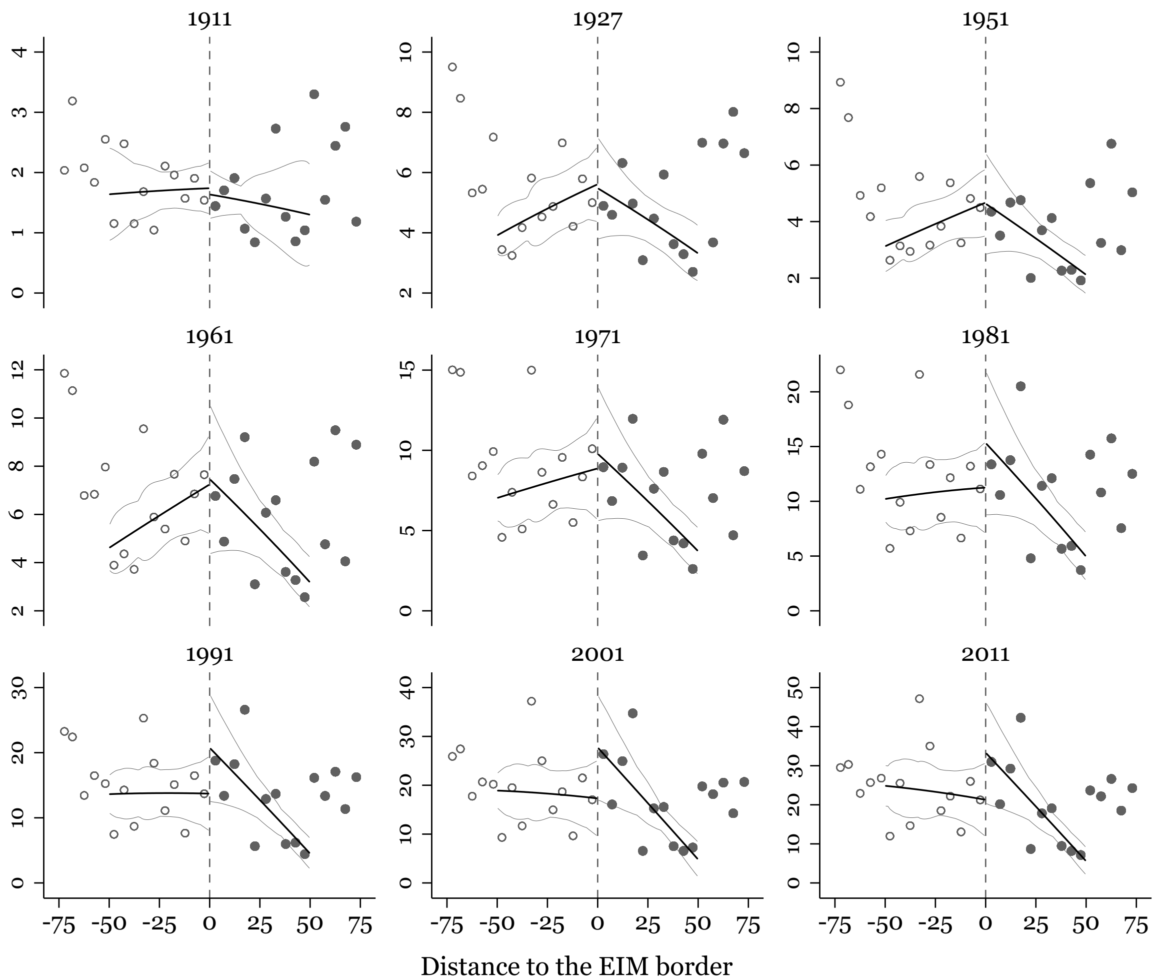
Notes: The outcome is employment density, measured as number of workers per km^2, for each census year. Negative distance denotes municipalities north of the EIM border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately north and south of the border using a 50-km symmetric bandwidth. The gray lines are 95 percent confidence intervals.

Figure F3. Manufacturing Employment Density Over Time at the EIM Border



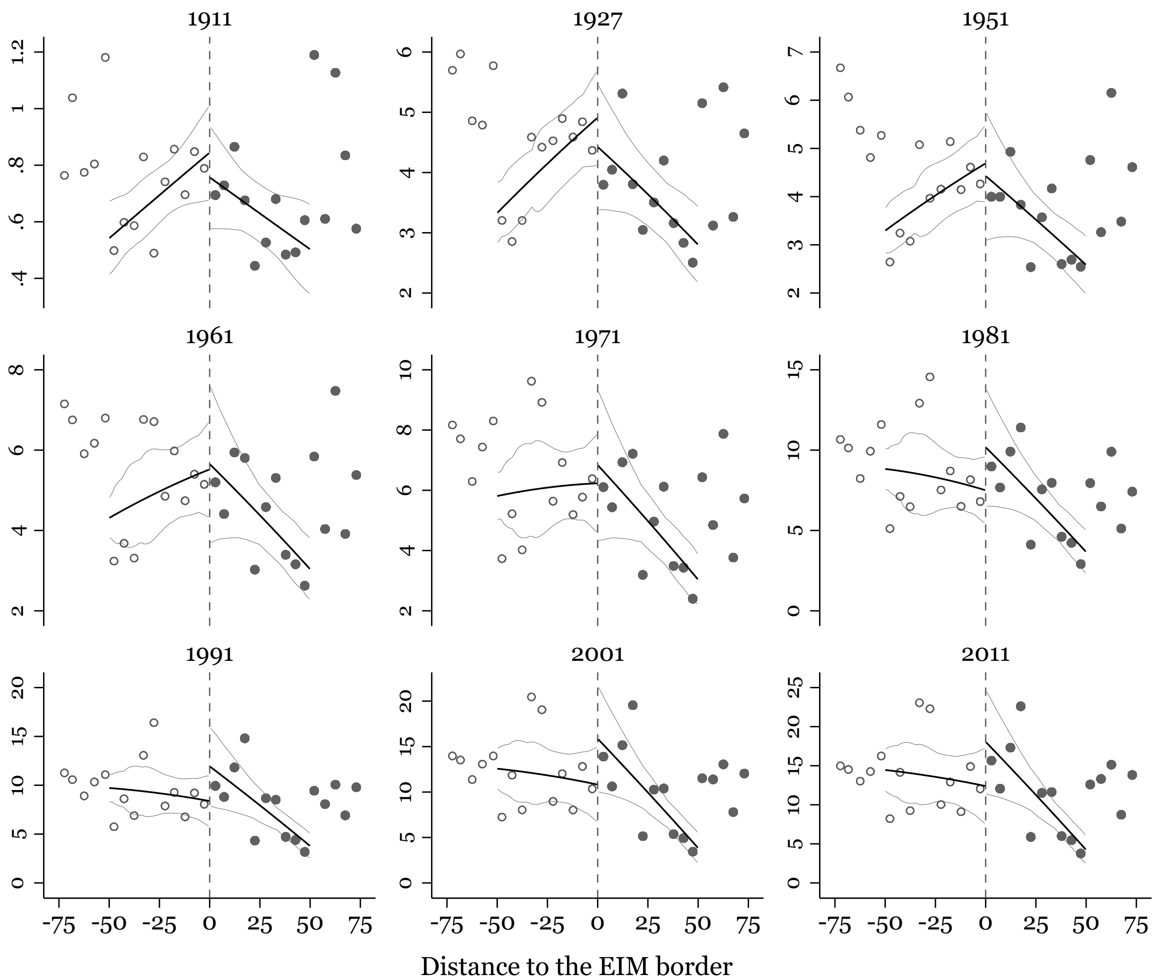
Notes: The outcome is manufacturing employment density, measured as number of manufacturing workers per km^2, for each census year. Negative distance denotes municipalities north of the EIM border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately north and south of the border using a 50-km symmetric bandwidth. The gray lines are 95 percent confidence intervals.

Figure F4. Services Employment Density Over Time at the EIM Border



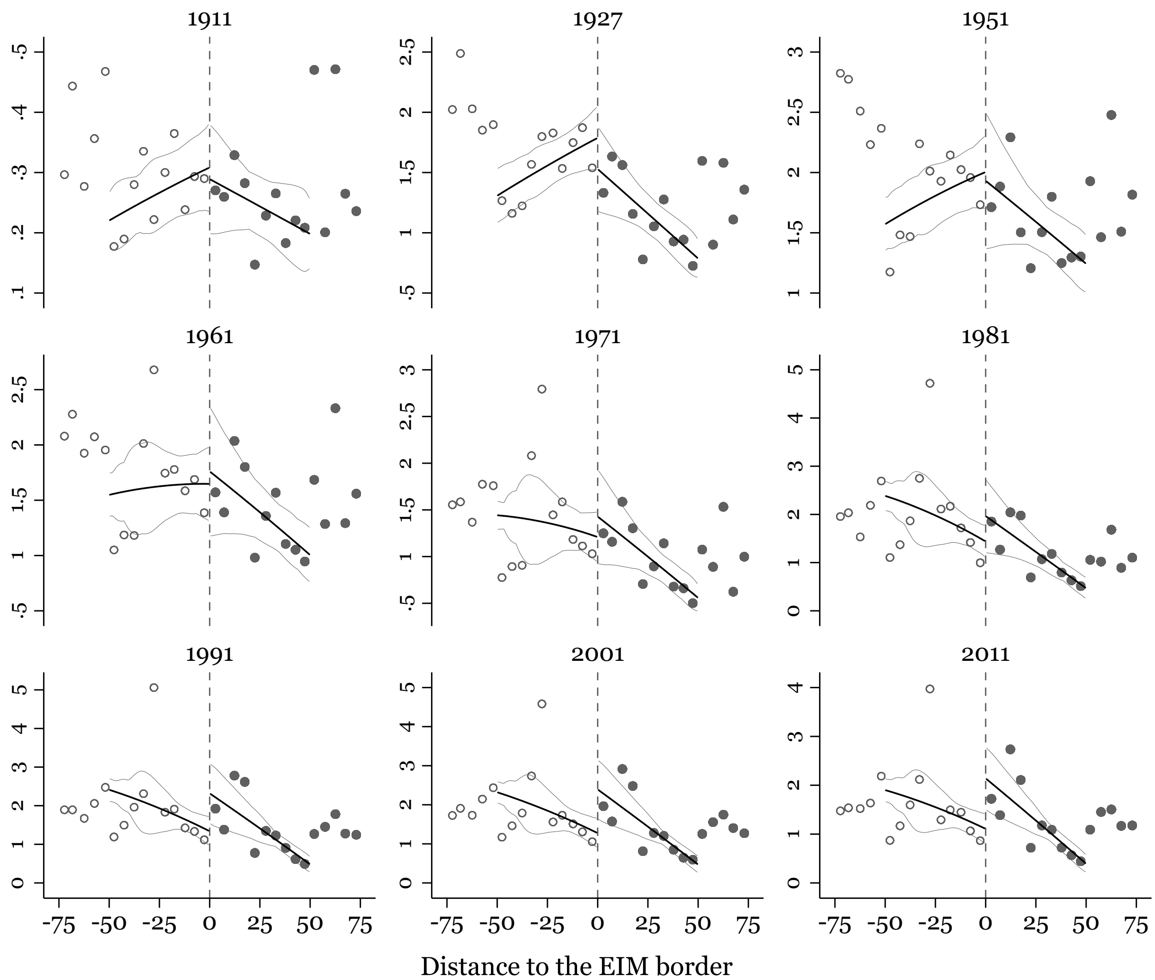
Notes: The outcome is services employment density, measured as number of services workers per km^2, for each census year. Negative distance denotes municipalities north of the EIM border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately north and south of the border using a 50-km symmetric bandwidth. The gray lines are 95 percent confidence intervals.

Figure F5. Establishment Density Over Time at the EIM Border



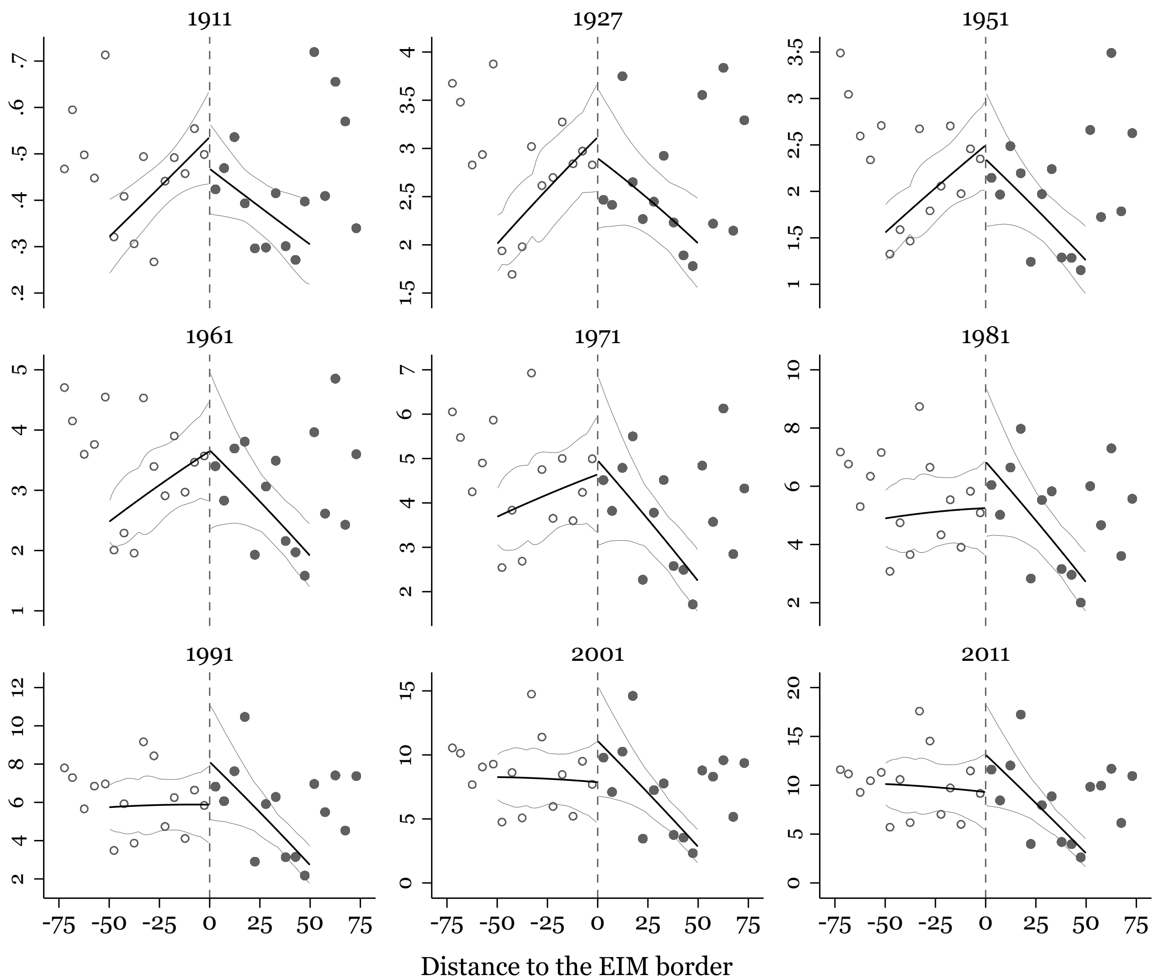
Notes: The outcome is establishment density, measured as number of establishments per km^2, for each census year. Negative distance denotes municipalities north of the EIM border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately north and south of the border using a 50-km symmetric bandwidth. The gray lines are 95 percent confidence intervals.

Figure F6. Manufacturing Establishment Density Over Time at the EIM Border



Notes: The outcome is manufacturing establishment density, measured as number of manufacturing establishments per km^2, for each census year. Negative distance denotes municipalities north of the EIM border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately north and south of the border using a 50-km symmetric bandwidth. The gray lines are 95 percent confidence intervals.

Figure F7. Services Establishment Density Over Time at the EIM Border

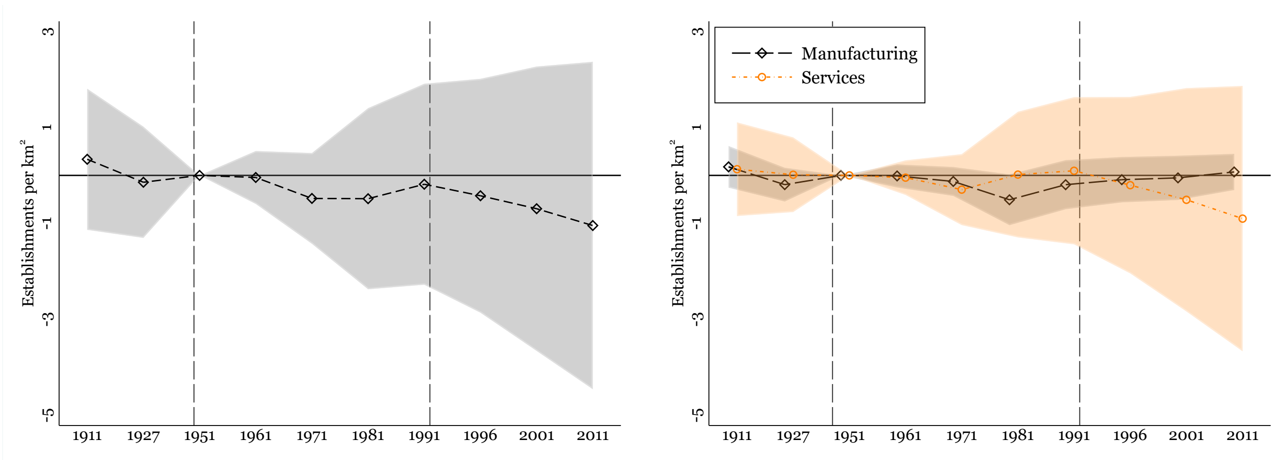


Notes: The outcome is services establishment density, measured as number of services establishments per km^2, for each census year. Negative distance denotes municipalities north of the EIM border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately north and south of the border using a 50-km symmetric bandwidth. The gray lines are 95 percent confidence intervals.

Figure F8. Establishment Density at the EIM Border: Longitudinal Estimates

(a) Establishment density

(b) Manufacturing versus services



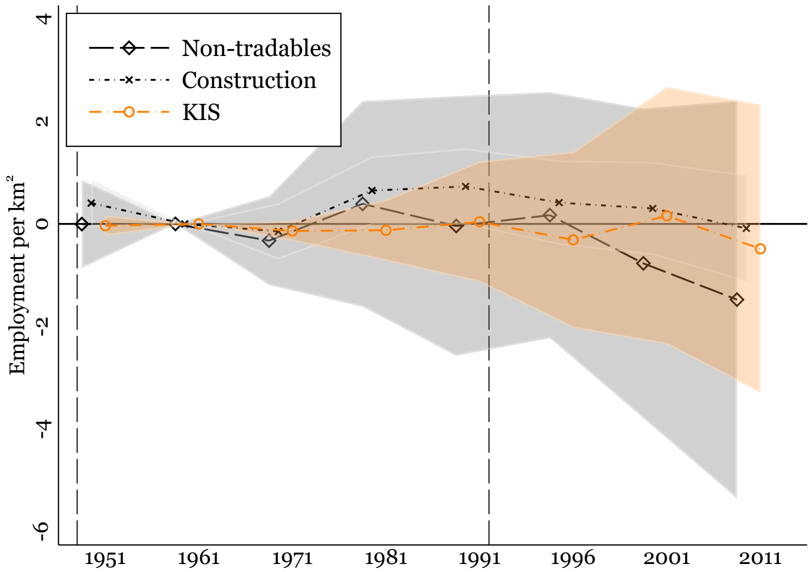
Notes: Coefficient estimates for Equation B4.2, comparing over time municipalities south and north of the EIM border—see Appendix B.4. The outcome is establishment density, measured as number of establishments per km^2. Panel (b) shows establishment density separately for manufacturing (black diamonds) and services (orange circles). Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the EIM.

Table F1. Employment and Establishment Density at the EIM Border: RD Estimates

	Employment density			Establishment density		
	Total	Manufacturing	Services	Total	Manufacturing	Services
	(1)	(2)	(3)	(4)	(5)	(6)
	Contemporaneous effect (1991)					
RD Estimate	18.59	15.36	3.44	1.94	0.71	1.03
	(9.93)	(4.02)	(5.01)	(2.40)	(0.42)	(1.81)
Mean around the border	30.78	12.77	13.53	8.64	1.66	5.76
Standard deviation	61.14	28.13	28.45	14.74	3.22	10.48
Observations	587	587	587	587	587	587
	Persistent effect (2011)					
RD Estimate	14.95	9.26	6.04	2.77	0.77	1.56
	(11.72)	(2.61)	(7.86)	(4.09)	(0.35)	(3.25)
Mean around the border	37.09	9.61	21.79	12.59	1.40	9.14
Standard deviation	71.38	19.60	46.82	24.01	2.61	18.81
Observations	587	587	587	587	587	587

Notes: Coefficient estimates from Equation B4.1 comparing municipalities south and north of the EIM border. The outcomes are employment density (Columns 1-3) and establishment density (Columns 4-6), measured as number of workers and establishments per km^2, respectively, and also showed separately for manufacturing (Columns 2 and 5) and services (Columns 3 and 6). All regressions are estimated over a 50-km symmetric bandwidth around the EIM border and control for a linear polynomial in the distance to the border and border segment effects. Mean and standard deviation computed within the estimation sample. Standard errors allow for spatial correlation (Conley, 1999).

Figure F9. Employment Density at the EIM Border: Decomposition Across Services



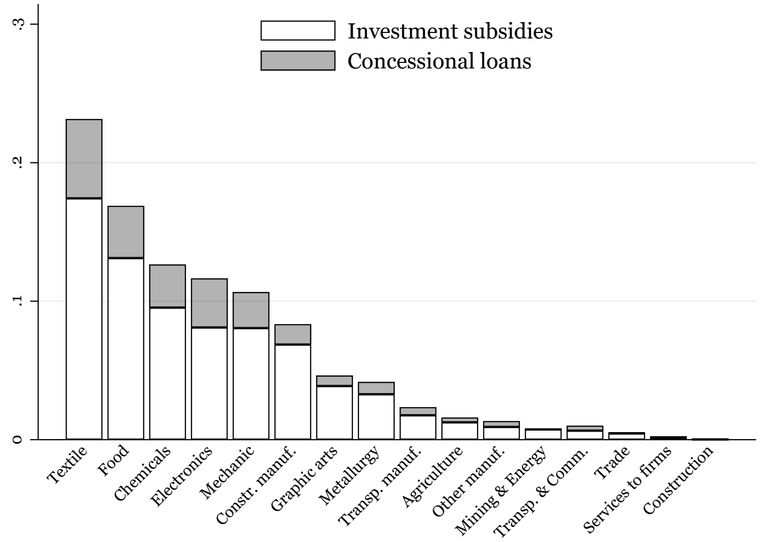
Notes: Coefficient estimates for Equation B4.2, comparing over time municipalities south and north of the EIM border—see Appendix B.4. Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the EIM. The outcome is employment density, measured as number of workers per km^2. "Non-tradables": wholesale and retail trade, hotels and restaurants and other (black diamonds). "KIS" (knowledge-intensive services): communication, finance and insurance and services to firms (orange circles). The black crosses denote employment density in the construction sector. We cannot perform the breakdown within services for the 1911 and 1927 historical censuses.

Table F2. Employment and Firm Shares Within Services and Manufacturing at the EIM Border: RD Estimates, Social Security Data

	Within services				Within manufacturing			
	Employment		Firms		Employment		Firms	
	KIS	Other serv.	KIS	Other serv.	High-tech	Low-tech	High-tech	Low-tech
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Contemporaneous effect (1991)							
RD Estimate	-0.02	0.02	-0.01	0.01	0.02	-0.02	-0.00	0.00
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Mean	0.13	0.87	0.11	0.89	0.14	0.86	0.13	0.87
S.D.	0.20	0.20	0.14	0.14	0.21	0.21	0.15	0.15
Obs.	526	526	526	526	509	509	509	509
	Persistent effect (2011)							
RD Estimate	0.00	-0.00	0.01	-0.01	0.12	-0.12	0.06	-0.06
	(0.02)	(0.02)	(0.01)	(0.01)	(0.04)	(0.04)	(0.03)	(0.03)
Mean	0.09	0.91	0.09	0.91	0.21	0.79	0.18	0.82
S.D.	0.13	0.13	0.09	0.09	0.26	0.26	0.20	0.20
Obs.	570	570	570	570	514	514	513	513

Notes: Coefficient estimates from Equation B4.1 comparing municipalities south and north of the EIM border. All regressions are estimated over a 50-km symmetric bandwidth around the EIM border and control for a linear polynomial in the distance to the border and border segment effects. Mean and standard deviation computed within the estimation sample. Standard errors allow for spatial correlation (Conley, 1999). Columns (1)-(4): the outcomes are the share of employment and establishments in KIS (Columns 1 and 3) and other services (Column 2 and 4), separately for workers (Columns 1 and 2) and firms (Columns (3 and 4). The shares are obtained from social security data on the universe of Italian firms in the private sector and the KIS classification is obtained from Eurostat/OECD. See Appendix A.3 for details. Columns (5)-(8): the outcomes are the share of employment (Columns 5 and 6) and firms (Columns 7 and 8) across manufacturing sub-sectors, grouped by technological intensity (high-technology in Columns 5 and 7, low technology in Columns 6 and 8). The shares are obtained from social security data on the universe of Italian firms and the technology classification is obtained from Eurostat/OECD. See Appendix A.3 for details.

Figure F10. EIM Firm Transfers at the EIM Border: Breakdown Across Industries



Notes: Breakdown of firm investment subsidies (white bars) and concessional loans (gray bars) across sectors based on the sector where recipient firm operates. The sample includes municipalities up to 50 km south of the EIM border.

Table F3. (Log) Wages at the EIM Border: RD Estimates

	Total	By sector		Within services	
		Manufacturing	Services	KIS	Other serv.
	(1)	(2)	(3)	(4)	(5)
			Contemporaneous effect (1991)		
RD Estimate	0.15	0.19	0.16	0.08	0.15
	(0.02)	(0.04)	(0.04)	(0.10)	(0.04)
Mean around the border	7.11	7.12	7.09	7.08	7.10
Standard deviation	0.17	0.25	0.29	0.47	0.24
Observations	580	509	526	331	519
			Persistent effect (2011)		
RD Estimate	0.04	0.04	0.06	0.09	0.06
	(0.03)	(0.05)	(0.04)	(0.09)	(0.04)
Mean around the border	7.08	7.12	6.93	7.05	6.91
Standard deviation	0.18	0.26	0.28	0.52	0.28
Observations	584	514	570	387	569

Notes: Coefficient estimates from Equation B4.1 comparing municipalities south and north of the EIM border. All regressions are estimated over a 50-km symmetric bandwidth around the EIM border and control for a linear polynomial in the distance to the border and border segment effects. Mean and standard deviation computed within the estimation sample. Standard errors allow for spatial correlation (Conley, 1999). The outcome is the mean (log) monthly wage paid by the firm, averaged across firms in a municipality (see Appendix A.3). We compute it for all firms (Column 1) and then separately by sector (Columns 2-5). Knowledge-intensive services (KIS) defined following the Eurostat/OECD classification (Appendix A.3).

Table F4. Human Capital and Skill Composition at the EIM Border: RD Estimates

	High school educ. (1)	Univ. degree (2)	Low-skill (3)	High-skill (4)
	Contemporaneous effect (1991)			
RD Estimate	-0.18	-0.28	-0.39	-1.55
	(0.74)	(0.51)	(0.62)	(0.83)
Mean around the border	16.87	5.65	10.96	17.32
Standard deviation	5.18	3.73	4.72	5.91
Observations	585	585	585	585
	Persistent effect (2011)			
RD Estimate	-0.34	0.01	0.71	-1.66
	(0.86)	(1.01)	(0.75)	(0.81)
Mean around the border	38.19	20.65	18.83	24.74
Standard deviation	6.20	7.51	4.92	5.55
Observations	587	587	587	587

Notes: Coefficient estimates from Equation B4.1 comparing municipalities south and north of the EIM border. All regressions are estimated over a 50-km symmetric bandwidth around the EIM border and control for a linear polynomial in the distance to the border and border segment effects. Mean and standard deviation computed within the estimation sample. Standard errors allow for spatial correlation (Conley, 1999). Column 1: "High school educ." is the share of people aged at least 6 with high school education or more. Column 2: "Univ. degree" is the share of the resident population aged 30-34 years old with a university degree. Column 3: "Low-skill" is the employment share of residents in low-skill jobs (unskilled occupations—Isco08 code 9). Column 4: "High-skill" is the employment share of residents in high-skill jobs (Legislators, Entrepreneurs, High Executives, Scientific and Highly Specialized Intellectual Professions, Technical Professions—Isco08 codes 1, 2 and 3).

Table F5. Other Outcomes at the EIM Border: RD Estimates

	House prices (1)	Rents (2)	Tax income (3)	Gini coeff. (4)	Krugman Ind. (5)
RD Estimate	-153.68	-0.57	-0.02	0.01	0.02
	(67.86)	(0.26)	(0.02)	(0.00)	(0.06)
Mean around the border	1106.11	4.14	9.18	0.37	1.06
Standard deviation	511.06	2.01	0.15	0.04	0.43
Observations	584	522	586	587	586

Notes: Coefficient estimates from Equation B4.1 comparing municipalities south and north of the EIM border. All regressions are estimated over a 50-km symmetric bandwidth around the EIM border and control for a linear polynomial in the distance to the border and border segment effects. Mean and standard deviation computed within the estimation sample. Standard errors allow for spatial correlation (Conley, 1999). "House prices" and "Rents" are residential real estate prices and rents as of Q1-2011, measured in € / squared meter. "Tax income" denote (log) tax income in € / capita in 2010. "Krugman Ind." is the Krugman Specialization Index for manufacturing in 2011 (see Appendix A.2). "Gini coeff." is the Gini coefficient as of 2011.