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

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Abstract

This paper studies a large place-based industrial policy (PBIP) aiming to establish industrial clusters in Italy in the 1960s-70s. Combining historical archives spanning one century with administrative data and leveraging exogenous variation in government intervention, we investigate both the immediate effects of PBIP and its long-term implications for local development. We find that the policy led to agglomeration of workers and firms in the targeted areas persisting well after its termination. By promoting high-technology manufacturing, PBIP boosted demand for business services and favored the emergence of a skilled local workforce. Over time, this shifted the local economy towards high-skill industries and produced a spillover from manufacturing – the only sector targeted by the program – to services. We observe a stark rise in knowledge-intensive services, along with higher local wages and human capital. Further evidence suggests that this virtuous cycle is due to the high agglomeration potential of treated clusters.

JEL Codes: J24, N94, O14, O25, R58
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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 to this trend, place-based industrial policies (PBIPs) seeking to bolster local manufacturing and establish industrial clusters have gained traction (Porter, 2000; Kline and Moretti, 2014b).[1] Despite their rising popularity, little is known about the persistent effects of PBIPs on local development. Leveraging a century's worth of data, this paper studies a historical program to assess whether PBIPs benefit the targeted locations in the long run, exploring the sources of persistence, their spillover effects and cost-effectiveness.

There is intense debate on these programs among economists and policymakers. While government intervention can correct market failures and foster long-run development, it may also lead to inefficiencies and misallocation, yielding only temporary benefits (Rodrik, 2019; Heblich et al., 2022). Whether PBIPs favor lasting concentration of economic activity in local communities is still unclear. In addition, PBIPs might not only impact the targeted industries and locations but produce spillover effects to the rest of the economy. Shedding light on these issues requires examining the impact of PBIP over time and possibly long after its termination. However, reliable evidence is scant as data on historical policies are hard to find and selection problems make causal analysis challenging (Juhász et al., 2023).

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 novel causal evidence of positive and long-lasting effects of PBIP, with local agglomeration of workers and firms continuing to grow even 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 economic 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. To direct firms and workers towards IDAs, the government set a higher subsidy rate on investments

[1] Many of the industrial policies passed by the United States Congress in 2022 involve the creation of industrial hubs, often in distressed areas, and are *"potentially the most significant place-based policy funding in U.S. history"* (Bartik et al., 2022). Similar shifts towards a place-based approach also feature in the industrial strategies of the European Union and the United Kingdom (Fai, 2018; Alessandrini et al., 2019).

(hence a lower cost of capital) for firms located in an IDA and financed additional infrastructures. IDA expenses totalled roughly €90 billion, or 0.5 percent of national GDP each year between 1960 and the end of the program in the late 1970s.

A key market failure that cluster policies such as the IDAs aim to address are agglomeration economies (Duranton and Puga, 2004; Moretti, 2011). Following government intervention, the targeted areas witness an increase in the density of firms and workers. In the presence of knowledge spillovers or thick market externalities, higher proximity between agents would boost local productivity. Then, the cluster keeps attracting workers and firms even after subsidies cease and until local prices grow high enough. Government subsidies that internalize these positive externalities have an efficiency justification.

A first test of the presence of agglomeration economies is thus whether the IDA program led to persistently higher economic density, which we compute as the number of workers (and establishments) per square kilometer (km^2). We reconstruct these outcomes for each municipality over one hundred years – 1911 to 2011 – by manually digitizing historical censuses. 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 all the expenses within the policy and rich administrative micro data for the population of private firms since 1990.

Valid identification requires isolating exogenous variation in IDA status – a challenging task given the selective nature of the policy. 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 – what 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 (RD) 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-constant discontinuities, we also rely on a difference-in-discontinuities (Diff-in-Disc) design that compares over time municipalities bordering IDA centers to those further away from them, imposing a parallel trends assumption (Grembi et al., 2016).

We estimate a positive effect on employment density emerging while IDAs were in place and continuing to grow afterwards. We measure a discontinuity of about 40 workers per 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 effect is still large at 60 workers per km^2 (60 percent of a standard deviation). We find similar results for firm density. These long-lasting effects are not driven by continued migration into the treated areas, and reflect – at least in part – higher labor force participation and lower unemployment of residents. The novel evidence of *increasing* effects of PBIP after termination stands somewhat in contrast with previous findings on industrial cluster policies, which indicate employment effects that are, at best, positive but fading over time (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 this effect stabilized as subsidies were phased out. In contrast, employment in services started to rise while IDAs were in place and kept growing after their termination. Despite not receiving subsidies, the services sector eventually became the main driver of long-run agglomeration in the IDAs.

These spillovers to services raise key questions. Why did non-targeted sectors respond to industrial policy? How can the effect on services be so persistent? To answer, we further decompose 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 (KIS, e.g., information and communication technology, finance, firm services). The creation of new high-skill jobs suggests that PBIP developed a skilled local workforce and stimulated knowledge spillovers, consistent with the presence of agglomeration economies.

We use an alternative design to address criticism and confirm our findings. Again inspired by the contiguity rule, we compare municipalities bordering IDA centers to a new control group: municipalities bordering "placebo centers" in the Center-North of Italy (outside of the EIM region). This exercise rebuts concerns that our results reflect urban growth, or displacement of economic activity from nearby areas, as the new control group is far away from IDAs and hence unlikely to experience strong spillovers (Allen and Arkolakis, 2023).

In fact, the spatial spillovers of PBIP to untreated areas are interesting in their own right. Placebo centers allow us to directly estimate these spillovers. Namely, we compare the control group of the baseline design (areas just outside of the minimum IDA border) to its counterpart in the Center-North (areas just outside of the border traced by municipalities contiguous to placebo centers). We find negative spillovers of the IDA policy on manufacturing employment equivalent to 20-30 percent of the baseline effect. However, this displacement only occurs while IDAs were in place and almost disappears in the long run.

As last robustness check, we run a triple differences specification that subtracts from the Diff-in-Disc coefficients around IDA centers (the baseline results) their counterpart obtained around placebo centers. The estimated effects change little compared to the baseline design, confirming long-run agglomeration in IDAs led by services and especially KIS.

The structural transformation towards skilled jobs is a result of the *type* of manufacturing stimulated in the IDAs. We estimate a larger share of high-technology manufacturing industries in treated areas at the end of the policy, which we argue has been crucial for the subsequent development of KIS, in two ways. First, by providing local supply of skilled workers – a thick labor market externality (Hanlon, 2020). Using matched employer-employee data to reconstruct job transitions, we document a growing share of KIS new hires formerly employed in high-technology manufacturing. Second, through another local multiplier effect, in the form of increased demand for business services such as consulting, human resources and legal services. We confirm in national input-output matrices that high-technology manufacturing firms demand more KIS than low-technology ones. We lack such input-output data at the municipal level, but exploit granular industry data from administrative records to show that business services jobs (and firms) are indeed more present in IDAs.

These results suggest that PBIP has successfully promoted long-run development and structural change primarily by creating "good jobs" (Rodrik and Stantcheva, 2021). Accordingly, the effect on local wages is positive and long-lasting. We also estimate a persistently larger share of residents with higher education and skills, consistent with human capital accumulation and knowledge spillovers. Firms in IDAs are more productive and tend to invest more than control firms in the long run, especially in KIS. Last, we find positive and persistent effects on local house prices and tax incomes and rule out an alternative source of persistence linked to continued public spending after the policy (von Ehrlich and Seidel, 2018). Taken together, these findings are consistent with agglomeration externalities being subsidized by PBIP and fueling a virtuous cycle in the targeted areas.

Further analysis shows that the IDAs were cost-effective. We calculate a long-term cost per job created of about €25,000, comparable to other regional policies examined in the literature (Criscuolo et al., 2019; Siegloch et al., 2022). We then make a more comprehensive assessment and compute the net surplus accruing to workers, firms and landlords following Busso et al. (2013). We find that the net gains generated by the IDA program only after its termination at least compensate for the total costs.

In the last part of the paper we conduct heterogeneity analysis and show how the long-run effects of PBIP depend on the characteristics of the targeted locations. We first run comparisons between different IDAs and find that IDAs with higher initial (1951) human capital are those where the effects are largest. We then contrast the successful experience of IDAs with that of other areas receiving similar subsidies within the EIM program. Namely, we conduct a spatial RD analysis at the border separating the EIM jurisdiction from the rest of Italy following Albanese et al. (2023). For manufacturing employment, we estimate a positive but fading effect qualitatively similar to that observed for the IDAs. However, services – especially KIS – did not respond to the intervention. There are also no effects on high-technology manufacturing, nor on education and wages.

Comparing these two experiences is instructive. The IDAs were high-potential poles explicitly chosen by the government as future clusters; in contrast, areas around the EIM border had less favorable geography and market access, and low density of workers and firms before the policy. While still suggestive, this evidence illustrates that industrial policy is unlikely to yield long-lasting benefits if implemented in peripheral regions, with initial conditions not suitable to future agglomeration.

Related literature and contributions. This paper makes several contributions to the literature. First, it relates to the small but growing body of empirical work on industrial policies (Juhász et al., 2023). Recent studies of historical programs have uncovered the effects of industrial policy on local development and structural transformation (Juhász, 2018; Hanlon, 2020; Mitrunen, 2020; Choi and Levchenko, 2021; Giorcelli and Li, 2022; Kantor and Whalley, 2022; Lane, 2022). Our work adds to the existing evidence by illustrating how these interventions can shape the transition towards manufacturing and eventually into advanced services. Specifically, we are the first to provide a detailed account of the dynamic response of the services sector, which is not the usual target of industrial policy.

Second, we contribute to the ongoing debate on place-based policies (Kline and Moretti, 2014b; Neumark and Simpson, 2015; Duranton and Venables, 2018; von Ehrlich and Overman, 2020). In response to skepticism about these programs (Glaeser and Gottlieb, 2008), many studies have explored their long-run effects to test for welfare relevant nonlinearities

(Kline and Moretti, 2014a).[2] Our focus is on cluster policies, for which most evidence is still short- and medium-run (Falck et al., 2010; Criscuolo et al., 2019; Lu et al., 2019; Cingano et al., 2022; Lapoint and Sakabe, 2022; Siegloch et al., 2022). We complement the nascent literature on the long-run effects of cluster policies (Giorcelli and Li, 2022; Heblich et al., 2022; Garin and Rothbaum, 2024) by offering new insights on the mechanisms underlying persistence. Our work illustrates how the services sector contributes to long-run effects through local multipliers and agglomeration economies in high-technology industries. Last, we note that initial conditions matter, and that a key goal of PBIPs – supporting peripheral areas (Bartik, 2020) – might not be fulfilled in places not suited to future agglomeration.

Third, our findings speak to the literature analyzing the manufacturing decline and its consequences (Moretti, 2012; Autor and Dorn, 2013; Charles et al., 2019; Gagliardi et al., 2023; Helm et al., 2023). If leading to specialization in a limited set of industries, cluster policy may undermine development as manufacturing districts must adjust to technological shifts (Barba Navaretti and Markovic, 2021).[3] Instead, we show that PBIP has expedited structural change as targeted areas transitioned into diversified poles integrating high-skill manufacturing and services.[4] The novel evidence we provide on the ability of PBIP to incentivize skilled jobs resonates with Rodrik and Stantcheva (2021), who advocate the creation of "good jobs" (and of firms demanding them) as a main target of industrial policy.

Fourth, our results add to the evidence on local multipliers (Moretti, 2010; Faggio and Overman, 2014; Becker et al., 2021) and, more broadly, on the spillovers of (place-based) industrial policies to non-targeted sectors and locations (Greenstone et al., 2010; Atalay et al., 2022; Giorcelli and Li, 2022; Lane, 2022; Siegloch et al., 2022). We are the first to break down the effects of PBIP across different classes of services, assessing how these programs shape the structure of the economy. We also provide new *dynamic* estimates of the spillover effects of place-based policy to nearby locations, showing displacement of economic activity away from non-targeted areas during the intervention but not in the long run.

Last, this paper produces new evidence on the EIM – the most ambitious regional program in Italy's history (Felice and Lepore, 2017). Recent studies (Colussi et al., 2020; Buscemi and Romani, 2022) consistently report a null impact of the EIM. Among these, Albanese et

[2]Agglomeration forces might take decades before emerging, which requires tracking the subsidized areas for long enough and ideally well after the termination of the policy (Hanlon and Heblich, 2020).

[3]Heblich et al. (2022) study the construction of large plants in China in the 1950s and document a boom-and-bust pattern in host counties, which developed a very specialized production structure with limited technology spillovers. Kim et al. (2021) find similar results for the South-Korean heavy industry drive.

[4]As showed in Gagliardi et al. (2023) for advanced economies, some manufacturing hubs navigated deindustrialization better than others depending on the share of college-educated workforce, which then led to growth in high-skill services. Our paper highlights the role that government policy can play in this process.

al. (2023) find that EIM transfers led to a transition out of agriculture into industry, halted the growth of services and did not raise employment in the long run. We show instead that the EIM has successfully promoted development in a few select clusters. Cerrato (2024) studies the aggregate implications of the EIM and finds gains in national industrial production. We instead examine more in depth a prominent facet of the EIM (the IDAs) and go beyond direct impacts on manufacturing, using administrative micro data to unveil the effects of the program on other areas of the economy and to identify the sources of persistence.

The paper is organized as follows. Section 2 provides an overview of the policy; Section 3 describes the data; Section 4 outlines the identification strategy; Section 5 presents the baseline results; Section 6 explores the mechanisms; Section 7 conducts cost-benefit analysis; Section 8 further discusses our findings. 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 large regional policy called *Extraordinary Intervention in the Mezzogiorno* (EIM) was put in place (and financed) by the central government to jump-start development in the South – an area covering 40 percent of Italy's surface (Law n. 646/1950).[5] 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).

At its onset in 1950, the main goal of the EIM was to enhance Southern agriculture and modernize its 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 markedly towards industrial policy to support businesses and attract investments in the South (Laws n. 634/1957 and n. 555/1959).

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 magnitude of subsidies 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 (Section 3 provides more detail on the data). Virtually all grants went to manufacturing firms, especially in heavy industries, with only

[5] GDP per capita in the South was roughly half of that of the Center-North in 1951 (Felice, 2017). See Iuzzolino et al. (2011) and De Philippis et al. (2022) for details on the Italian North-South divide. The term Mezzogiorno ("Midday") is conventionally used to identify the South of Italy.

negligible funding to the services sector (1-2 percent of total subsidies, see Figure A1.1). These years saw a dramatic increase in EIM expenses, which during the 1970s reached 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 agglomeration, with the goal of "*establishing positive externalities thanks to the proximity to other industries and workers*" (Cassa's Annual Report, 1958-59).

An IDA was created upon the initiative of a group of local authorities (municipalities and provinces) called a *consortium*, which submitted a development plan to the government for approval. 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 detailed information on economic, demographic and geographic characteristics. The choice 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.[6]

Each IDA was centered around a provincial capital and extended to more municipalities up to 25 km away from it, subject to a minimum population threshold for the whole area (200,000 people as of 1958). The minimum set of municipalities forming the IDA had to be the center and all contiguous municipalities – a rule we exploit for identification (Section 4). The government imposed that the candidate area showed a "*propensity for industrial concentration*" (Ministerial Circular n. 21354/1959). Other requirements related to the geological properties of the area (e.g., low seismicity) and to the presence of basic infrastructure.

Following approval of the plan, the Cassa could subsidize the investments of consortia in their IDA, including connections to transport and energy services, or the construction of plants and houses for workers. The initial subsidy rate for these expenses was 50 percent, which rose to 85 percent in 1961. In addition, the investment grants for individual firms in the EIM area were more generous for firms located in IDAs. This was achieved in two ways. First, the investment subsidy rate was larger for IDA firms. Second, only small- and medium-sized firms in small EIM municipalities could access grants, while there were no size limits for firms in IDAs. See Appendix A.1 for details.

The IDA program was de-facto in place from 1960 until the late 1970s, when grants for IDA firms were equalized to those for other EIM firms. Transfers continued also through

[6] 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.

the 1980s, but with no distinction between IDAs and other EIM areas. The EIM ended with Law n. 488/1992, as the system of state holdings was dismantled or privatized. The Law introduced a new set of firm subsidies that also covered depressed areas 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, disentangling the mechanisms and making cost-benefit assessments requires rich longitudinal data spanning a long time period. This paper draws on several unique data sources.

Interventions from the Cassa. We collect data on all interventions from the Cassa from the ASET database.[7] Records for all (roughly 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 grant applications. The data also include the infrastructure projects run by the Cassa (about 75,000), reporting the financial resources allocated as well as the year, location and type of infrastructure.

Panel (a) in Figure 1 shows total EIM expenses by year, scaled by the total population in the EIM region in 1951. 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. Most expenses were concentrated in IDAs, especially during the peak in the 1960s and 1970s (Panel (b)). Investment grants went disproportionately to capital intensive industries such as chemical, metallurgy and transport manufacturing – see Appendix A.1.

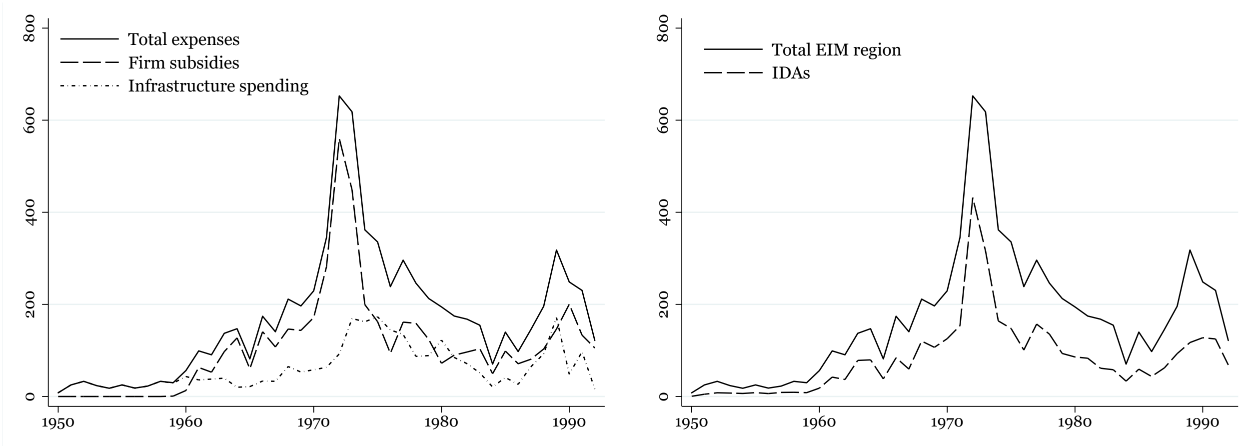
The ASET archives also record a list of the IDAs, along with the included municipalities, which we digitize and plot in Figure 2. A total of 14 IDAs comprising 328 municipalities have been established throughout Southern Italy. These are indicated by the yellow regions surrounding the brown IDA centers (the main cities of the South). On average, IDA municipalities received EIM funding of around €10,000 (cumulated between 1950 and 1992 and measured in 2011 prices) per 1951 resident, twice as much as other EIM municipalities (the number does not change much if excluding IDA centers). IDAs absorbed more than half of the overall EIM expenses (cumulative €165 billion), despite covering one tenth of the surface of the entire EIM region and hosting one third of its population.[8]

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

[8]We cannot observe the infrastructure expenses borne by consortia (and subsidized by the Cassa).

Figure 1. EIM expenses

(a) Expenses breakdown (b) Full EIM area and IDAs



Notes: EIM expenses in € (2011 prices) scaled by total population in the EIM region in 1951. Concessional loans to firms are excluded.

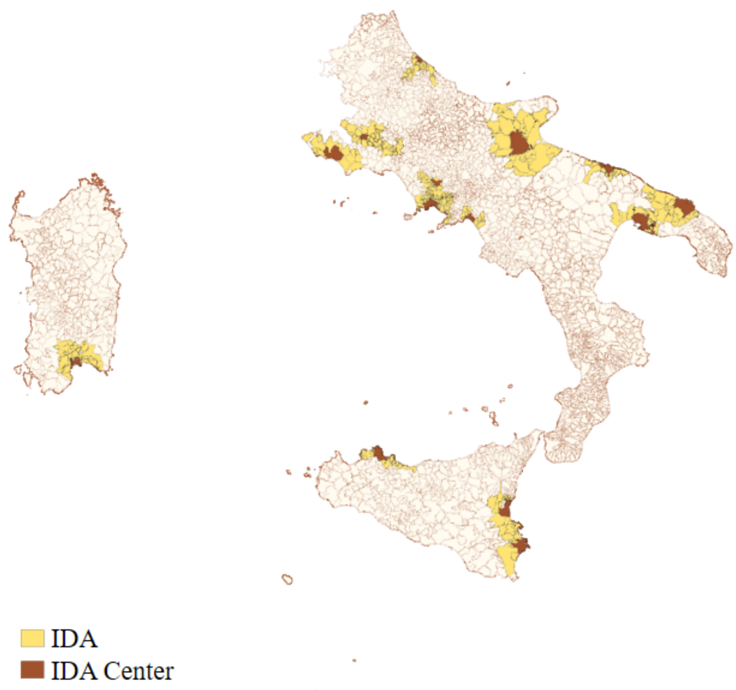
Industrial censuses. The main outcome variable of the paper (employment density) is computed using the number of workers per municipality from decennial industrial censuses spanning six decades (1951 to 2011, including an intermediate census in 1996), sourced from the Italian statistical institute (Istat).[9] The data report employment and establishment counts in the private sector, separately for manufacturing and services. 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 policy, which is essential for identification purposes.[10] We thus reconstruct municipality-level employment and number of establishments long before the start of the EIM by hand-digitizing the 1911 and 1927 industrial censuses, available in the historical archives of Istat (see Appendix A.2).

Social security data. The third main data source of the paper is the administrative archive on the universe of Italian employers in the non-agricultural private sector from social security records (INPS), available at the Bank of Italy. The data start in 1990 and include information on firm employment counts, 6-digit sector, location, workforce composition and average wages. Importantly, the granular sector-level information will allow us to distinguish manufacturing activities by technological intensity and service activities by knowl-

[9]Because our main outcome is at decennial frequency, the staggered establishment of IDAs throughout the 1960s (see Section 2) is not exploited for identification.

[10]EIM interventions began in the early 1950s and involved infrastructure works only. The Cassa's industrial policy (including the IDA program) started in the 1960s.

Figure 2. The Industrial Development Areas



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

edge content using the Eurostat/OECD classification. We complement the data with income statements collected by Cerved, matched using firm tax identifiers. The data are available for incorporated limited liability companies and report detailed balance sheet information. Last, we obtain matched employer-employee data by merging the firm dataset with a 7 percent random sample of Italian workers. We collapse the micro data at a more aggregate level of analysis (the municipality) as we cannot match the ASET establishment-level subsidy data with the INPS records. We provide more detail in Appendix A.3.

Other data sources. We draw on several other sources. These include decennial population censuses between 1951 and 2011, reporting relevant municipality-level information on demography and labor markets. We also collect data on geographic characteristics (mean elevation, mountain surface, seismicity) from Istat. The other sources we use are the Open-Coesione database (funding within Law n. 488/1992 and EU structural funds), the Italian Ministry of the Interior (election data), the Italian Finance Ministry (taxable income), the Osservatorio del Mercato Immobiliare at the Italian Tax Office (house prices) and AIDA PA (municipality balance sheets and spending).

4. Identification strategy

The selective nature of the IDA program makes identification of causal effects challenging. The targeted clusters were not randomly picked but differed from other areas in many dimensions, potentially unobserved and correlated with our outcomes. IDA municipalities were positively selected, as their choice was explicitly informed by agglomeration potential (Section 2). Before the start of the program, IDAs had a larger density of workers and firms relative to other EIM municipalities, their geography was better suited to industrialization and their residents were more educated and less likely to work in agriculture (Table 1).

A causal evaluation of the IDA program thus requires isolating exogenous variation in IDA status to account for selection. 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 centers in Figure 2) and then included municipalities in its surroundings (in yellow in Figure 2) up to a minimum population threshold.[11] Importantly, the government required that the minimum set of municipalities forming an IDA should be 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. Figure 3 Panel (a) provides an illustration. 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 a outside-cutoff region (in blue). The outside region may include both municipalities that are part of the IDA (in light blue) and municipalities that are not (in dark blue). Below, we clarify how we choose the specific extension of the outside region in our estimation.

Our baseline 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 region, that is, the IDA center and its bordering neighbors. To identify municipalities in the within region, we define the binary instrument $W_m = \mathbb{1}[\delta_m \leq 0]$. Let also IDA_m be a treatment indicator taking value of one if municipality m belongs to any of the 14 IDAs depicted in Figure 2. 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 RD

[11] An IDA could include municipalities not farther than 25 km from the IDA center. There is no discontinuity in IDA status at the 25 km distance cutoff.

Table 1. IDA municipalities – descriptive statistics

	IDA muni.	IDA muni. excl. centers	Other EIM muni.
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: Sample restricted to the EIM region. Employment and establishments (total and manufacturing) are sourced from the 1951 industrial census. "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. "Coastal location" is a dummy equal to one for municipalities located by the sea. Standard deviations in parentheses.

setting where IDA_m is the treatment variable, W_m is the instrument and Y_m is the outcome:

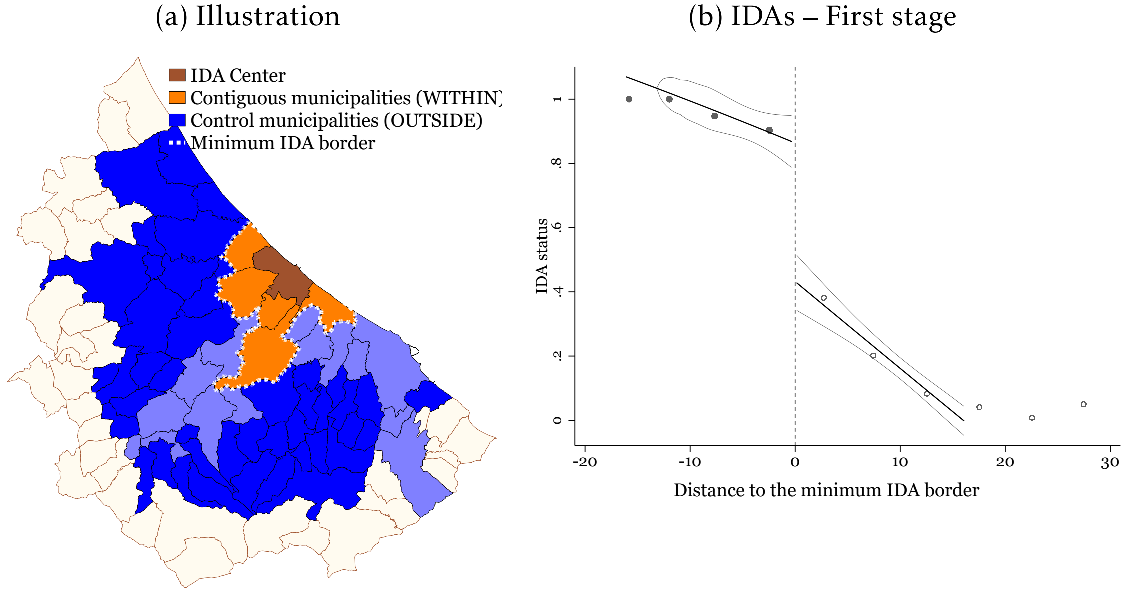
$$IDA_m = \mu_{i(m)} + \vartheta \cdot W_m + \varphi(\delta_m) + u_m \tag{1a}$$

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

Where Equation 1a is the first-stage regression and Equation 1b is the reduced form. $\varphi(\delta_m)$ 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. Y_m, IDA_m and W_m are defined above.

The peculiarities of this design impose restrictions on the choice of the bandwidth. Within the minimum IDA border, there are only 14 IDA centers and 137 bordering municipalities. This limited sample size requires picking a bandwidth wide enough to include all

Figure 3. The minimum IDA border



Notes: Panel (a) shows the minimum IDA border for one of the IDAs (Pescara). The IDA center (the municipality of Pescara) is in brown and the contiguous municipalities are in orange. Their outer boundary traces the minimum IDA border (the 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 variable is $Pr(IDA_m = 1 \mid \delta_m)$. Negative distance denotes municipalities within the minimum IDA border. See Footnote 14 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 either side of the border using a symmetric 16-km bandwidth. The gray lines are 95 percent confidence intervals. See text for details.

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 the choice of different bandwidths.[12]

This identification strategy rests on three main assumptions, which we now describe intuitively while leaving a more formal treatment to Appendix B.2. First, IDA status must discontinuously jump at the minimum IDA border – a first stage assumption. To illustrate the idea, 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, $Pr(IDA_m = 1 \mid \delta_m)$.[13] 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.[14]

[12]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, and even when adopting a different identification strategy.

[13]Two IDAs (Napoli and Caserta) have been excluded from the sample due to the proximity of their centers (about 25 km). This reduces the sample within the minimum IDA border to 12 centers and 112 bordering municipalities. Results will not change when including these two IDAs.

[14]The probability of belonging to an IDA is not exactly one within the cutoff, as very few (10) municipalities

Table 2. IDAs – First stage

	IDA status	EIM expenses
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 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. EIM expenses measured in thousand € (2011 prices) per 1951 resident, winsorized at 1 and 99 percent. Standard errors clustered by IDA region in parentheses. See text for details. * p<0.10, ** p<0.05, *** p<0.01

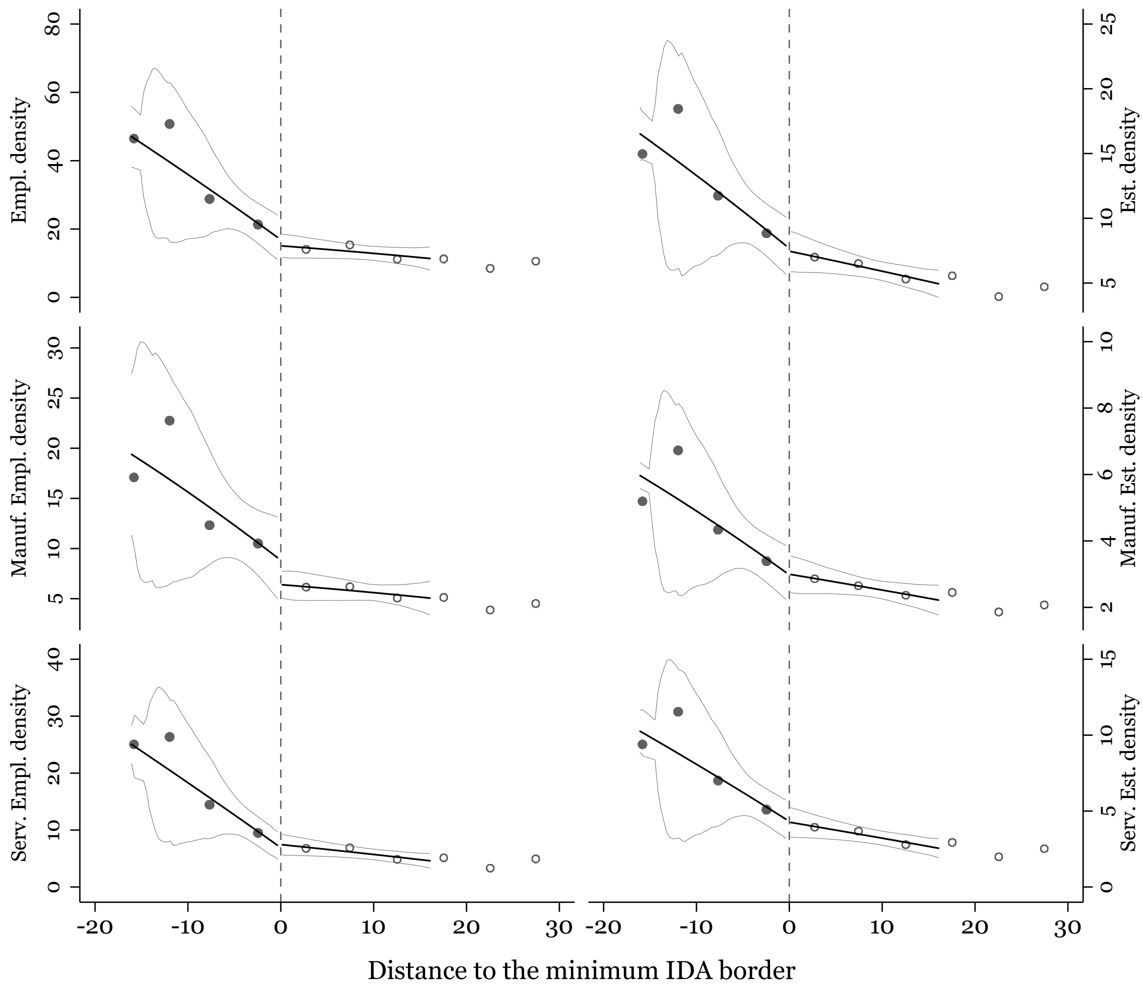
Table 2 reports the estimation output of the first-stage Equation 1a. The drop in IDA status detected in Figure 3 Panel (b) is quantified at 39 percentage points, and associated with less generous EIM funding by €5,720 per capita. This discontinuity in EIM expenses is almost entirely driven by firm subsidies, although our data only capture the infrastructures expenses from the Cassa and not those borne by the IDA's consortium.

The second assumption is that potential outcomes are continuous at the cutoff. The continuity assumption 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. This condition essentially becomes an exclusion restriction in a fuzzy RD setting (Cattaneo and Titiunik, 2022).

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 certainly related to the distance to a large city (the IDA center), there are less reasons to expect discontinuous jumps in such relationship. To confirm this, we look for discontinuities in lagged outcomes at the cutoff. Figure 4 shows RD plots for employment and establishment density in 1951 (a decade before the introduction of the IDAs). Unsurprisingly, agglomeration in 1951 was larger 10-15 km within the boundary, corresponding to the IDA centers. Yet there is no discontinuity at the cutoff itself, as municipalities contiguous to the IDA center were very similar to those further away from the center before the start of the policy.

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 for a limited stretch of the perimeter*" (Ministerial Circular n. 21354/1959).

Figure 4. Balancing at the minimum IDA border, 1951



Notes: Number of workers and establishments sourced from the 1951 industrial census. 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 either side of the border using a symmetric 16-km bandwidth. The gray lines are 95 percent confidence intervals. See text for details.

Appendix Figure B1.1 shows RD plots for many other pre-determined covariates. There are little or no discontinuities in labor market and demographic characteristics including the employment rate, population density, education and population age and gender composition. There is also balancing in geographical traits and, importantly, in voting outcomes before the policy (measured as the votes share for the incumbent Christian Democratic party). The lack of a discontinuity in electoral preferences reassures that IDA inclusion was not driven by political considerations.[15] To address concerns about unobserved confounders at

[15]We also check for imbalances in other sources of 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, likely implying no difference in Marshall Plan funding

the cutoff, we will test our results under an alternative identification design that, again exploiting the contiguity rule, uses a new control group composed of municipalities bordering provincial capitals in the Center-North of Italy.

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 the sub-population of compliers – see Appendix B.2 and Hahn et al. (2001).

This empirical 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 identification by accounting for unobserved, time-constant municipality characteristics. The regression form is a difference-in-discontinuities (Diff-in-Disc) design (Grembi et al., 2016) – a dynamic specification of the reduced-form Equation 1b:

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

Where $Y_{m,t}$ is the outcome for municipality m and census year t, μ_m are municipality effects and σ_t are census year effects capturing aggregate shocks. The specification tracks municipalities contiguous to IDA centers over time (excluding the centers themselves) and compares them to municipalities up to 16 km away from the minimum IDA border. The coefficients of interest ρ_j capture the difference in 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.[16]

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 further away, due, for example, to

(Gagliarducci et al., 2020; Bianchi and Giorcelli, 2023).

[16] 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.

urban growth stemming from the centers. We propose an alternative design to rebut these concerns. Namely, we focus on placebo centers – provincial capitals in the Center-North of Italy that would have likely been candidate IDA centers had they been part of the EIM region. In turn, again exploiting the contiguity rule, municipalities bordering these cities can be used as new control group and compared over time to municipalities bordering IDA centers. By using locations far away from IDAs as control, this exercise rules out strong spatial spillovers to the control group. Placebo centers are also used to directly estimate these spatial spillovers, by comparing the control group in the baseline design (municipalities just outside of the minimum IDA border) to their counterpart in the Center-North around placebo centers. Last, we run a triple differences specification that compares the evolution of outcomes around IDA centers (as per Equation 2) versus around placebo centers, subtracting any differential trend at the cutoff driven by urban growth. Appendix B.3 describes these designs, and the underlying assumptions, more in detail.

The EIM border. The last analysis we conduct, showed in Section 8, compares our results for IDAs to those derived from a spatial RD design at the border separating the EIM jurisdiction from the rest of Italy (see Appendix B.4). This exercise will be useful to understand how the effects of government transfers depend on the initial conditions of subsidized areas, as it will contrast high-potential locations (the IDAs) to regions with worse market access and low initial agglomeration (around the EIM border).

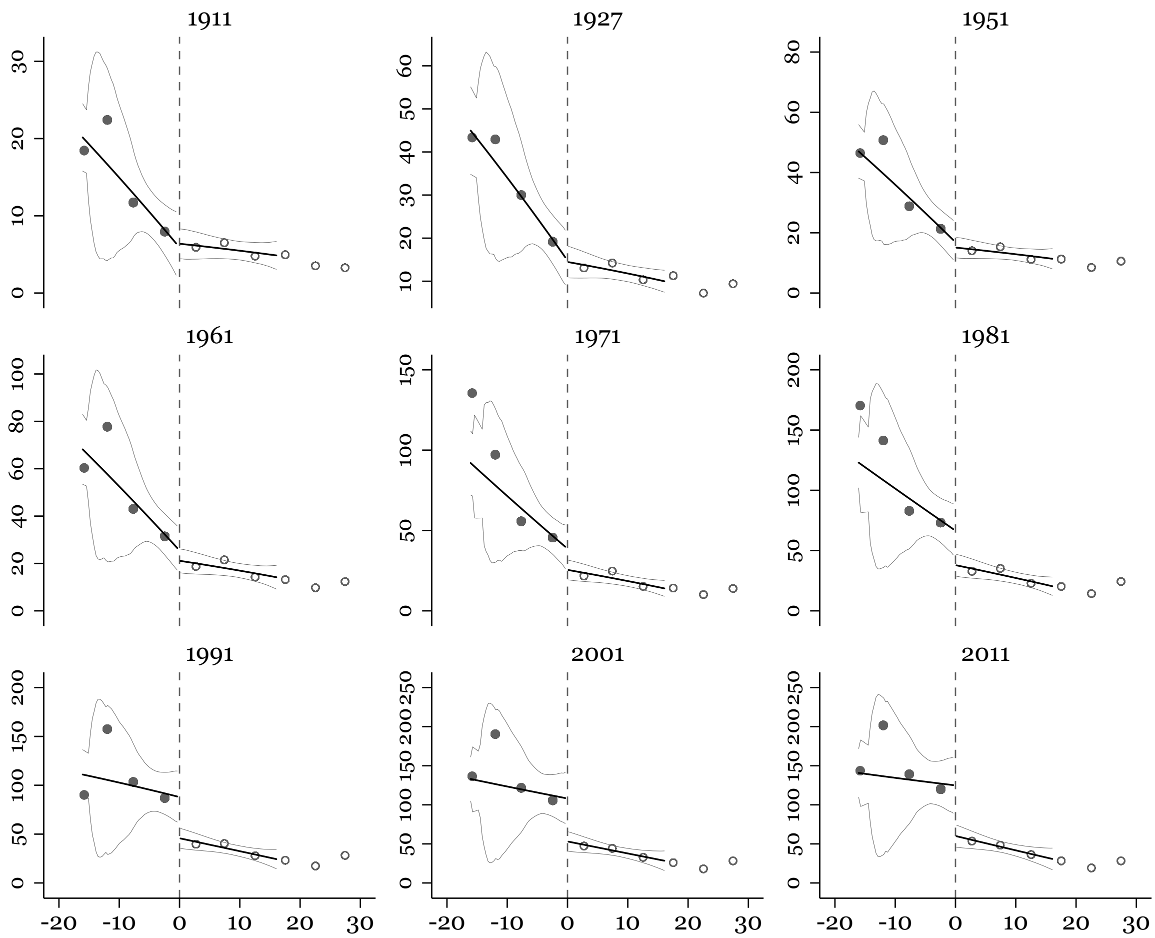
5. Results

How has the IDA policy affected local employment? Viewed through the lens of a simple model of spatial equilibrium (Kline, 2010; Kline and Moretti, 2014b), a place-based policy that alters the relative cost of capital across locations shifts the (relative) labor demand curve up and, in turn, raises employment in the targeted area.[17] 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

[17] The same effect would arise in response to other IDA measures raising local productivity, such as infrastructure works.

Figure 5. Employment density



Notes: 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 either side of the border using a symmetric 16-km bandwidth. The gray lines are 95 percent confidence intervals. See text for details.

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.[18]

[18]The noisier intervals in the bins within the cutoff (e.g., -20 km and -15 km) are due to the smaller number of observations in these bins, which include only a subset of all the IDAs. We also notice that the policy appears to have led to a change in slope within the cutoff, with some employment shifting from the IDA center to the contiguous municipalities. This phenomenon, which we view as a further effect of the policy, may be due to decreasing returns to scale in production in the IDA center and cannot be quantified using our design.

Table 3. Employment density – Baseline

	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: Column (1) shows the estimation output of Equation 1b. Column (2) reports the fuzzy RD estimates. Column (3) replaces IDA status with EIM subsidies 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. Standard errors clustered by IDA region in parentheses. See text for details. * p<0.10, ** p<0.05, *** p<0.01

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).[19] Column (1) reports the reduced-form estimates of 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). In logarithmic terms, these effects are equivalent to 51 percent in 1991 and 55 percent in 2011 and are comparable in magnitude to those in von Ehrlich and Seidel (2018) (Table C7). 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

[19] Appendix Table C1 shows results for firm density. Even though IDAs were effectively in place until 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. In addition, we show the effect in 1991 rather than in 1981 to preserve consistency with the results (showed later) obtained from social security data, which are not available before 1990. That said, results for 1981 do not differ meaningfully from those for 1991.

2011. Column (3) replaces IDA status with EIM funding per municipality resident in 1951 as treatment variable. A rise in subsidies of €1000 (2011 prices) per 1951 resident (about 13 percent of the mean, 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.[20]

Robustness tests. The baseline estimates are robust to several checks, presented in Appendix C. Table C2 reports robustness tests to i) more flexible polynomial 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. The estimated discontinuity declines but remains large and significant when using a quadratic or cubic RD polynomial and when excluding IDA centers. The effect stays roughly unchanged both in magnitude and significance if controlling for the distance to the IDA center or excluding IDA region dummies. Tables C3 and C4 show that results hold when allowing for spatial correlation in standard errors (Conley, 1999), or conducting local randomization inference (Cattaneo et al., 2016). Table C5 confirms that results do not change if including two IDAs (Napoli and Caserta), which are excluded in the baseline analysis because of the short distance between the two centers. Figure C2 shows that the fuzzy RD coefficient remains stable as we replicate the baseline estimation excluding one IDA region at a time, confirming that results are not driven by a specific IDA. Last, Table C6 presents non-parametric estimates obtained following Calonico et al. (2014). We weigh each municipality using a triangular kernel function giving more weight to places close to the cutoff. We also compute an MSE-optimal bandwidth that can differ within and outside of the cutoff. This procedure delivers indeed quite 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 small number of observations within the cutoff.

Bandwidth choice and spillovers. Figure C3 shows the LATE estimate obtained over a varying range of bandwidths around the cutoff, both in 1991 and 2011. Deriving our effects on a narrower or broader sample is a first assessment of whether the baseline estimates incorporate spatial spillovers. The positive effects we find may reflect displacement of workers and firms from control areas close to the cutoff. If driven by such displacement, coefficient estimates should shrink when using a broader control group farther away from the cutoff.

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

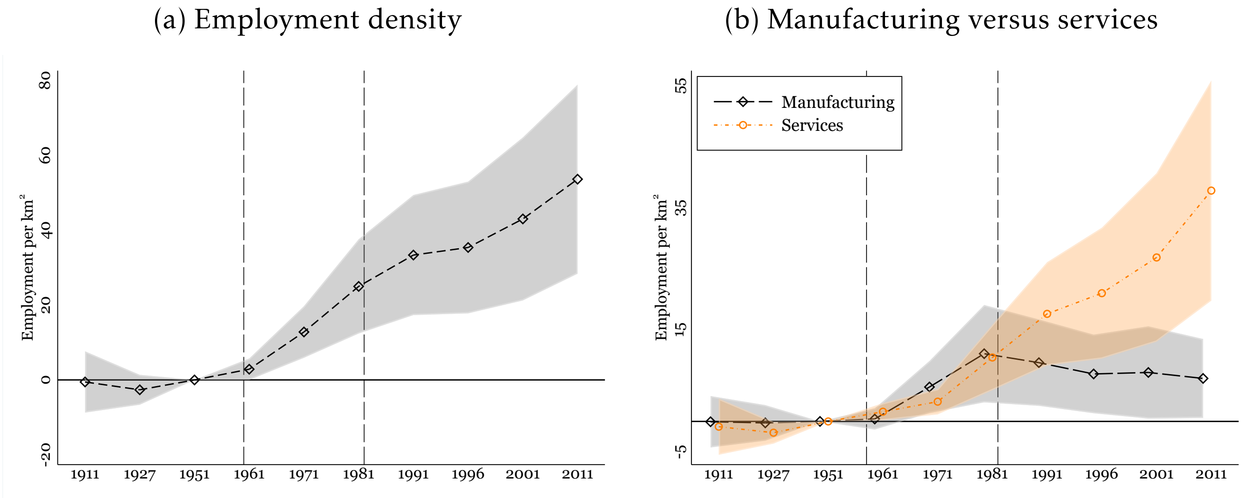
Indeed, the effect declines as more and more municipalities are added to the sample outside of the border, but the impact of the policy remains large and overall stable. This suggests that displacement effects, albeit present, are likely of limited magnitude (see also Figure 5). We address these issues more in detail in the next paragraphs.

Population, migration, participation. The main outcome (employment density) is based on the municipality of work. Results may thus reflect workers commuting around the cutoff. Table C7 shows however that the effect on population density (which is instead based on the municipality of residence) is not far from that on employment density, suggesting that worker commuting is not a key driver of our results. A more concrete possibility is that the policy led to migration into IDAs. Data available starting in 1991 show no significant difference in migration rates at the cutoff in 1991 and 2011 – see Table C8 (we also find no effect on commuting, consistent with the effects on population in Table C7). Migration into IDAs might have been higher during the policy years, in response to the subsidies. We unfortunately lack municipality-level migration data before 1991 to directly test it, and will explore possible migration into IDAs using the alternative design discussed at the end of this Section. For now, we notice that the strong persistence we observe could hardly originate solely from migration from untreated areas. While displacement effects should be expected during the policy years (as confirmed in Cerrato (2024) using province-level data), they should not be too large (as non-IDA municipalities still had access to EIM subsidies) and are unlikely to persist in the long run. Indeed, Table C9 shows that the policy also led to the creation of new jobs in treated areas, as the employment rate and labor market participation of residents rose and the unemployment rate decreased during the 1970s and 1980s.[21]

Difference-in-discontinuities. Figure 6 Panel (a) shows our most robust estimates – the ρ_j coefficients of the Diff-in-Disc design in Equation 2. First, we find evidence in favor 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 Diff-in-Disc 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.

[21]Our analysis refers to the private sector only, and there is limited data on public sector employment. In 2011, we observe no effect on the population share of public employees at the cutoff (2-SLS point estimate: 1.12, standard error: 8.14, mean outcome in the estimation sample: 31.35 percent).

Figure 6. Difference-in-discontinuities



Notes: Coefficient estimates for Equation 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. See text for details.

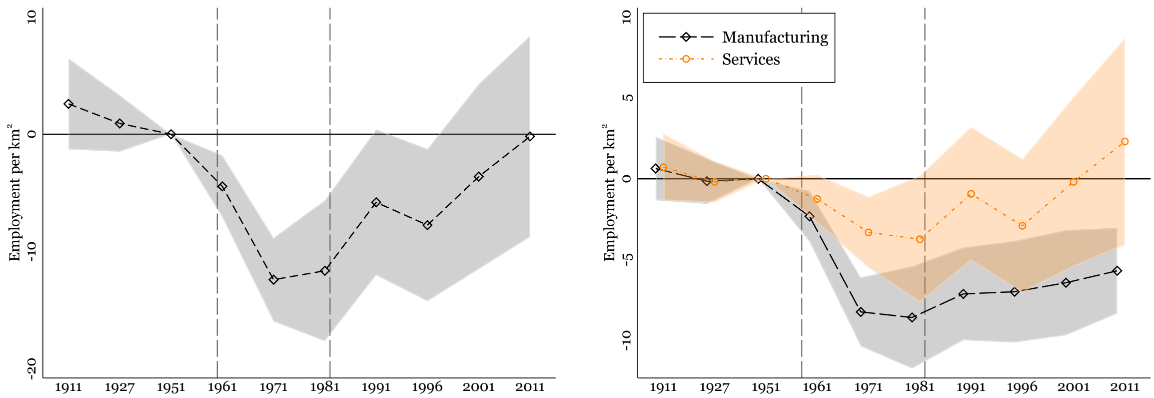
Manufacturing versus services. How does such stark persistence originate? We decompose employment density between manufacturing and services and show the coefficient estimates in Figure 6 Panel (b). The rising agglomeration during the 1960s is driven largely by manufacturing employment and, to a smaller extent, services. The manufacturing boost stabilizes towards the end of the policy in the 1980s and moderately declines afterwards. In contrast, the decades after the end of the EIM see a substantial increase in agglomeration in the services sector, which is at the basis of the persistent effect of the policy.[22]

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 likely been IDA centers had they been part of the EIM region (see Section 4 and Appendix B.3 for details). We leverage this source of variation in three ways. In the first exercise, we run a simple event study analysis comparing treated municipalities bordering IDA centers with control municipalities bordering placebo centers before and after the institution of the IDAs (Equation B3.1), and plot the coefficients in Figures C9 and C10. The two groups are on parallel trends before the policy. Once the IDAs are introduced, economic density increases in the treated areas and the long-term effect is largely concentrated in services, in line with the main results. While these coefficients cannot be directly compared to the baseline RD estimates, the choice of a new control group away from the IDAs addresses two main issues.

[22]Figure C4 reports the Diff-in-Disc results for firm density. Figures C5-C8 and Table C10 show the RD plots and the cross-sectional fuzzy RD estimates separately by manufacturing and services.

Figure 7. Estimating the spatial spillovers of the IDA program

(a) Employment density (b) Manufacturing versus services



Notes: Coefficient estimates for Equation B3.1. Sample restricted to municipalities up to 16 km outside of the minimum IDA border (treatment group) and municipalities up to 16 km outside of the placebo border traced by municipalities bordering placebo centers (control group). The treatment group excludes IDA municipalities. 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. See text for details.

First, it makes spatial spillovers to control units unlikely. Second, it does not suffer from concerns that control municipalities are not part of IDAs because of unobserved reasons.

Estimating spatial spillovers. In a second exercise, we aim to directly estimate spatial spillovers. We run the same event study as above but 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. This set-up enables us to investigate possible displacement effects to areas right outside of the minimum IDA border. Figure 7 shows the results. We document 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 an estimated RD effect of 30 workers per km^2 in 1981 (Figure 6). According to these estimates, roughly one third of the effect of IDAs while they were in place reflects an employment shift around the cutoff. These displacement effects are largely concentrated in manufacturing, and are instead barely noticeable in the services sector. Most importantly, they tend to fade in the long term. In 2011, we observe no spillover of the IDA policy to nearby areas. The persistent effect of PBIP therefore does not appear to be driven by continued displacement of economic activity.[23]

[23]The results for firm density are similar, and showed in Figure C11.

Triple differences. Last, we pool these groups of municipalities together and estimate a triple differences specification (Equation B3.2). Essentially, we compare 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 the Diff-in-Disc of Equation 2, due to, say, urban growth stemming from the IDA center and affecting only contiguous municipalities – see Appendix B.3 for a discussion. We show the estimates in Appendix Figures C12 and C13. Although less precisely estimated – most likely a result of the more demanding specification – the point estimates are very similar to those in the main findings (Figure 6) at around 50 workers per km^2 in 2011. This suggests an event-study coefficient around placebo centers that is close to zero.

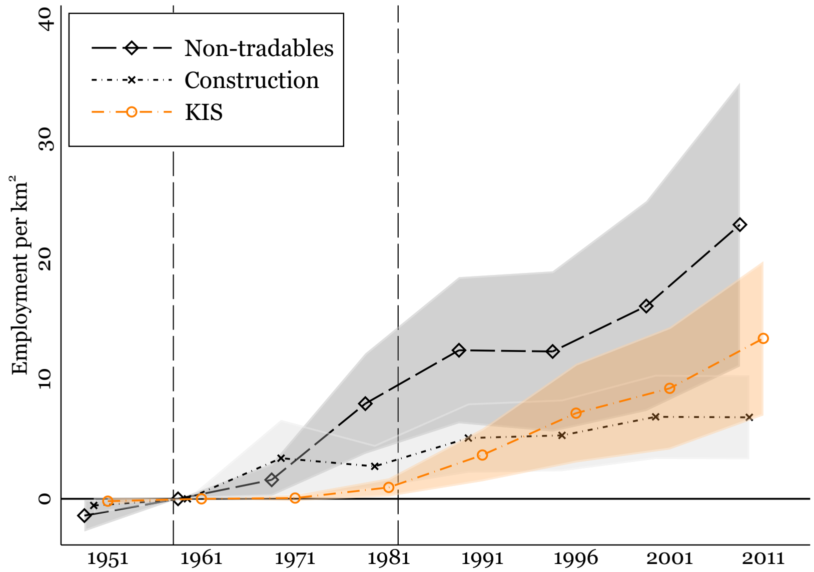
6. Mechanisms

Our results indicate stark persistence in the effects of PBIP and highlight clear sectoral patterns. We document an immediate response of manufacturing (the only recipient of subsidies) 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 can the rise in services – not the target of the policy – be rationalized?

The increase in services while IDAs were in place is most likely a result of multiplier effects, as the stimulus to local manufacturing boosts demand for local goods and services (Moretti, 2010). This implies that the contemporaneous effect on services employment should have occurred mostly in non-tradables such as retail and hospitality. However, multiplier effects cannot fully explain the continued response in services, given the relative stabilization in manufacturing employment (which was likely due to the end of subsidies and also reflected the structural decline of manufacturing starting in the 1980s).

Instead, the enduring growth of the services sector after the end of the policy is consistent with the presence of agglomeration economies and suggests that the targeted locations have undergone a process of structural transformation. For example, IDAs might continue to benefit from knowledge spillovers and a specialized labor pool developed during the policy years, which would be reflected in a larger share of high-skill jobs. Long-term effects on employment in knowledge-intensive services (KIS) such as information technology, finance, or services to firms, would be consistent with these observations.

Figure 8. Employment density – Sectoral breakdown



Notes: Coefficient estimates for Equation 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" include wholesale and retail trade, hotels and restaurants and other. KIS include communication, finance and insurance and services to firms. See text for details.

Non-tradables versus KIS. We now test the above predictions by decomposing the effect on services. As discussed, the immediate impact on services employment while IDAs were in place is most likely driven by multiplier effects. A boost to the local tradable sector translates into higher demand for local goods and services, which should raise labor demand in the local non-tradable sector. Performing simple calculations using our estimates, we find that one additional manufacturing job per km^2 is associated with 0.95 more services jobs per km^2 at the peak of the policy in 1981.[24] As noted above, these pecuniary externalities can account for the contemporaneous rise in services but cannot by themselves explain our persistent effects. Assuming a multiplier of one 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.

Figure 8 shows that, as expected, non-tradables (plus construction) account for most of the increase in services employment during the policy years. With time, however, we document a steady increase in KIS in treated areas.[25] To zoom into these developments we

[24]This number is obtained by dividing the point estimate for services by that for manufacturing in Figure 6. It is smaller than the long-term multiplier of 1.6 obtained for the United States in Moretti (2010). The smaller multiplier in our setting might be driven by different labor supply elasticity due, for example, to lower mobility (Moretti and Thulin, 2012).

[25]The lack of an effect on KIS while IDAs were in place is not surprising: mean KIS employment density in the estimation sample in the 1960s-70s was still very low at 2-3 workers per km^2. The results for firm

turn to the social security micro data, which are available at a much finer sectoral level and allow us to define KIS following the Eurostat/OECD classification (see Appendix A.3). We replicate the baseline fuzzy RD design (Table 3) and show results in Table D1, which reports coefficient estimates separately for the shares of KIS and other services in 1991 and 2011 (the firm data is available only starting in 1990). IDA status leads to a 8 percentage points larger share of workers and 6 percentage points larger share of firms in KIS. The effects are economically large and persist well after the end of the policy.

The role of high-technology manufacturing. Did the policy have any effect on the *composition* of manufacturing? Can this explain the rise of KIS? We inspect this in Table D2, where we distinguish between high- and low-technology manufacturing industries using the Eurostat/OECD classification. At the end of the policy, treated municipalities had a much larger share of high-technology manufacturing workers and firms compared to control ones. 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 providing demand for business services such as consulting, legal and information technology – a local demand multiplier.[26]

Both channels seem to be at play. Figure D4 plots the cumulative share of new hires (job-to-job) in KIS from high-technology manufacturing between 1991 and 2011.[27] In the two decades after the end of IDAs, the share of KIS new hires from high-technology manufacturing rapidly increased in treated municipalities relative to control ones. Examining the second channel is more complicated. National input-output tables confirm that high-technology manufacturing industries' demand for skilled services is twice as large than for low-technology industries – see the orange bars in Figure D5. While we cannot observe input-output linkages at the municipality level to directly assess this channel, we leverage granular sector information in the administrative data. In Appendix Tables D3 and D4, 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, insurance, consulting, legal and other professional activities in treated municipalities.

density, showed in Appendix Figure D1, are similar. We also observe continued agglomeration in non-tradable services, which could be driven by contemporaneous local multiplier effects (from manufacturing or KIS), or by endogenous agglomeration forces in urban amenities (Leonardi and Moretti, 2022). These results are confirmed with the alternative approach using placebo centers – see Appendix Figures D2 and D3.

[26] Larger shares of high-technology manufacturing also imply higher local multipliers in non-tradables, as workers in the local tradable sector command higher earnings and demand more local services (Moretti, 2010).

[27] The majority of KIS hires between 1991 and 2011 are from non-employment (including higher education). The share of KIS hires via job-to-job transitions is 30 percent in treated areas and 25 percent in control ones.

Table 4. (Log) wages – Fuzzy RD estimates

	Total	By sector		Within services	
		Manufacturing	Services	KIS	Other serv.
			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: Replication of Table 3, Column (2). Outcome computed as the natural logarithm of the average monthly wage paid by the firm, then averaged across firms in a municipality. See Appendix A.3 and text for details. * p<0.10, ** p<0.05, *** p<0.01

Wages, skills and human capital. The higher incidence of KIS jobs in IDAs should be reflected in higher wages and a more skilled workforce. Table 4 shows a large positive effect on wages of about 13 percent in 1991, which persists in 2011 at 10 percent. The wage effect is present in both manufacturing and services, and most pronounced in KIS at about 27 percent.[28] The IDA policy also stimulated human capital accumulation and skills among the resident population in the long term (Table 5). The share of high-school educated is 10-11 percentage points larger in 1991 and 2011, and the share of young people with a university degree is 5 and 9 points larger in 1991 and 2011, respectively. We also estimate a large positive effect (10-11 percentage points) on the share of high-skilled occupations (managers and professionals), at the expenses of low-skilled ones (routine jobs).

Firms. Do IDA firms differ from firms in control areas as a result of the policy? Table D6 shows a prevalence of large and high-paying firms in IDAs in 1991 and 2011. Table D7 shows results for balance sheet outcomes in 2011.[29] For manufacturing and KIS firms, we

[28]Table D5 uses AKM worker effects as outcome (Abowd et al., 1999). We estimate a positive and persistent effect of the policy, driven by services and especially KIS workers.

[29]The coverage of the income statements data from Cerved is quite low in the 1990s (less than 20 percent of the universe of firms). We therefore only show the more informative long-term effects.

Table 5. Education and occupations – Fuzzy RD estimates

	High school educ.	Univ. degree	Low-skill	High-skill
	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: Replication of Table 3, Column (2). "High school educ." is the share of people aged at least 6 with high school education or more. "Univ. degree" is the share of the resident population aged 30-34 years old with a university degree. "Low-skill" denotes the employment share of those in low-skill jobs (unskilled occupations – Isco08 code 8). "High-skill" denotes the employment share of those in high-skill jobs (Legislators, Entrepreneurs, High Executives, Scientific and Highly Specialized Intellectual Professions, Technical Professions – Isco08 codes 1, 2 and 3). See text for details. * p<0.10, ** p<0.05, *** p<0.01

estimate positive long-run effects on labor productivity, investment and sales. Manufacturing firms also earn higher profits per worker. Last, Figure D6 shows year-by-year estimates of the fuzzy RD coefficient when using cumulative firm entry and exit rates (starting in 1990) as outcome. While there are no systematically different patterns in aggregate firm dynamics, we notice interesting heterogeneity. Firm birth and death rates are affected positively in KIS, suggesting high business dynamism. The effect for manufacturing is instead negative, but imprecisely estimated.

Agglomeration economies. While identifying the market failure tackled by government intervention is challenging, our evidence suggests that the IDA policy has addressed agglomeration economies in the targeted areas. We present additional findings consistent with the presence of agglomeration economies in Tables D8 and D9. First, we document sizable long-term effects on local incomes and house prices.[30] Second, sectoral specialization within manufacturing measured with the Krugman Specialization Index (Krugman,

[30] As in Lang et al. (2022), we also find that PBIP has not promoted equality, as evidenced by the higher Gini coefficient. On a similar note, Figure D7 reports quantile treatment effects estimated following Frandsen et al. (2012) and shows higher effects on employment and firm density at higher deciles of the distribution.

1992) has *decreased* following the policy, suggesting that subsidies benefitted not only the targeted industries. Third, we rule out an alternative channel of persistence linked to continued public investment in treated areas after the end of the policy. We test this hypothesis by estimating our fuzzy RD model for the (log of) municipal expenditures sourced from municipal balance sheets between 2000 and 2010, broken down into different items. We add two more outcomes: the cumulative EU structural funds received between 2007 and 2013 and the total subsidies within Law n. 488/1992, introduced right at the end of the EIM. We find no discontinuity in any of these variables, which points to agglomeration economies as the main source of persistence (von Ehrlich and Seidel, 2018; Garin and Rothbaum, 2024).[31]

7. Cost-benefit analysis

While our findings clearly highlight a positive impact of the policy, whether these benefits outweigh the very high costs remains to be addressed. We now use our estimates to inform a cost-benefit analysis of the IDA program and assess its cost-effectiveness in the long run. 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 €1000 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.[32] Using the long-run Diff-in-Disc estimate delivers a similar cost per job of $21,716 ($32,575 including deadweight loss), which remains roughly stable when substituting the estimates from our alternative identification strategies (Equations B3.1 and B3.2). The cost per job of the IDA policy falls in the range of estimates of 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).[33]

[31] Another local development policy conducted in Italy after 1992 – the *Area Contracts* – only involved one of the IDAs (Salerno) and brought relatively modest investments (€1.9 billion between 1998 and 2007).

[32] 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, we cannot rule out that the IDAs induced migration while they were in place (Section 5). We therefore impose a 50 percent deadweight loss as in Criscuolo et al. (2019) and Siegloch et al. (2022).

[33] Our cost per job estimate is smaller than those in Cerqua and Pellegrini (2014) and Cingano et al. (2022) for the investment subsidy program introduced in Italy right after the EIM (Law n.488/1992).

Cost-benefit analysis. We then conduct a more comprehensive back-of-the-envelope analysis of the benefits of the IDA policy. Our approach builds on the methods 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 benefits of the program long after its termination, and compare them with the total costs.

The gains of the IDA policy accrue to workers, firms and landlords in the form of higher wages, profits and rents, respectively. To compute these gains, we proceed in five steps: *i*) for each of the outcomes of interest j (wage bill, firm profits and housing rents), we calculate the observed amount each year from 1991 to 2011, $observed_j$; *ii*) we estimate the impact of the policy on (the log of) each outcome j over the 1991-2011 period, $\hat{\pi}_j$; *iii*) we use these estimates to compute the counterfactual amount in the absence of the policy: $counterfactual_j = observed_j/(1+\hat{\pi}_j)$; *iv*) for each year and outcome, we obtain the net benefit as the difference between the observed and the counterfactual flow; *v*) we aggregate these yearly net amounts between 1991 and 2011 and apply a 10 percent discount rate (roughly the one-year interest rate in Italy in the early 1990s) to derive their present discounted value.

We find that IDAs generated a gain of €86 billion between 1991 and 2011, with most benefits accruing to workers (€52 billion) and firms (€33 billion).[34] Total IDA costs can be computed in the ASET data and amount to €88 billion. The gains generated by IDAs after their termination thus roughly cover the full cost of the program. In turn, this suggests net benefits assuming that the policy generated surplus also while it was in place or after 2011.

8. Discussion and further implications

What features of the IDAs made them a successful policy example? How can PBIPs not only stimulate the targeted industries, but also foster long-run development?

Heterogeneity. We first explore possible heterogeneity of the effects across IDAs, asking whether persistence is linked to specific characteristics of an area. We split the group of 12 IDA regions in our sample into two sub-groups based on whether an IDA region is above or below the median of the following variables: elevation, slope, cumulative EIM subsidies, services share in 1951, share of high-technology manufacturing in 1991 and high-school education in 1951. We then conduct analysis separately for IDAs above and below the median.

[34] Landlords capture only a small portion of the gains in the form of housing rents. We show in Appendix E that further €10 billion add to the landlords' surplus coming from the long-run increase in housing value.

Figure F1 shows the resulting Diff-in-Disc coefficients. We measure no significant difference in employment effects between IDAs based on their geographical traits or funding within the EIM. A larger share of services at the onset of the policy seems to lead to higher long-run effects, but the difference between the estimated coefficients is small. The most striking differential effects are found when splitting the sample of IDAs based on the incidence of high-technology manufacturing in 1991 (clearly an outcome of the policy) and education levels in 1951. IDAs where the policy stimulated high-technology industries more, and IDAs with larger initial human capital endowment, are also those where the policy had a larger employment impact in the long term.[35] Still, some persistence in the effect of the IDA policy remains visible across all these heterogeneity cuts. Admittedly, our set-up is not very well suited to heterogeneity analysis because of the relatively small sample size and the RD design. To investigate the sources of persistence further, we outline next the results of our analysis in other areas of the South, which also received EIM subsidies.

The EIM border. As summarized in Appendix B.4 and detailed in Albanese et al. (2023), the northern boundary separating the EIM region from the rest of Italy gives rise to a spatial RD design that compares areas south of the border, which were subsidized by the Cassa, to areas north of it. In the interest of brevity, we show in Figure 9 the most robust estimates from a Diff-in-Disc design run at the EIM border (Equation B4.2).[36] Panel (a) shows the estimates for employment density. Areas north and south of the border were on parallel trends before the beginning of the policy. A positive effect emerges starting in the 1970s, albeit not statistically significant. The coefficient peaks at the end of the EIM in 1991 but eventually declines, suggesting lack of persistence in the impact of the intervention at the EIM border. Panel (b) breaks down the effect on employment density into manufacturing and services. Similarly to what was found for 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 government subsidies.

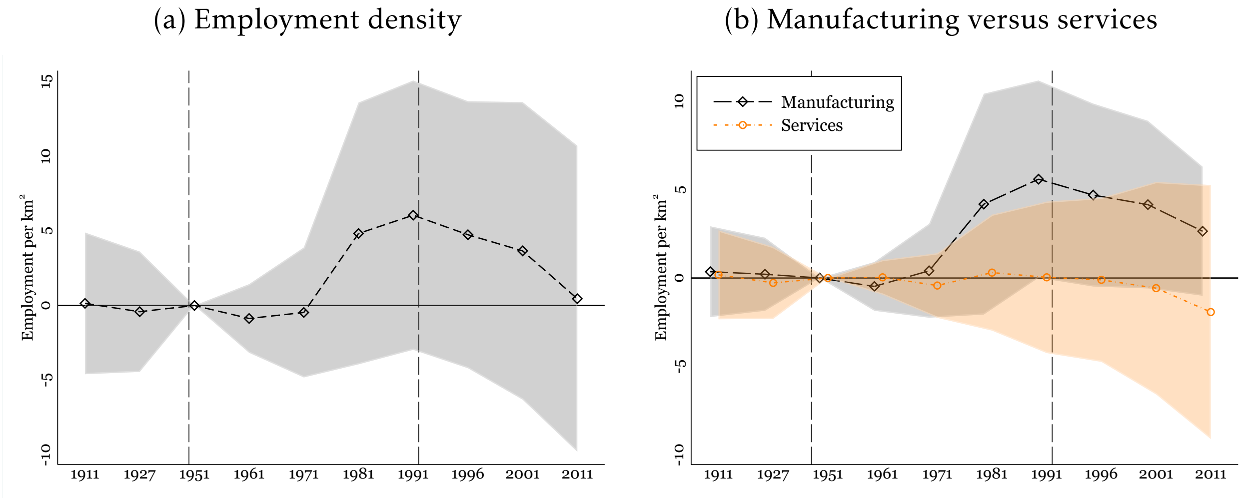
The results listed in the previous sections do not hold at the EIM border (Appendix F). The incidence of KIS workers and firms is not larger south of the border, nor is the share of high-technology manufacturing.[37] Wages are significantly higher south of the border in

[35]The results on human capital 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.

[36]Figure F8 shows the effects on firm density. We show raw RD plots at the border in Appendix F, Figures F2 to F7. Appendix Tables F1 and F2 report cross-sectional RD regression estimates for 1991 and 2011.

[37]EIM firm subsidies at the border went disproportionately 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).

Figure 9. The EIM border - Difference-in-discontinuities



Notes: Coefficient estimates for Equation B4.2. 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 EIM. See text for details.

1991, but only in manufacturing and non-tradable services. By 2011, the wage effect has disappeared. We find no discontinuities in human capital, and even a small negative effect on the share of high-skill occupations. There is a higher share of large firms south of the border, but not of high-paying firms. Firm value added, sales and profits are positively affected, but exclusively for manufacturing and non-tradables and not in KIS. Last, we find no effects on local incomes and even negative long-run effects on house prices.

The IDAs vs the EIM border. While government intervention brought enduring agglomeration and structural transformations in the IDAs, its effects at the EIM border were concentrated in manufacturing and dissipated in the long run.[38] Contrasting these two experiences can be instructive. Table F10 compares municipalities bordering IDA centers to municipalities up to 50 km south of the EIM border. Interestingly, the two groups do not differ much in the amount of funding from the Cassa. There are however substantial differences in pre-existing agglomeration of workers and firms, which was about three times larger in IDAs. Places south of the border had instead less favorable geography, a larger share of workers in agriculture and slightly less educated population before the policy. Put differently, the IDAs were explicitly selected as hubs where agglomeration forces could be stimulated; the EIM border was instead located in peripheral areas of Central Italy – an environment with poor market access and less suitable to the formation of local clusters. This evidence, albeit

[38]These considerations relate to the external validity of our results, which we discuss in Appendix G following the insights of Angrist and Rokkanen (2015) and Bertanha and Imbens (2020).

suggestive, points to the fact that PBIP can have persistent effects when it targets areas with better initial conditions, while its effects are more likely to be short-lived (and limited to the targeted industries) in peripheral regions.[39]

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 grow in popularity, many questions arise about their effectiveness in fostering long-run development in the subsidized areas. Can policies targeting the formation of industrial clusters successfully promote structural change? What role do they play 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 indeed generate virtuous cycles in the targeted communities, by promoting agglomeration of workers and firms that persists well after the end of the intervention. We show that the success of PBIPs is 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 services jobs with high knowledge content suggests that PBIP expedited structural change and technological adaptation. We stress that the policy-induced promotion of high-technology manufacturing has played a fundamental role in this process, through both increased demand of business-oriented services and the establishment of a high-human capital local labor force that persisted in the long run.

As advocated in Rodrik and Stantcheva (2021) and Rodrik (2022), the success 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 illustrate how initial conditions matter, as the stimulus to high-skill services jobs appears more likely in places with higher agglomeration potential. We observe instead a short-lived effect, limited to the initial boost to manufacturing, in peripheral areas. Taken together, our evidence has relevant implications for the future of industrial policy, but also warrants further investigation and provides ground for future research.

[39]While we stress the role of initial conditions, another 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-fulfilling (Kline, 2010). The policymaker committed to establishing local hubs in IDAs, while there was no such explicit commitment for the areas around the border.

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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 firm investment grants (starting in the 1960s).

Infrastructure spending. The policy goal during the first decade of the EIM was modernizing Southern infrastructure. The Cassa was in charge of planning, execution and monitoring of initiatives in four areas (agriculture, drains and aqueducts, transport and tourism development) subject to the government's allocation of the total funds across them. 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. In the policymaker's words, firms located in the South (or willing to locate there) had to be compensated "*for the natural inferiority of the Mezzogiorno relative to other areas, with its subsequent costs and risks*" (Cassa's Annual Report, 1957-58). The main policy item was firm investment grants. Grant applications were submitted by firms to special credit institutions, which were in charge of investigating the merit and feasibility of the proposed investment (including the estimated increase in employment). The results of the investigation were then forwarded to the Cassa, which decided on the application 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.[40] During the 1960s and the 1970s, the key variables determining 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 percent higher, separately for each of these three criteria). The maximum subsidy rate, originally set at 20 percent of the investment, has been periodically increased and reached up to 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.

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

The IDAs. The establishment process for IDAs is described in Section 2. Here we clarify how investment grants differed for firms located in an IDA. Firms in IDA municipalities were entitled to larger subsidies from the Cassa, in two ways. First, the subsidy rate on investments was up to 6.5 percent higher for IDA firms than for firms in the rest of the EIM region, as mentioned in the previous paragraph. Second, all IDA firms could access grants regardless of size, while there where limits to both firm size (up to 500 workers, and investment below €1.5 million) and municipality size (up to 75,000 people) elsewhere in the EIM region.[41] These size limits were removed in 1967. Investment subsidy rates were instead equalized between IDA and non-IDA firms only in the late 1970s.

The *Industrialization Nuclei*. Together with the IDAs, the government also introduced the so-called *Industrialization Nuclei* to favor "*minor concentration*" – Footnote 41. The Nuclei were less extensive areas (very often 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.

Figure A1.1 breaks down firm investment subsidies and low-interest loans across sectors. Panel (a) shows that about 30 percent of the total subsidies went to the chemical sector, while between 7 and 15 percent was absorbed by other industries such as metallurgy, food and textile. Within IDAs (Panel (b)), chemicals remain the most subsidized sector at almost

[41] To provide more context, the Cassa was pursuing two policy goals. The first ("*industrial concentration*") was to establish large industrial clusters (the IDAs) or smaller ones ("*Industrialization Nuclei*", briefly described in the next paragraph). The second ("*industrial diffusion*") was to favor industrial development in peripheral regions by supporting firms in municipalities with limited industrial activity.

30 percent of total subsidies, followed by other heavy industries such as metals (20 percent) and transportation manufacturing (10 percent). We notice that incentives to firms are almost entirely in the form of grants, while concessional loans are relatively limited. Also, the share of subsidies to services firms is negligible.

Last, Figure A1.2 plots the spatial distribution of EIM expenses across the roughly 3,000 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.[42] While firm subsidies are largely concentrated in the IDAs, infrastructure spending is most pronounced in the internal areas.

Appendix Table A1.1. Cumulative Cassa's expenses per decade

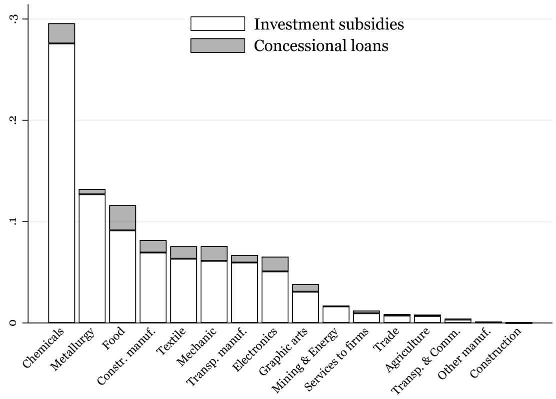
	Total expenses		Infrastructure spending		Firm subsidies	
	Raw amount	Per capita	Raw amount	Per capita	Raw amount	Per capita
1950-1959	5,309	236.4	5,290	235.5	19	0.8
1960-1969	29,990	1,335.2	8,607	383.2	21,382	952.0
1970-1979	79,439	3,536.9	26,368	1,174.0	53,071	2,362.9
1980-1989	37,270	1,659.4	16,781	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: 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. See text for details.

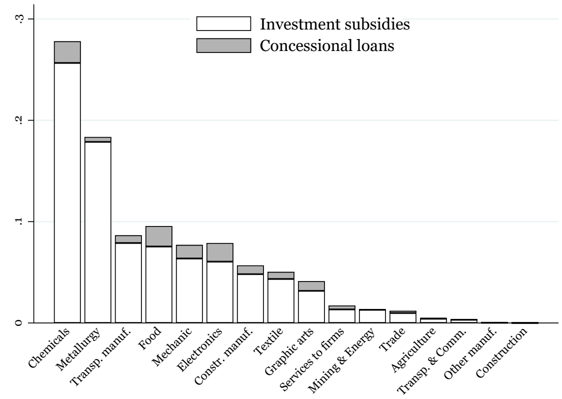
[42] The EIM's jurisdiction also included some small islands of Tuscany, which we exclude from the sample.

Appendix Figure A1.1. Incentives to firms – breakdown

(a) Full EIM area



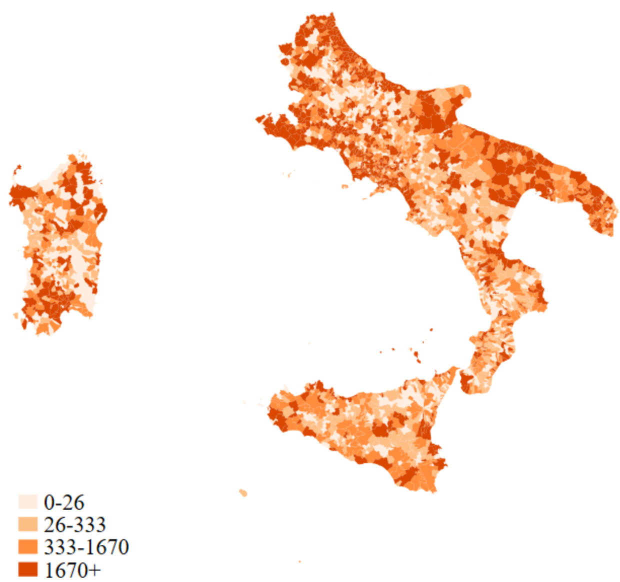
(b) IDAs



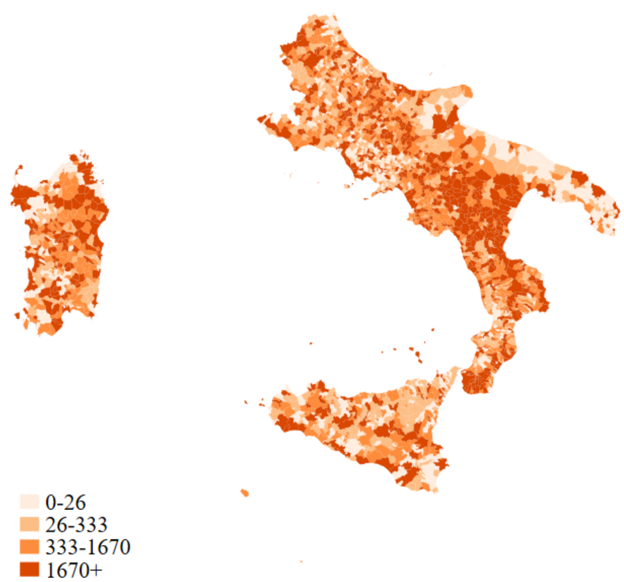
Notes: Sector breakdown of firm investment subsidies and concessional loans. Panel (a) includes all EIM municipalities. Panel (b) includes IDAs only.

Appendix Figure A1.2. Cassa's expenses (1950-1992)

(a) Firm subsidies



(b) Infrastructure expenses



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

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

Table A2.1 shows descriptive statistics for employment and firm density (computed as the number of workers and establishments per km^2) across census years, separately for the EIM area and the rest of Italy. The data also report a broad sector breakdown, which allows to differentiate 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).[43]

We exploit the within-manufacturing sectoral breakdown to compute a measure of sectoral concentration – the Krugman Specialization Index – following 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 total 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 total number of manufacturing workers in the reference group in census year t. The index provides a simple measure of sectoral specialization in municipality m relative to a reference group, which we set here as all Italian regions except for the more advanced 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.

[43] The 1927 and 1911 censuses only allow a broad distinction between manufacturing and services. In particular the 1911 data, sourced from the Census of Factories and Industrial Enterprises, only covered firms in manufacturing and "collective needs" services.

Appendix Table A2.1. Industrial census – descriptive statistics

	1911	1927	1951	1961	1971	1981	1991	1996	2001	2011
					Panel (a): Employment density					
EIM area										
Mean	5.70	12.39	13.81	18.18	21.27	31.11	35.35	34.31	40.45	43.91
S.D.	(14.73)	(26.11)	(31.55)	(46.85)	(59.39)	(80.52)	(85.55)	(86.50)	(99.42)	(104.39)
Rest of Italy										
Mean	14.87	25.76	29.00	41.46	54.67	70.23	75.06	76.45	84.90	84.94
S.D.	(29.60)	(47.26)	(60.68)	(84.46)	(104.40)	(125.18)	(130.86)	(133.14)	(145.25)	(142.54)
					Panel (b): Establishment density					
EIM area										
Mean	0.98	5.66	5.84	6.89	7.54	9.52	11.26	12.76	14.46	16.21
S.D.	(1.42)	(8.33)	(8.78)	(11.44)	(13.72)	(18.22)	(21.65)	(26.70)	(30.77)	(34.53)
Rest of Italy										
Mean	1.18	6.51	6.65	8.42	10.68	15.09	16.50	18.05	21.12	22.71
S.D.	(1.39)	(7.29)	(8.46)	(11.85)	(15.67)	(22.10)	(24.57)	(28.59)	(33.72)	(36.41)

Notes: Descriptive statistics for worker and firm density separately for the EIM area and the rest of Italy. Variables winsorized at 1 and 99 percent.

A.3. Appendix A3: Administrative data

Firm-level data. We collect data on the universe of firms in the Italian private sector from the Social Security archives (INPS) between 1990 and 2015, available at the Bank of Italy. For each firm, the dataset reports the number of employees, the average monthly earnings, the 6-digit sector (classified according to Eurostat's NACE Rev. 2 groups) and the location (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 and include information on 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 perform further classifications. Specifically, we break down services into knowledge-intensive and other services, and manufacturing into high- and low-technology according to the Eurostat/OECD classification.[44]

Worker-level data. In addition to the firm-level information, we use administrative worker-level data from the INPS archives consisting of the work and pay history between 1990 and 2011 of a random sample of employees. These are linked with the firm database using tax identifiers to obtain matched employer-employee data. The data cover more than 6.5 percent of the universe of Italian employees in the non-agricultural private sector. For the period of analysis and for each worker-firm match, we observe all the information related to the social security contributions on a yearly basis (earnings, weeks worked, contract type) and some demographic characteristics (gender, year of birth, region of residence). The contract information includes the annual gross earnings, the number of weeks and days worked, whether the schedule is part-time or full-time, whether the contract is fixed-term or open-ended (since 1998), and the broad occupation (apprentice, blue-collar, white-collar, middle manager, executive).

The data record all labor market transitions of workers included in the sample. Therefore, they can be used to compute hiring at the municipality level, as discussed in Section 6 and showed for example in Figure D4. We define hirings in a given year t as the municipality-level sum of non-employment to employment and firm-to-firm transitions

[44] See here: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Knowledge-intensive_services_(KIS) and here https://www.oecd.org/sti/ind/48350231.pdf

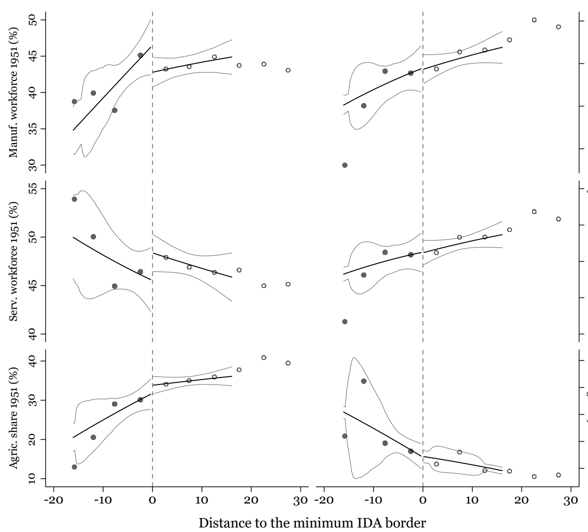
happening between $t-1$ and t. We also exploit the data to compute the AKM worker fixed effects (Abowd et al., 1999). Specifically, for the period 1990-2011, we estimate a two-way fixed effects regression of log weekly earnings on worker and firm fixed effects, controlling for a cubic polynomial in age, a dummy for white-collar workers, a dummy for part-time workers – all interacted with a dummy for female workers – and year dummies. The estimation of the AKM regression requires to restrict the sample to the largest connected group of workers and firms linked by worker mobility. Connected groups contain all workers that have ever been employed by one of the firms in the group, and all firms that have employed one of the workers in the group. We use the full sample between 1990 and 2011 in order to maximize the size of the largest connected group, which comprises around 97 percent of workers in the full sample.

B. Appendix B: Identification

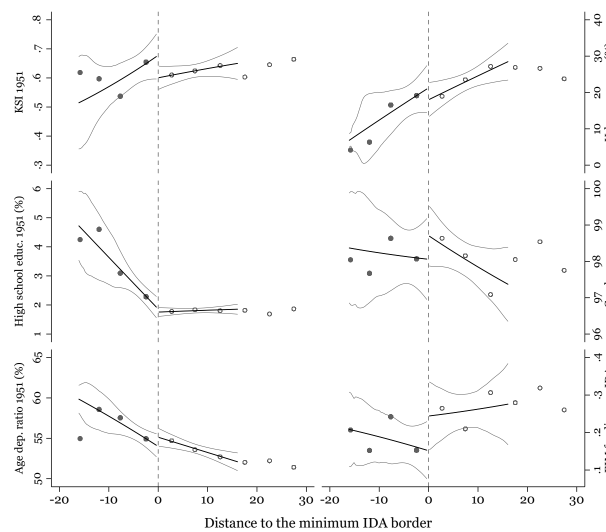
B.1. Appendix B1

Appendix Figure B1.1. Balancing at the minimum IDA border

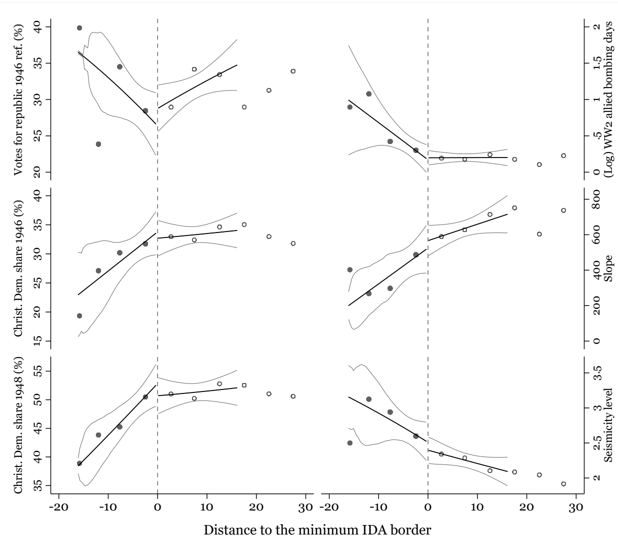
(a)



(b)



(c)



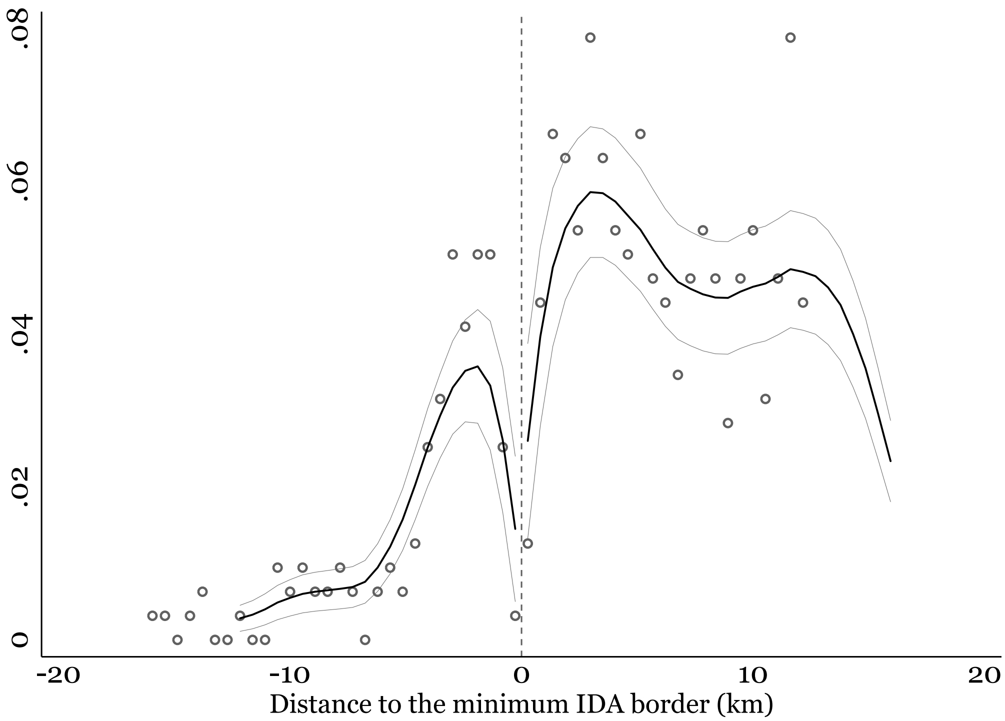
Notes: Panel (a): "Manuf. workforce" and "Serv. workforce" are the shares of manufacturing and services workers in the 1951 industrial census. "Agric. share" computed as the number of agriculture workers per 100 residents aged at least 15. "Empl. rate" is the ratio of employed people to total residents aged 15 years and older. "Part. rate" is the ratio of the resident working population to the resident population of the same age group. "Pop. density" measured as number of inhabitants per km^2. Panel (b): "KSI 1951" is the Krugman Specialization Index computed within manufacturing in 1951 (see Appendix A.2). "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 during the 1950s. 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 (log) 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 either 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. See text for details.

Appendix Table B1.1. Balancing tests, minimum IDA border

	(1)	(2)	(3)	(4)	(5)	(6)
(a)	Empl.	Manuf. Empl.	Serv. Empl.	Est.	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)	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)	KSI	High school	Age dep.	Urban pop.	Gender	Pre-IDA exp.
RD Estimate	0.06	0.57	-0.85	2.52	-0.58	-0.06
	(0.05)	(0.23)**	(0.54)	(3.90)	(0.59)	(0.07)
Mean	0.63	1.97	54.05	21.95	98.05	0.24
S.D.	0.26	1.20	5.95	25.05	4.78	0.46
Observations	587	563	563	537	563	563
R^2	0.12	0.17	0.46	0.63	0.25	0.07
(d)	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: All outcomes as of 1951, unless noted otherwise. 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. Standard errors clustered by IDA region in parentheses. See Figure 4, Figure B1.1 and text for details. * p<0.10, ** p<0.05, *** p<0.01

Appendix Figure B1.2. McCrary Test at the minimum IDA border



Notes: Output of a McCrary (2008) test of continuity in the density of the running variable.

B.2. Appendix B2

Main identification. Here, we describe more formally the main identification strategy of the paper, which is sketched intuitively in Section 4. The outer boundaries of the municipalities contiguous to the IDA center trace a "minimum" IDA border $\mathcal{J}$ that separates two regions within ($\mathbb{W}$) and outside ($\mathbb{O}$) 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 $\delta_m \equiv d(\ell_m, \mathcal{J})$ 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 region $\mathbb{W}$. 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. This identification strategy rests on three main assumptions:

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

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 to exist in the proximity of the cutoff: always-takers ($IDA_m(\delta_m) = 1$), never-takers ($IDA_m(\delta_m) = 0$) and compliers ($IDA_m(\delta_m) = W_m$).

Proposition 1. *Under A1, A2 and A3 the fuzzy RD estimand* $\beta = \pi/\vartheta$ *identifies the local average treatment effect (LATE) for the sub-population of compliers.*

Proof. Here we show that, under Assumptions A1, A2 and A3, the fuzzy RD estimand $\beta = \pi/\vartheta$ identifies the average causal effect for compliers at the cutoff (Hahn et al., 2001; Imbens and Lemieux, 2008):

$$\beta = \frac{\lim_{\delta_m \to 0^-} E[Y_m \mid \delta_m] - \lim_{\delta_m \to 0^+} E[Y_m \mid \delta_m]}{\lim_{\delta_m \to 0^-} Pr(IDA_m = 1 \mid \delta_m) - \lim_{\delta_m \to 0^+} Pr(IDA_m = 1 \mid \delta_m)} \tag{B2.1}$$

$$= E[Y_m(1) - Y_m(0) \mid \theta = \theta_C,\ \delta_m = 0]$$

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). Also define $\epsilon > 0$ small enough that $-\epsilon$ and $+\epsilon$ belong to neighborhood $\mathbb{S}$ of the cutoff where there are no defier municipalities, as per Assumption A3.

1) We first focus on the numerator in B2.1. Consider $\delta_m = \epsilon$, so that we are slightly outside of the minimum IDA border:

$$\begin{aligned} E[Y_m \mid \delta_m = \epsilon] = E[Y_m \mid IDA_m = 1,\ \delta_m = \epsilon] \cdot Pr(IDA_m = 1 \mid \delta_m = \epsilon) + \\ + E[Y_m \mid IDA_m = 0,\ \delta_m = \epsilon] \cdot Pr(IDA_m = 0 \mid \delta_m = \epsilon) \end{aligned}$$

And

$$\begin{aligned} Pr(Y_m \le y,\ IDA_m = 1 \mid \delta_m = \epsilon) &= Pr(Y_m(1) \le y,\ IDA_m(\epsilon) = 1 \mid \delta_m = \epsilon) \\ &= Pr(Y_m(1) \le y,\ \theta = \theta_A \mid \delta_m = \epsilon) \\ &= Pr(Y_m(1) \le y \mid \theta = \theta_A,\ \delta_m = \epsilon) \cdot Pr(\theta = \theta_A \mid \delta_m = \epsilon) \end{aligned}$$

where the second equality uses Assumption A3. Similarly,

$$\begin{aligned} Pr(Y_m \le y,\ IDA_m = 0 \mid \delta_m = \epsilon) &= Pr(Y_m(0) \le y,\ IDA_m(\epsilon) = 0 \mid \delta_m = \epsilon) \\ &= Pr(Y_m(0) \le y,\ \theta = \theta_N \mid \delta_m = \epsilon) + Pr(Y_m(0) \le y,\ \theta = \theta_C \mid \delta_m = \epsilon) \\ &= Pr(Y_m(0) \le y \mid \theta = \theta_N,\ \delta_m = \epsilon) \cdot Pr(\theta = \theta_N \mid \delta_m = \epsilon) + \\ &+ Pr(Y_m(0) \le y \mid \theta = \theta_C,\ \delta_m = \epsilon) \cdot Pr(\theta = \theta_C \mid \delta_m = \epsilon) \end{aligned}$$

Hence:

$$
\begin{aligned}
E[Y_m \mid \delta_m = \epsilon] = E[Y_m(1) \mid \theta = \theta_A,\ \delta_m = \epsilon] \cdot Pr(\theta = \theta_A \mid \delta_m = \epsilon) + \\
E[Y_m(0) \mid \theta = \theta_N,\ \delta_m = \epsilon] \cdot Pr(\theta = \theta_N \mid \delta_m = \epsilon) + \\
E[Y_m(0) \mid \theta = \theta_C,\ \delta_m = \epsilon] \cdot Pr(\theta = \theta_C \mid \delta_m = \epsilon)
\end{aligned}
$$

and, using the continuity assumption A2:

$$
\begin{aligned}
\lim_{\epsilon \to 0} E[Y_m \mid \delta_m = \epsilon] = E[Y_m(1) \mid \theta = \theta_A,\ \delta_m = 0] \cdot Pr(\theta = \theta_A \mid \delta_m = 0) + \\
E[Y_m(0) \mid \theta = \theta_N,\ \delta_m = 0] \cdot Pr(\theta = \theta_N \mid \delta_m = 0) + \\
E[Y_m(0) \mid \theta = \theta_C,\ \delta_m = 0] \cdot Pr(\theta = \theta_C \mid \delta_m = 0)
\end{aligned}
\tag{B2.2}
$$

Consider now $\delta_m = -\epsilon$, so that we are slightly within the minimum IDA border and focus on municipalities contiguous to the IDA center:

$$
\begin{aligned}
E[Y_m \mid \delta_m = -\epsilon] = E[Y_m \mid IDA_m = 1,\ \delta_m = -\epsilon] \cdot Pr(IDA_m = 1 \mid \delta_m = -\epsilon) + \\
+ E[Y_m \mid IDA_m = 0,\ \delta_m = -\epsilon] \cdot Pr(IDA_m = 0 \mid \delta_m = -\epsilon)
\end{aligned}
$$

And

$$
\begin{aligned}
Pr(Y_m \leq y,\ IDA_m = 1 \mid \delta_m = -\epsilon) &= Pr(Y_m(1) \leq y,\ IDA_m(-\epsilon) = 1 \mid \delta_m = -\epsilon) \\
&= Pr(Y_m(1) \leq y,\ \theta = \theta_A \mid \delta_m = -\epsilon) + Pr(Y_m(1) \leq y,\ \theta = \theta_C \mid \delta_m = -\epsilon) \\
&= Pr(Y_m(1) \leq y \mid \theta = \theta_A,\ \delta_m = -\epsilon) \cdot Pr(\theta = \theta_A \mid \delta_m = -\epsilon) + \\
&+ Pr(Y_m(1) \leq y \mid \theta = \theta_C,\ \delta_m = -\epsilon) \cdot Pr(\theta = \theta_C \mid \delta_m = -\epsilon)
\end{aligned}
$$

Similarly,

$$
\begin{aligned}
Pr(Y_m \leq y,\ IDA_m = 0 \mid \delta_m = -\epsilon) &= Pr(Y_m(0) \leq y,\ IDA_m(-\epsilon) = 0 \mid \delta_m = -\epsilon) \\
&= Pr(Y_m(0) \leq y,\ \theta = \theta_N \mid \delta_m = -\epsilon) \\
&= Pr(Y_m(0) \leq y \mid \theta = \theta_N,\ \delta_m = -\epsilon) \cdot Pr(\theta = \theta_N \mid \delta_m = -\epsilon)
\end{aligned}
$$

Where the second equality again uses Assumption A3. Then:

$$E[Y_m \mid \delta_m = -\epsilon] = E[Y_m(1) \mid \theta = \theta_A,\ \delta_m = -\epsilon] \cdot Pr(\theta = \theta_A \mid \delta_m = -\epsilon) +$$
$$E[Y_m(1) \mid \theta = \theta_C,\ \delta_m = -\epsilon] \cdot Pr(\theta = \theta_C \mid \delta_m = -\epsilon) +$$
$$E[Y_m(0) \mid \theta = \theta_N,\ \delta_m = -\epsilon] \cdot Pr(\theta = \theta_N \mid \delta_m = -\epsilon)$$

Taking the limit and using the continuity assumption A2:

$$\begin{aligned}\lim_{\epsilon \to 0} E[Y_m \mid \delta_m = -\epsilon] = {} & E[Y_m(1) \mid \theta = \theta_A,\ \delta_m = 0] \cdot Pr(\theta = \theta_A \mid \delta_m = 0) + \\ & E[Y_m(1) \mid \theta = \theta_C,\ \delta_m = 0] \cdot Pr(\theta = \theta_C \mid \delta_m = 0) + \\ & E[Y_m(0) \mid \theta = \theta_N,\ \delta_m = 0] \cdot Pr(\theta = \theta_N \mid \delta_m = 0)\end{aligned} \tag{B2.3}$$

Subtracting Equation B2.2 from B2.3:

$$\lim_{\epsilon \to 0} E[Y_m \mid \delta_m = -\epsilon] - \lim_{\epsilon \to 0} E[Y_m \mid \delta_m = \epsilon] = E[Y_m(1) - Y_m(0) \mid \theta = \theta_C,\ \delta_m = 0] \cdot Pr(\theta = \theta_C \mid \delta_m = 0)$$

2) We now focus on the denominator in B2.1. For $\delta_m = \epsilon$, and using A3:

$$Pr(IDA_m = 1 \mid \delta_m = \epsilon) = Pr(\theta = \theta_A \mid \delta_m = \epsilon)$$

Taking the limit and using A2:

$$\lim_{\epsilon \to 0} Pr(IDA_m = 1 \mid \delta_m = \epsilon) = Pr(\theta = \theta_A \mid \delta_m = 0) \tag{B2.4}$$

Similarly for $\delta_m = -\epsilon$:

$$Pr(IDA_m = 1 \mid \delta_m = -\epsilon) = Pr(\theta = \theta_A \mid \delta_m = -\epsilon) + Pr(\theta = \theta_C \mid \delta_m = -\epsilon)$$

And:

$$\lim_{\epsilon \to 0} Pr(IDA_m = 1 \mid \delta_m = -\epsilon) = Pr(\theta = \theta_A \mid \delta_m = 0) + Pr(\theta = \theta_C \mid \delta_m = 0) \tag{B2.5}$$

Subtracting B2.4 from B2.5:

$$\lim_{\epsilon \to 0} Pr(IDA_m = 1 \mid \delta_m = -\epsilon) - Pr(IDA_m = 1 \mid \delta_m = \epsilon) = Pr(\theta = \theta_C \mid \delta_m = 0)$$

Taking things together:

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

$$= \frac{E[Y_m(1) \; - \; Y_m(0) \mid \theta = \theta_C, \; \delta_m = 0] \; \cdot \; Pr(\theta = \theta_C \mid \delta_m = 0)}{Pr(\theta = \theta_C \mid \delta_m = 0)}$$

$$= E[Y_m(1) \; - \; Y_m(0) \mid \theta = \theta_C, \; \delta_m = 0]$$

Which proves the result.

(Fuzzy) Difference in discontinuities. We now discuss identification for the Diff-in-Disc design introduced at the end of Section 4, drawing on the analysis in Grembi et al. (2016) and Millán-Quijano (2020). Let the time indicator $P = \mathbb{1}[year \geq 1960]$ denote the census years after the introduction of the IDAs. 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 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 A3). 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 $Y_m^p = Y_m^p(1, 1) \cdot IDA_m^p \cdot W_m^p + Y_m^p(1, 0) \cdot IDA_m^p \cdot (1 - W_m^p) + Y_m^p(0, 1) \cdot (1 - IDA_m^p) \cdot W_m^p + Y_m^p(0, 0) \cdot (1 - IDA_m^p) \cdot (1 - W_m^p)$.

The Diff-in-Disc set-up is more robust than the cross-sectional fuzzy RD 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 first 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* $w = 0,1$.

With derivations similar to those above, and using Assumption A2b, one can show that the numerator in Equation B2.1 at time $p = 1$ (when the IDAs are in place) is now:

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

The cross-sectional reduced-form estimator identifies not only the treatment effect of interest (that of IDA status, on the first row), but also that of simply being contiguous to an IDA center. The contiguity effect is expressed as a weighted average of the effect for IDA always-takers and never-takers, on the second and third row above. To correctly identify the impact of IDA status, the confounding effect due to contiguity to IDA centers has to be cancelled 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 $p = 0$ derives from 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 effect of bordering IDA centers is time-constant and therefore cancels out when taking first differences.[45] In turn, the fuzzy Diff-in-Disc 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.

[45] 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.

B.3. Appendix B3: Placebo centers

We describe here an alternative identification design that exploits provincial capitals in the Center-North of Italy, which would have likely been IDA centers had they been part of the EIM jurisdiction. To ease exposition, we refer to these provincial capitals as "placebo centers". Figure B3.1 provides an illustration. Placebo centers are in black and their bordering municipalities are in grey. For comparability purposes, we exclude the most industrialized regions in the North of Italy (Lombardy, Veneto and Piemonte), as well as smaller regions close to the Alps (Valle d'Aosta, Friuli Venezia Giulia and Trentino Alto Adige). We leverage this source of variation in three ways.

Simple event study. In a first approach, we pool together the 120 municipalities bordering IDA centers (in orange in Figure B3.1) and the 243 municipalities bordering placebo centers (in grey in Figure B3.1). We compare these two groups before and after the institution of IDAs in a simple event study design. Let T_m be a treatment indicator denoting municipalities in the EIM area (those bordering IDA centers) and let $P = \mathbb{1}[year \geq 1960]$ be the time indicator defined above. Define again potential outcomes $Y_m(t)$ with $T_m = t \in \{0,1\}$, so that the observed outcome $Y_m = Y_m(1) \cdot T_m \cdot P + Y_m(0) \cdot (1 - T_m \cdot P)$. The causal effect of interest is $E[Y_m(1) - Y_m(0) \mid T_m = 1,\ P = 1]$. In the standard difference-in-differences (DID) regression:

$$Y_m = \beta_0 + \beta_1 \cdot T_m + \beta_2 \cdot P + \rho \cdot T_m \cdot P + \epsilon_m$$

The DID coefficient ρ identifies:

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

Under the standard assumption:

B3.1. Parallel trends 1. *There are common time trends in the control outcome across the two groups defined by T_m : $E[Y_m(0) \mid T_m = 1,\ P = 1] - E[Y_m(0) \mid T_m = 1,\ P = 0] = E[Y_m(0) \mid T_m = 0,\ P = 1] - E[Y_m(0) \mid T_m = 0,\ P = 0]$.*

the DID coefficient identifies the causal effect of interest.

In practice, we estimate a dynamic version of the standard DID model that allows to assess parallel trends empirically:

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

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. The coefficients of interest ρ_j capture the difference in outcomes between municipalities bordering IDA centers and those bordering placebo centers, relative to the difference in 1951. Inspection of the ρ_{1911} and ρ_{1927} coefficients provides a test of the parallel trends assumption.

Testing for displacement. This source of variation is also exploited to investigate possible spillover effects of the IDA policy to the control group in the baseline identification strategy. Namely, we use municipalities up to 16 km outside of the "placebo" boundary traced by municipalities bordering placebo centers as a counterfactual for municipalities up to 16 km outside of the minimum IDA border (the control group in the baseline design). We estimate the same specification of Equation B3.1, where again $T_m = 1$ for municipalities in the EIM area.[46]

Triple differences. In a last approach, we estimate an unified model that pools together municipalities (i) bordering IDA centers; ii) bordering placebo centers; and iii) up to 16 km away from the first two groups. The resulting sample comprises 1478 municipalities, 622 of which are in the EIM area (these are used in the baseline analysis, see Section 4). Let W_m be an indicator denoting municipalities bordering either IDA centers or placebo centers (the union of the orange and grey municipalities in Figure B3.1). Let also T_m be the indicator denoting municipalities in the EIM area, defined above, and $P = \mathbb{1}[year \geq 1960]$. The observed outcome can again 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:

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

[46] 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, in light blue in Figure 3 Panel (a)).

The triple DID coefficient ρ now identifies:

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

In this case, identification of the effect of interest requires an even weaker assumption than either A4 or B3.1. Namely:

B3.2. Parallel trends 2. *Any differential time trends in the control outcome between contiguous and not contiguous municipalities must be the same in the EIM area and in the Center-North:*

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

By allowing for differential pre-trends, this approach imposes less restrictive identifying assumptions than both the Diff-in-Disc design comparing municipalities within and outside of the minimum IDA border, as well as the event study design comparing municipalities bordering IDA centers to municipalities bordering placebo centers. Valid identification requires that any differential time trend in the control outcome is the same across the two groups, so that it would cancel out when taking the triple difference.

We specify the following dynamic triple differences specification:

$$Y_{m,t} = \mu_m + \sum_{j \neq 1951} \gamma_j \cdot \mathbb{1}[t=j] \cdot W_m + \sum_{j \neq 1951} \eta_j \cdot \mathbb{1}[t=j] \cdot T_m + \sum_{j \neq 1951} \rho_j \cdot \mathbb{1}[t=j] \cdot W_m \cdot T_m + \epsilon_{m,t} \quad \text{(B3.2)}$$

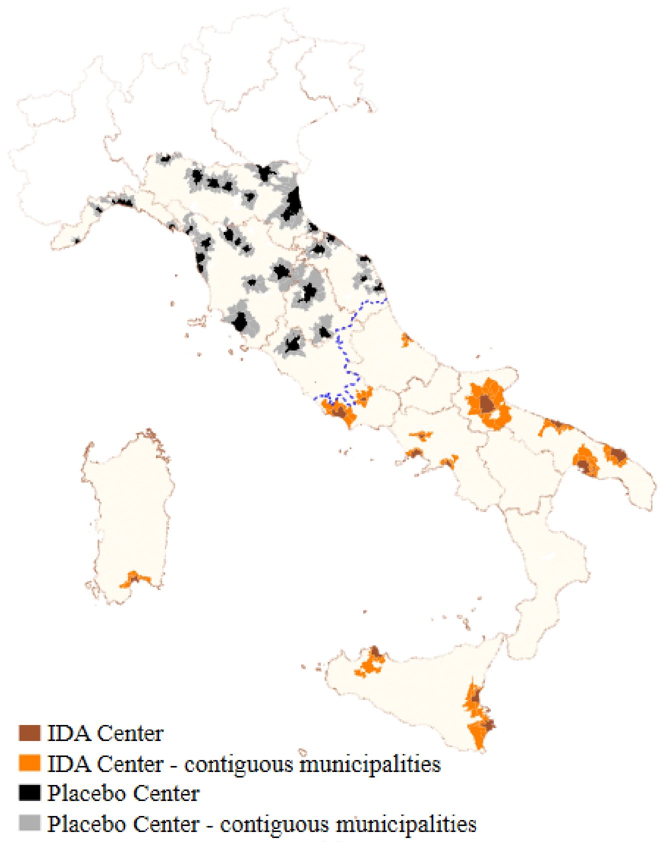
Where $Y_{m,t}$ is the outcome of interest for municipality m and census year t and μ_m are municipality fixed effects. The coefficients of interest ρ_j capture the difference between two differences in census year j relative to the baseline difference in 1951: the difference in outcomes between municipalities bordering IDA centers and those right outside of the minimum IDA border (the baseline results showed in the paper, see Figure 6); and the difference in outcomes between municipalities bordering placebo centers and those farther away. If Assumption B3.2 holds, the event study coefficients before the introduction of IDAs ρ_{1911} and ρ_{1927} should be undistinguishable from zero.

Last, we notice that the triple difference design automatically accounts for the possible spillover effects described above. Re-arranging the expression for the ρ parameter in the fully saturated model:

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

Where the "within" difference is identified by the event study in B3.1, while the "outside" difference is an estimate of possible spillovers of the IDA policy to nearby control areas.

Appendix Figure B3.1. Alternative identification – graphical illustration



Notes: The map shows municipalities bordering IDA centers in orange and municipalities bordering placebo centers in gray. Placebo centers are provincial capitals in the Center-North of Italy. The dashed blue line is the EIM border. See text for details.

B.4. Appendix B4: The EIM border

We describe briefly the second identification strategy of the paper, which exploits the discontinuity taking place at the northern boundary of the EIM jurisdiction.[47] 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 towards Central Italy to include areas of Lazio and Marche (Figure B4.1 Panel (a)). The list of the additional municipalities was set in 1950 and the EIM area remained since unchanged until the termination of the policy in 1992. Figure B4.1 Panel (b) plots Cassa's expenses around the border, clearly showing a stark jump equivalent to roughly 15,000 euros per capita.[48]

As described in Albanese et al. (2023), the RD continuity assumption is likely satisfied at the EIM border. A close inspection of the historical 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, such as land reclamations and river engineering, 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 place-based policies realized before, during or after the EIM. Balancing tests in Albanese et al. (2023) reveal no meaningful discontinuity in pre-determined municipality characteristics.

The baseline specification is a sharp RD design (Dell, 2010) that uses distance to the border ι_m as running variable (with negative values denoting control municipalities north of the border) and $B_m = \mathbb{1}[\iota_m \geq 0]$ as treatment indicator:

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

Where Y_m is the outcome of interest for municipality m, λ_b are border-segment fixed effects denoting the segment of the border closest to municipality m and $\varphi(\iota_m)$ is a linear RD polynomial. The specification is estimated on a baseline bandwidth of 50 km north and south of the EIM border.[49] Standard errors allow for arbitrary correlation across space following Conley (1999). Under the continuity assumption, the RD coefficient κ estimates the causal effect of the treatment at the cutoff (Imbens and Lemieux, 2008). Proving this result is easy

[47] More details on the EIM border and its suitability as a RD cutoff are available in Albanese et al. (2023).

[48] 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.

[49] We obtain this bandwidth as a simple average of MSE-optimal bandwidths, derived following Calonico et al. (2014) using employment density across sectors and census years as outcome.

when considering in the proof of Appendix B.2 that a sharp RD design is a special case of fuzzy RD with perfect compliance: $\lim_{\iota_m \to 0^-} Pr(B_m = 1 \mid \iota_m) - \lim_{\iota_m \to 0^+} Pr(B_m = 1 \mid \iota_m) = 1$.

To further improve on internal validity, we again specify a dynamic version of Equation B4.1 in the form of a Diff-in-Disc design:

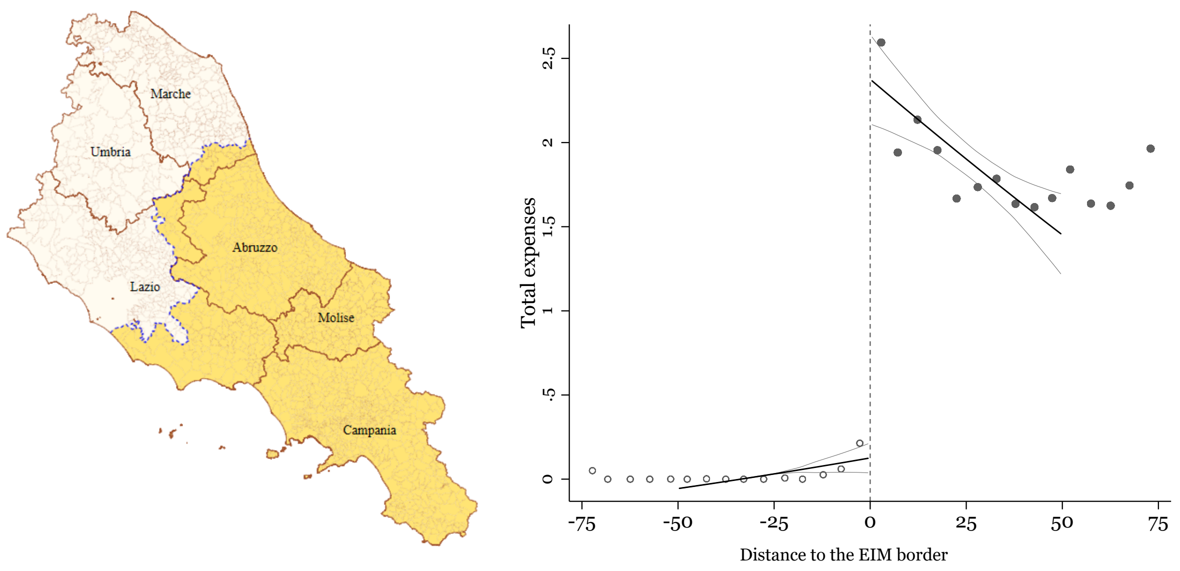
$$Y_{m,t} = \mu_m + \sigma_t + \sum_{j \neq 1951} \rho_j \cdot \mathbb{1}[t = j] \cdot B_m + \epsilon_{m,t} \tag{B4.2}$$

Where notation is the same as in Equation 2. The sample uses a 50-km symmetric bandwidth around the border and standard errors are clustered at the municipality level.

Appendix Figure B4.1. The EIM border

(a) The border

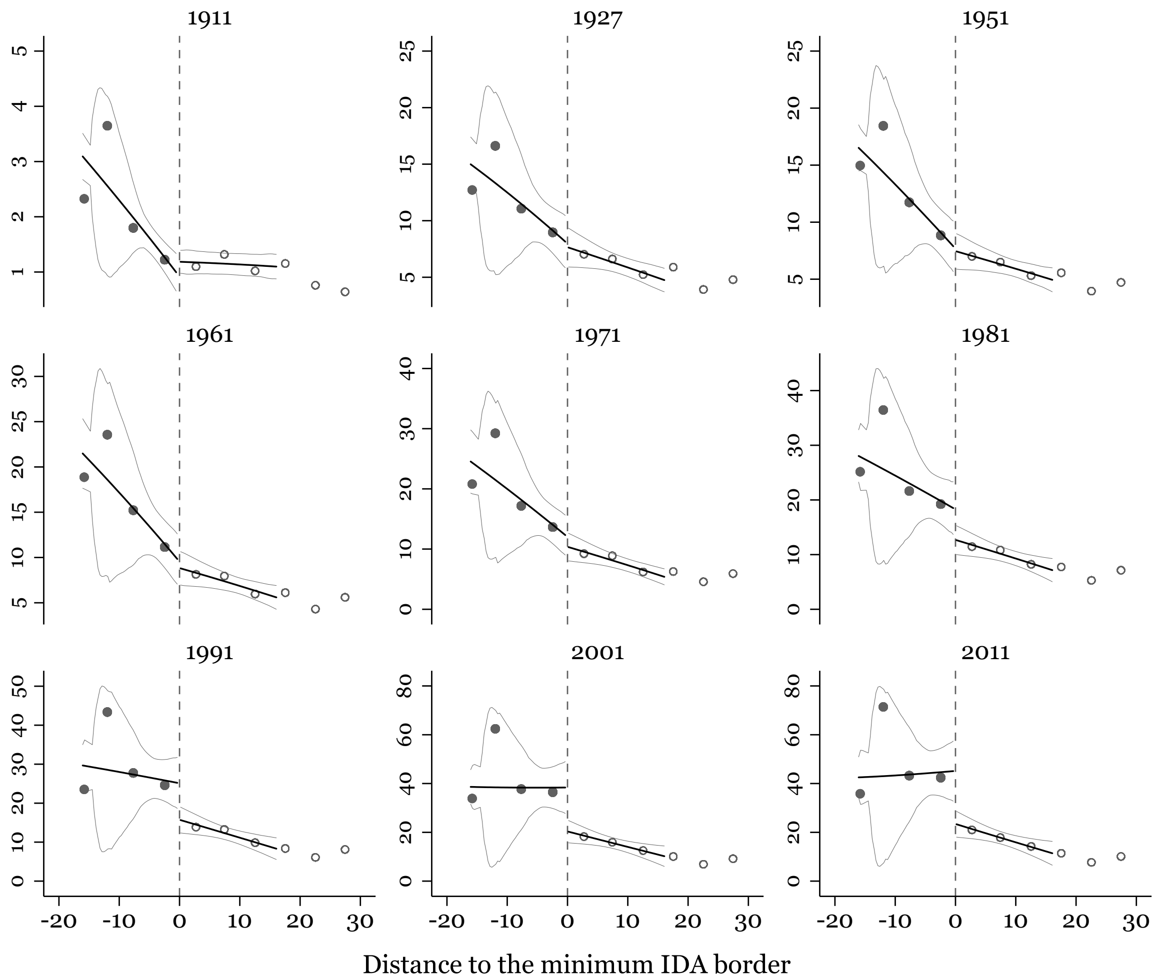
(b) Total EIM expenses



Notes: Panel (a) shows the EIM border as the dashed blue line. 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. See text for details.

C. Appendix C: Results

Appendix Figure C1. Establishment density



Notes: 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 either side of the border using a symmetric 16-km bandwidth. The gray lines are 95 percent confidence intervals. See text for details.

Appendix Table C1. Establishment density – Baseline

	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: Column (1) shows the estimation output of Equation 1b. Column (2) reports the fuzzy RD estimates. Column (3) replaces IDA status with EIM subsidies 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 from the border and IDA region effects. Standard errors clustered by IDA region in parentheses. See text for details. * p<0.10, ** p<0.05, *** p<0.01

Appendix Table C2. Employment density – Robustness tests

	(1) 2^{nd} order	(2) 3^{rd} order	(3) Excl. centers	(4) Distance to center	(5) No IDA region eff.
			Contemporaneous effect (1991)		
RD Estimate	82.35	92.91	81.44	111.98	107.72
	(38.96)**	(40.20)**	(41.01)*	(43.71)**	(40.82)**
Mean around the border	47.62	47.62	42.39	47.62	47.62
Standard deviation	79.68	79.68	66.86	79.68	79.68
Observations	586	586	574	586	586
KP F-stat	26.03	12.69	18.52	18.60	22.58
			Persistent effect (2011)		
RD Estimate	123.04	140.17	126.85	162.57	157.70
	(61.84)*	(67.47)**	(60.08)**	(63.91)**	(59.35)**
Mean around the border	62.97	62.97	56.39	62.97	62.97
Standard deviation	108.15	108.15	93.55	108.15	108.15
Observations	586	586	574	586	586
KP F-stat	26.03	12.69	18.52	18.60	22.58

Notes: Replication of Table 3, Column (2), robustness checks. 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. See text for details. * p<0.10, ** p<0.05, *** p<0.01

Appendix Table C3. Employment and establishment density – Conley standard errors

	Employment per km^2		Establishments per km^2	
	1991	2011	1991	2011
RD Estimate	43.31	62.99	9.18	19.83
	(12.00)***	(16.81)***	(3.25)***	(5.90)***
Mean around the border	47.62	62.97	15.08	23.10
Standard deviation	79.68	108.15	21.98	37.88
Observations	586	586	586	586

Notes: Replication of Table 3, Column (1). Standard errors allow for spatial correlation (Conley, 1999). See text for details. * p<0.10, ** p<0.05, *** p<0.01

Appendix Table C4. Employment and establishment 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

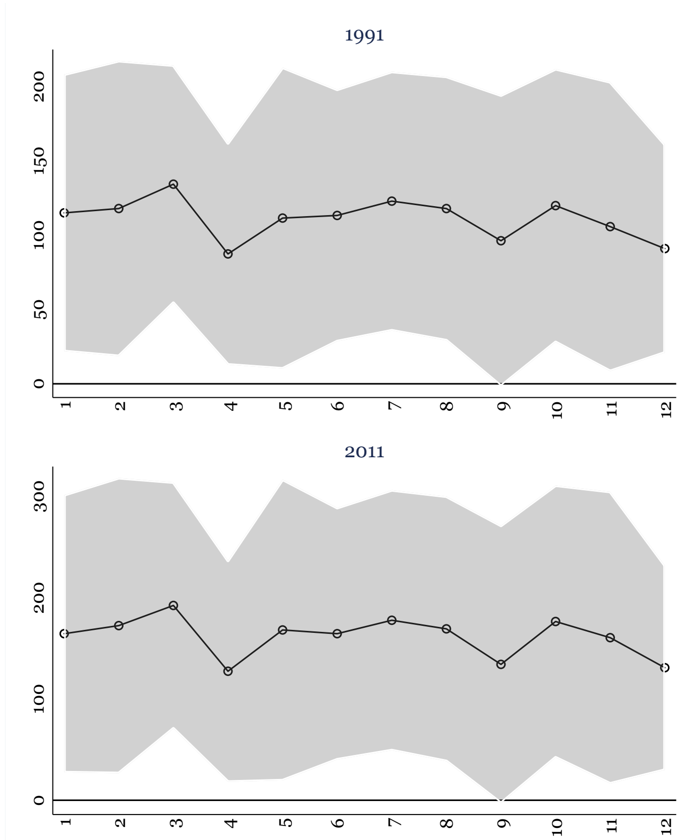
Notes: Estimation output for the fuzzy RD desing using local randomization inference as proposed in Cattaneo et al. (2016), with 1,000 replications, uniform kernel and without specifying a polynomial for the outcome transformation model – see the *rdrandinf* command in Cattaneo et al. (2016). The window-selection procedure is built on balance tests for RD under local randomization – see the *rdwinselect* command in Cattaneo et al. (2016). See text for details. * p<0.10, ** p<0.05, *** p<0.01

Appendix Table C5. Employment density – All IDAs

	Reduced form	2-SLS	
		IDA status	EIM subsidies
	(1)	(2)	(3)
	Contemporaneous effect (1991)		
RD Estimate	50.01	157.95	8.44
	(19.19)**	(68.70)**	(4.01)**
Mean around the border	70.49	70.49	69.78
Standard deviation	111.57	111.57	111.24
Observations	775	775	744
R^2	0.40		
KP F-stat		15.42	7.87
	Persistent effect (2011)		
RD Estimate	64.04	202.25	10.36
	(24.82)**	(83.97)**	(4.63)**
Mean around the border	96.25	96.25	94.95
Standard deviation	149.60	149.60	148.15
Observations	775	775	744
R^2	0.45		
KP F-stat		15.42	7.87

Notes: Replication of Table 3, including also the Napoli and Caserta IDAs (excluded from the baseline analysis because of the small distance between the two IDA centers). Standard errors clustered by IDA region in parentheses. See text for details. * p<0.10, ** p<0.05, *** p<0.01

Appendix Figure C2. Employment density – Exclude individual IDAs



Notes: Estimates of the fuzzy RD coefficient and 95 percent confidence intervals excluding one IDA region at a time in 1991 (top panel) and 2011 (bottom panel). Each point on the horizontal axis denotes a specification where one of the IDA regions is removed from the sample.

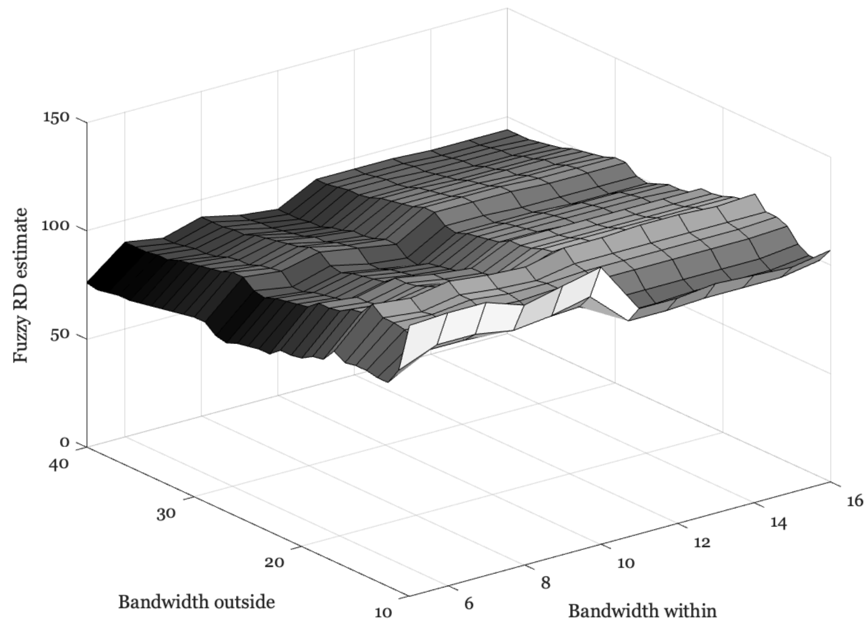
Appendix Table C6. Employment density – Non-parametric fuzzy RD estimates

	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

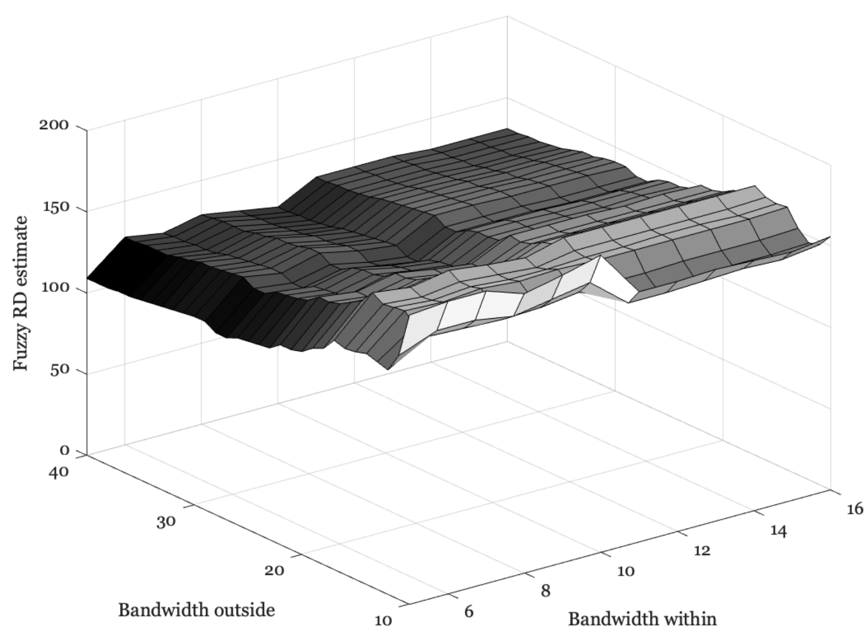
Notes: Fuzzy RD estimates obtained using the non-parametric estimation and robust bias-corrected inference method proposed by Calonico et al. (2014). The optimal bandwidth is computed by minimizing the Mean Squared Error separately left and right of the cutoff. Observations are weighted using a triangular kernel. The specification controls for IDA region effects and standard errors are clustered by IDA region. See text for details. * p<0.10, ** p<0.05, *** p<0.01

Appendix Figure C3. Employment density – robustness to bandwidth choice

(a) 1991



(b) 2011



Notes: Estimates of the fuzzy RD coefficient using varying bandwidths around the RD cutoff in 1991 (top) and 2011 (bottom).

Appendix Table C7. (Log) Employment and population density estimates

	(Log) Employment density		(Log) Population density	
	Red. Form	2-SLS	Red. Form	2-SLS
	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: Replication of Table 3, Columns (1)-(2). Outcomes defined as the logarithm of the number of workers per km^2 and of the number of residents per km^2. Standard errors clustered by IDA region in parentheses. See text for details. * p<0.10, ** p<0.05, *** p<0.01

Appendix Table C8. Migration and relocation – Fuzzy RD estimates

	Net migration	Mobil.	Mobil. work
	Contemporaneous effect (1991)		
RD Estimate	0.02	5.35	69.44
	(0.09)	(2.96)*	(38.37)*
Mean around the border	-0.02	19.35	108.48
Standard deviation	0.31	8.48	92.48
Observations	587	587	587
	Persistent effect (2011)		
RD Estimate	-0.30	4.19	62.07
	(0.24)	(3.06)	(46.61)
Mean around the border	-0.04	25.75	155.80
Standard deviation	0.63	9.52	115.50
Observations	587	587	587

Notes: Replication of Table 3, Column (2). "Net migration" is the net inflow of immigrants into the municipality as a share of resident population. "Mobil." is the share of resident population who travel daily for work or study outside the municipality of residence to the resident population aged up to 64. "Mobil. work" is the share of resident population commuting daily for work outside the municipality of residence to resident population commuting daily for work within the municipality of residence. See text for details. * p<0.10, ** p<0.05, *** p<0.01

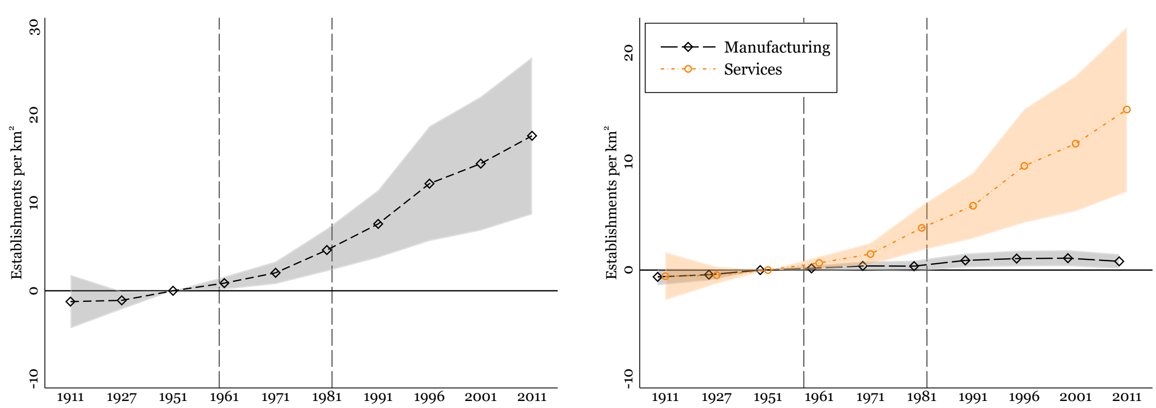
Appendix Table C9. Employment and participation rate – Fuzzy RD estimates

	1981	1991	2011
		Employment rate	
RD Estimate	4.75	3.97	1.90
	(1.60)***	(1.69)**	(1.31)
Mean around the border	36.23	33.88	38.33
Standard deviation	5.78	5.68	4.66
Observations	581	587	587
		Participation rate	
RD Estimate	3.45	3.40	3.09
	(1.26)**	(1.17)***	(1.32)**
Mean around the border	46.91	47.21	46.13
Standard deviation	5.99	4.51	4.50
Observations	581	587	587
		Unemployment rate	
RD Estimate	-4.65	-3.56	1.51
	(2.31)**	(2.17)	(1.75)
Mean around the border	22.75	28.33	16.97
Standard deviation	7.67	9.32	5.18
Observations	581	587	587

Notes: Replication of Table 3, Column (2). "Employment rate" is the ratio of employed people to total residents aged 15 years and older. "Participation rate" is the ratio of the resident working population to the resident population of the same age group. "Unemployment rate" is the ratio of the resident population 15 years and older seeking employment to resident population 15 years and older in employment. See text for details. * p<0.10, ** p<0.05, *** p<0.01

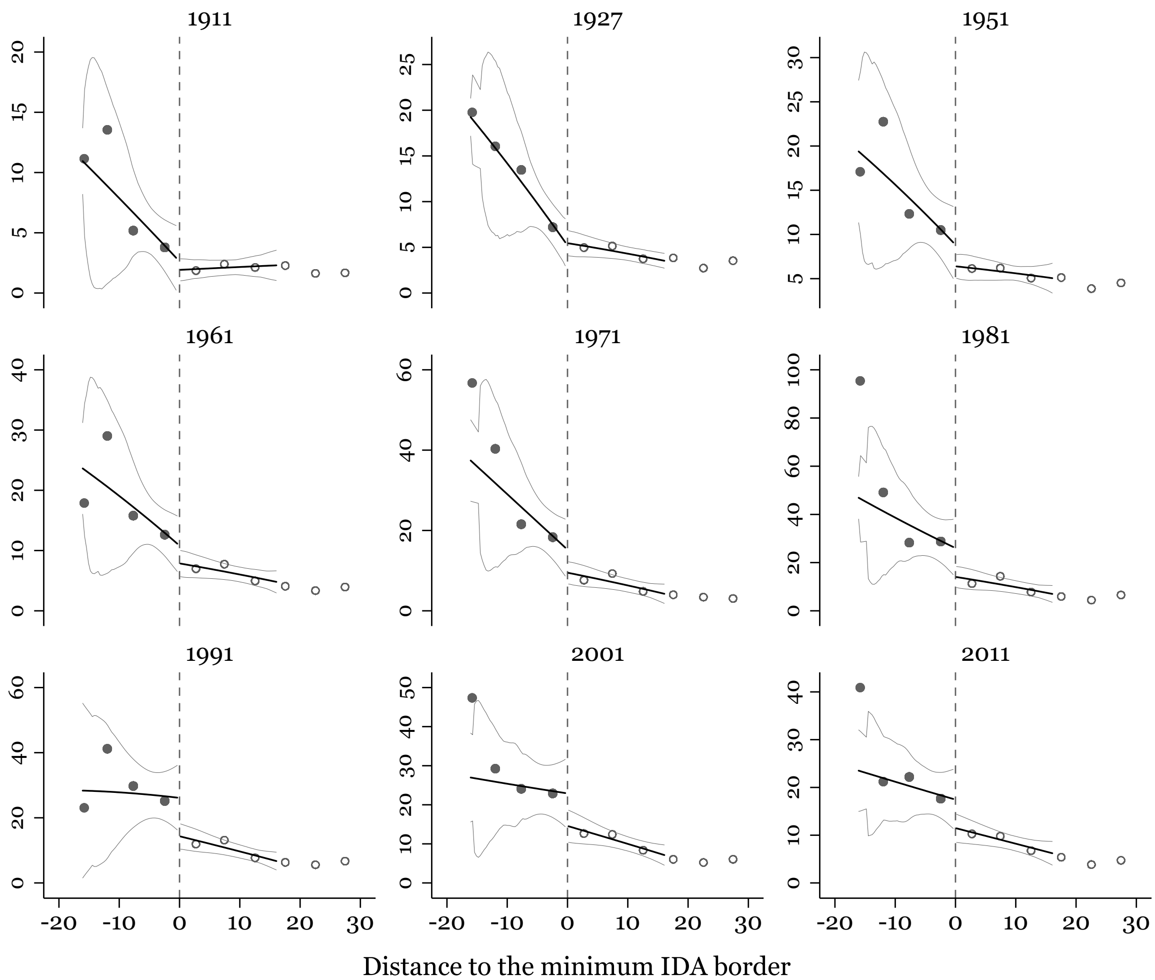
Appendix Figure C4. Establishment density – Diff-in-Disc

(a) Establishment density (b) Manufacturing versus services



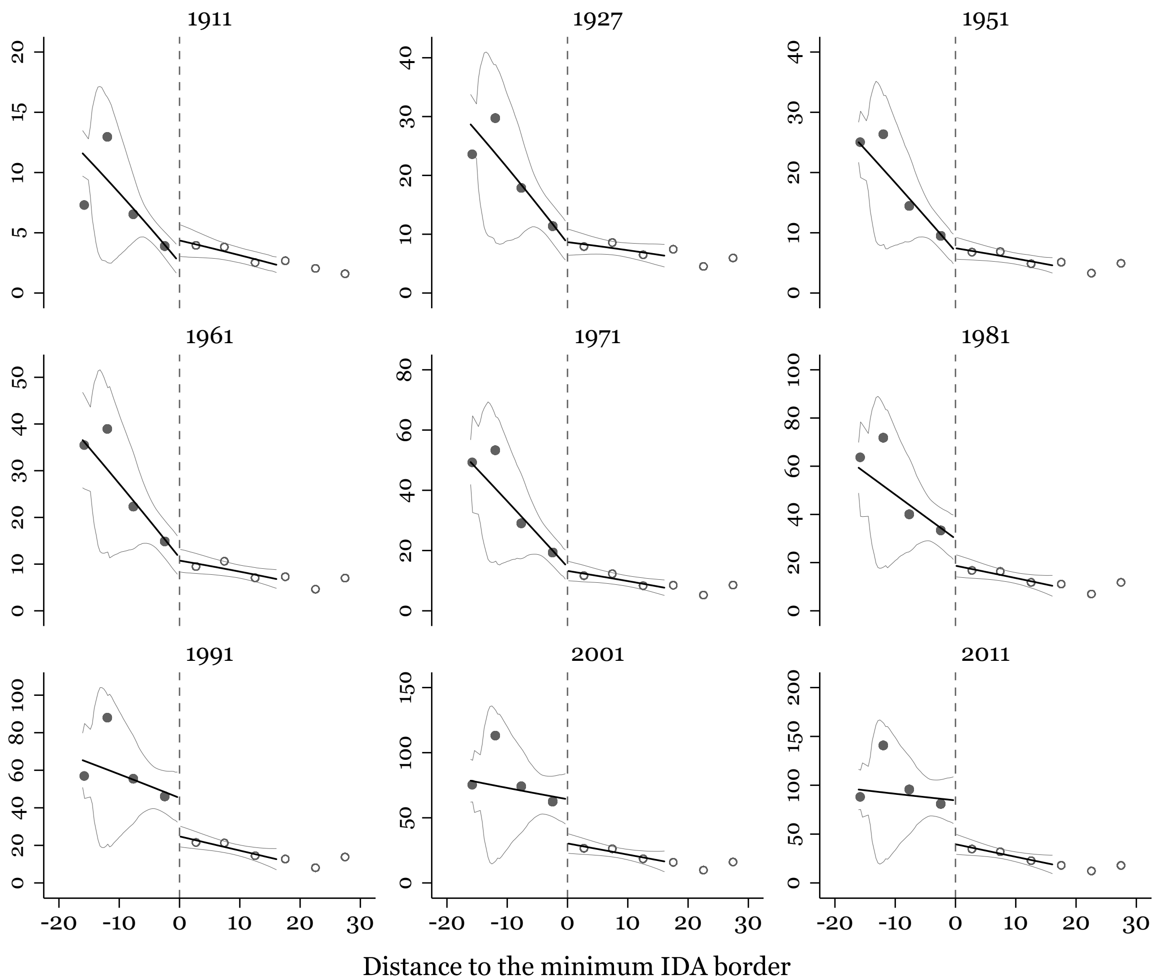
Notes: Coefficient estimates for Equation 2. Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the IDAs. See text for details.

Appendix Figure C5. Manufacturing employment density



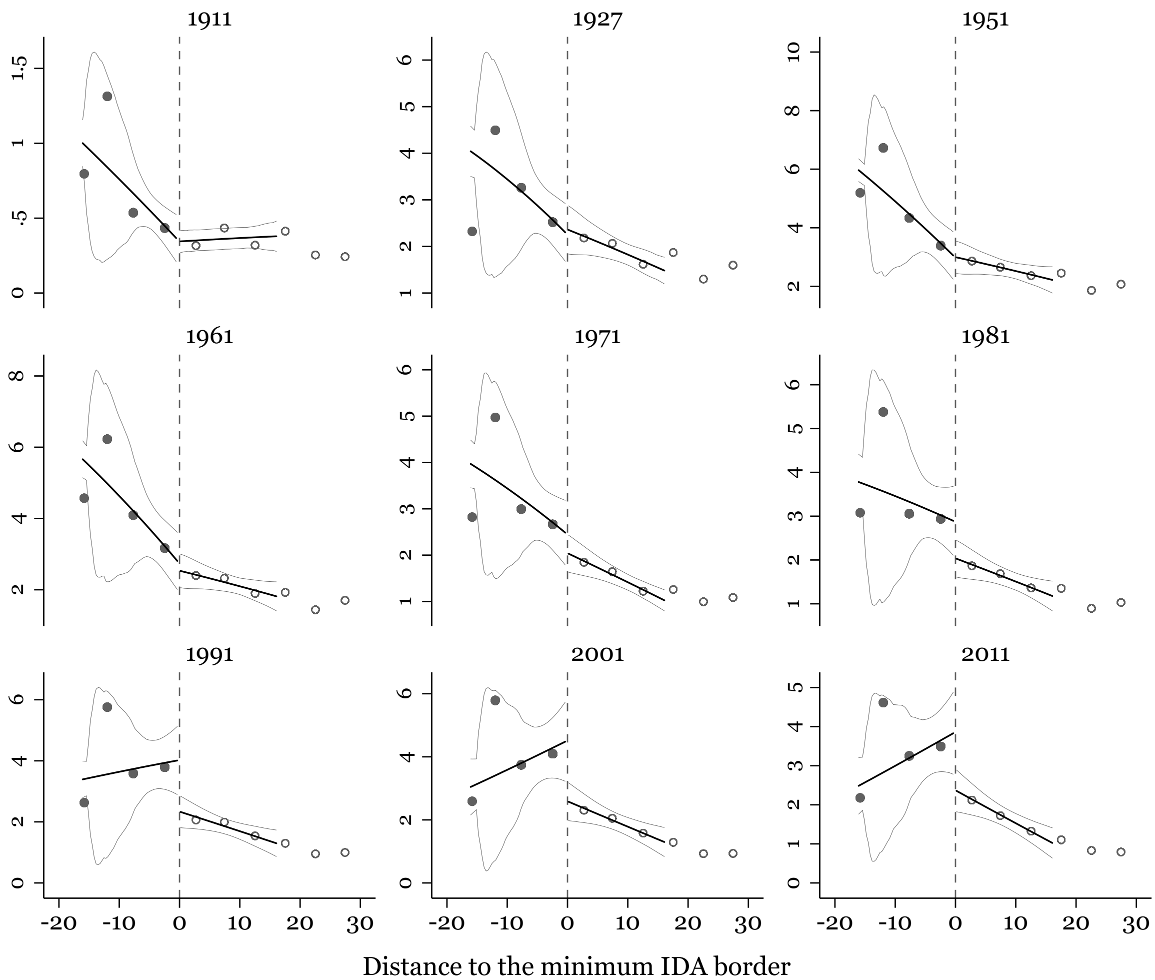
Notes: Negative distance denotes municipalities within the minimum IDA border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately at either side of the border using a symmetric 16-km bandwidth. The gray lines are 95 percent confidence intervals. See text for details.

Appendix Figure C6. Services employment density



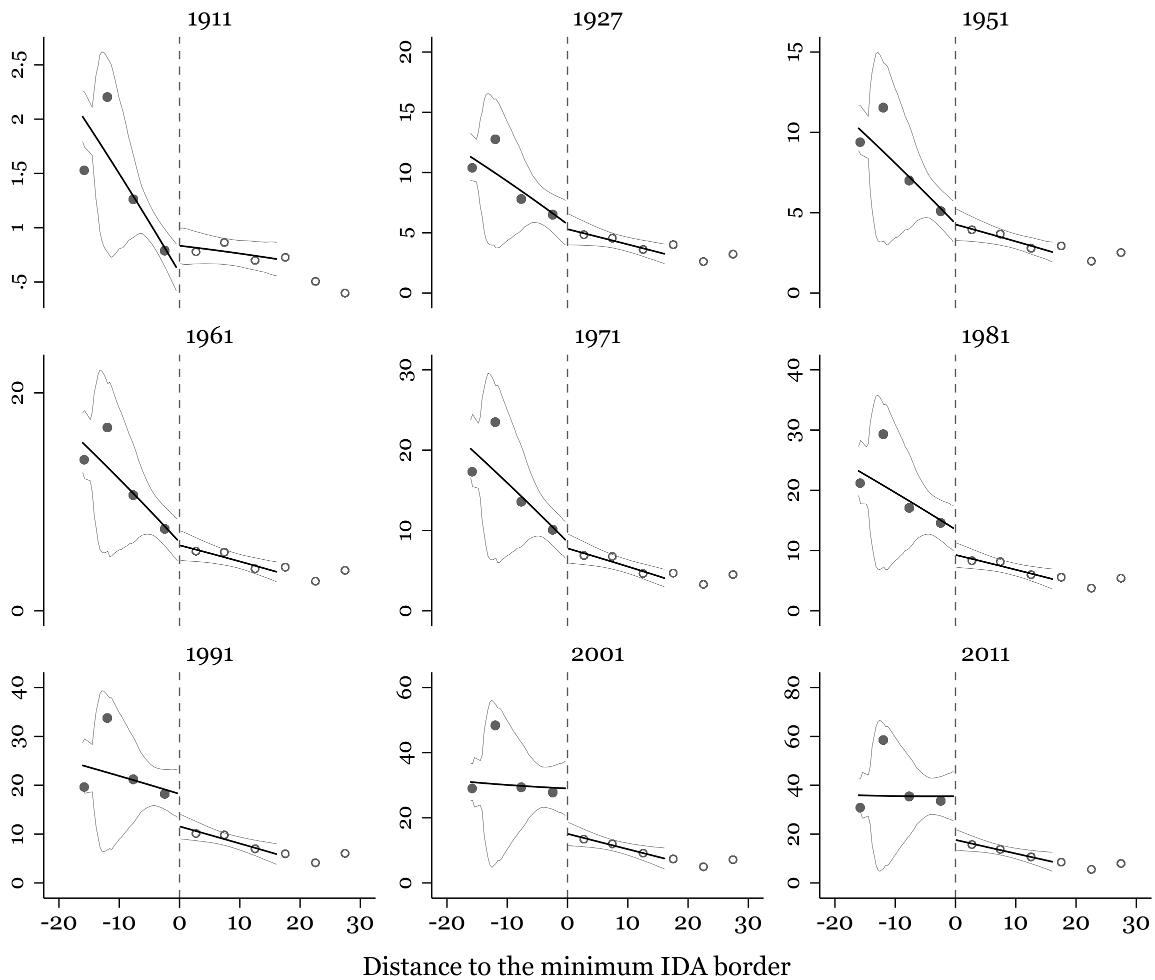
Notes: Negative distance denotes municipalities within the minimum IDA border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately at either side of the border using a symmetric 16-km bandwidth. The gray lines are 95 percent confidence intervals. See text for details.

Appendix Figure C7. Manufacturing establishment density



Notes: 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 either side of the border using a symmetric 16-km bandwidth. The gray lines are 95 percent confidence intervals. See text for details.

Appendix Figure C8. Services establishment density



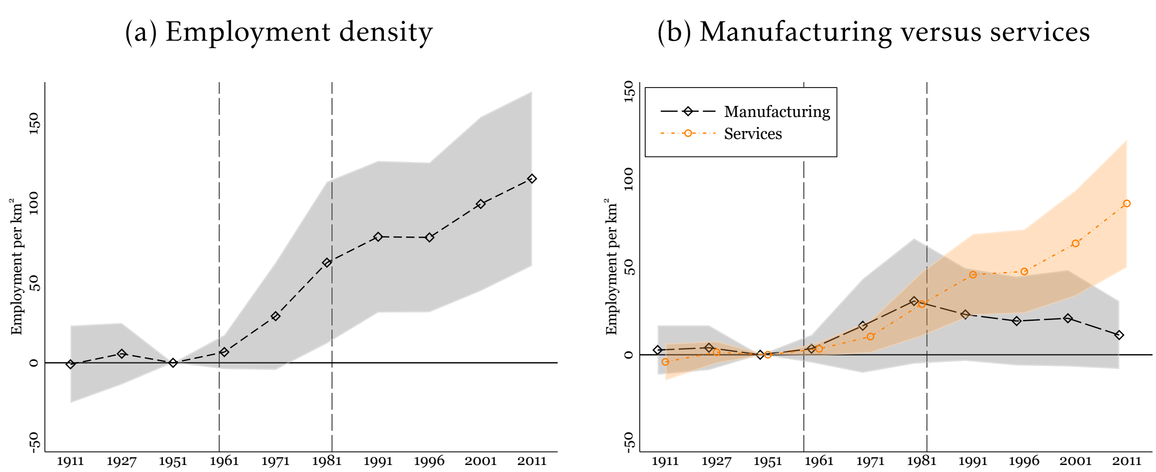
Notes: Negative distance denotes municipalities within the minimum IDA border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately at either side of the border using a symmetric 16-km bandwidth. The gray lines are 95 percent confidence intervals. See text for details.

Appendix Table C10. Manufacturing and services densities – Fuzzy RD estimates

	Employment density		Establishment density	
	Manufacturing	Services	Manufacturing	Services
	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: Replication of Table 3, Column (2). See text for details. * p<0.10, ** p<0.05, *** p<0.01

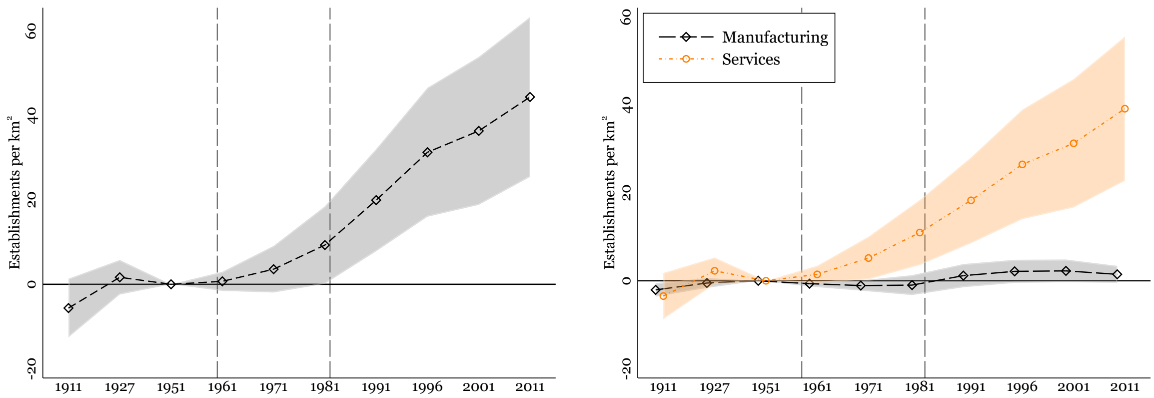
Appendix Figure C9. Event study using Center-North (within) – Empl. density



Notes: Coefficient estimates for Equation B3.1. Sample restricted to municipalities within the minimum IDA border excluding IDA centers (treatment group) and municipalities bordering placebo centers (control group). 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. See text for details.

Appendix Figure C10. Event study using Center-North (within) – Est. density

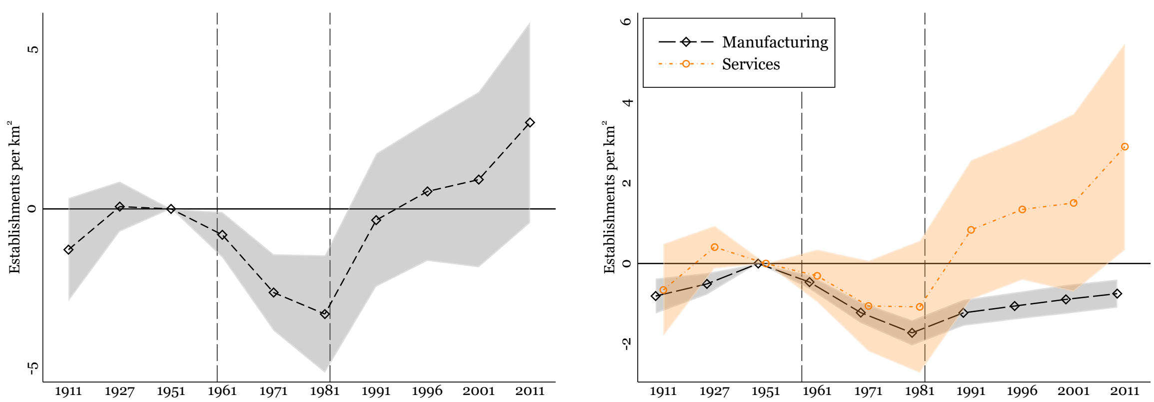
(a) Establishment density | (b) Manufacturing versus services



Notes: Coefficient estimates for Equation B3.1. Sample restricted to municipalities within the minimum IDA border excluding IDA centers (treatment group) and municipalities bordering placebo centers (control group). 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. See text for details.

Appendix Figure C11. Event study using Center-North (outside) – Est. density

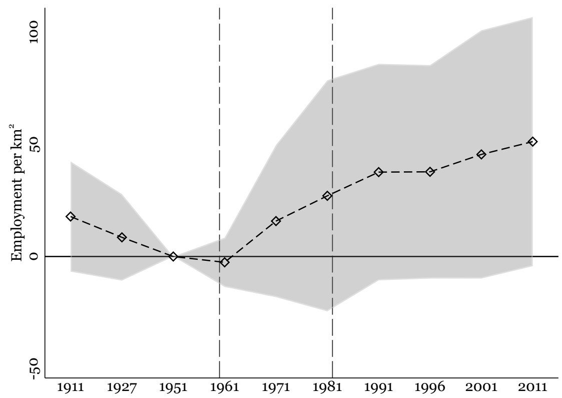
(a) Establishment density | (b) Manufacturing versus services



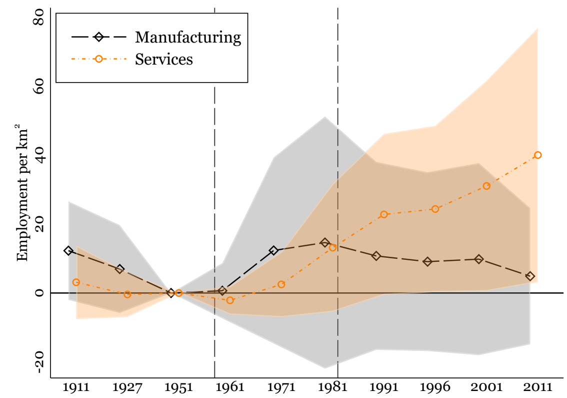
Notes: Coefficient estimates for Equation B3.1. Sample restricted to municipalities up to 16 km outside of the minimum IDA border (treatment group) and municipalities up to 16 km outside of the placebo border traced by municipalities bordering placebo centers (control group). The treatment group excludes IDA municipalities. 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. See text for details.

Appendix Figure C12. Triple differences – Empl. density

(a) Employment density



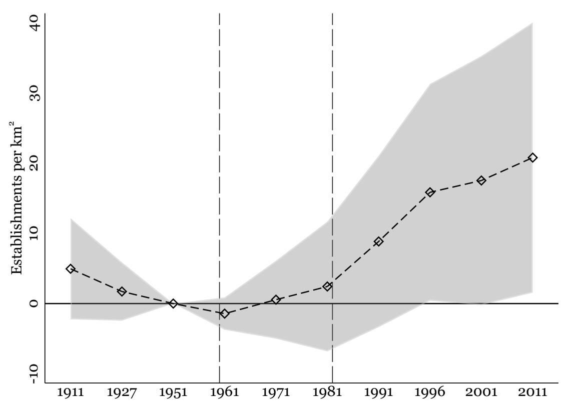
(b) Manufacturing versus services



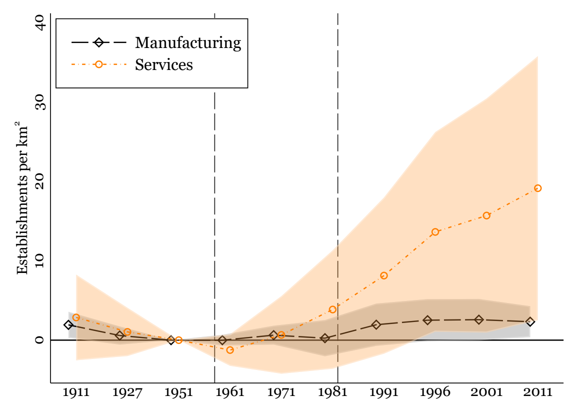
Notes: Coefficient estimates for Equation B3.2. Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the IDAs. See text for details.

Appendix Figure C13. Triple differences – Est. density

(a) Establishment density



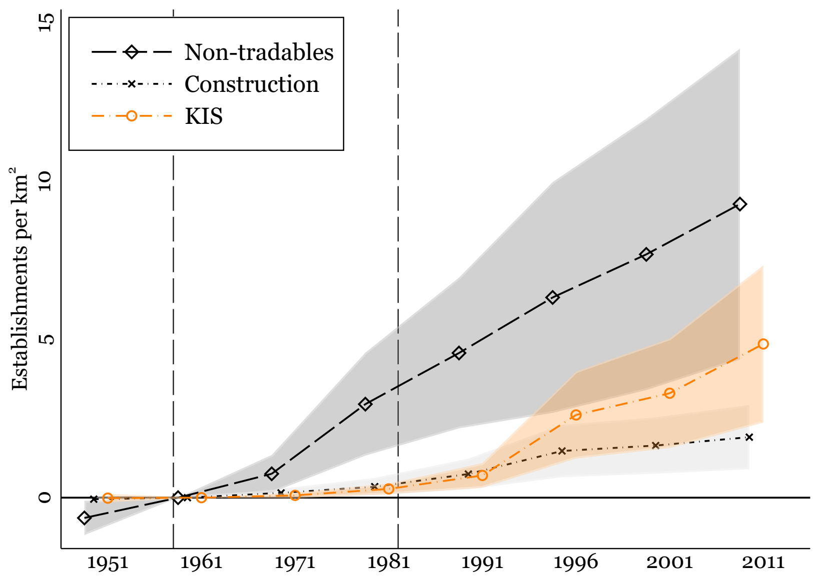
(b) Manufacturing versus services



Notes: Coefficient estimates for Equation B3.2. 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. See text for details.

D. Appendix D: Mechanisms

Appendix Figure D1. Establishment density – Services breakdown

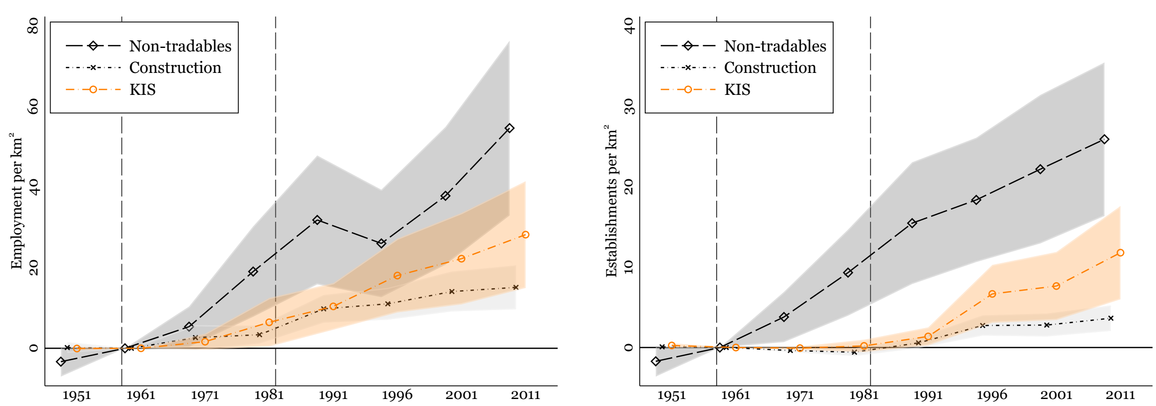


Notes: Coefficient estimates for Equation 2. Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the IDAs. "Non-tradables" include wholesale and retail trade, hotels and restaurants and other services (education, health, arts and entertainment, other). "KIS" (knowledge-intensive services) include communication, finance and insurance and services to firms. See text for details.

Appendix Figure D2. Event study using Center-North (within) – Services breakdown

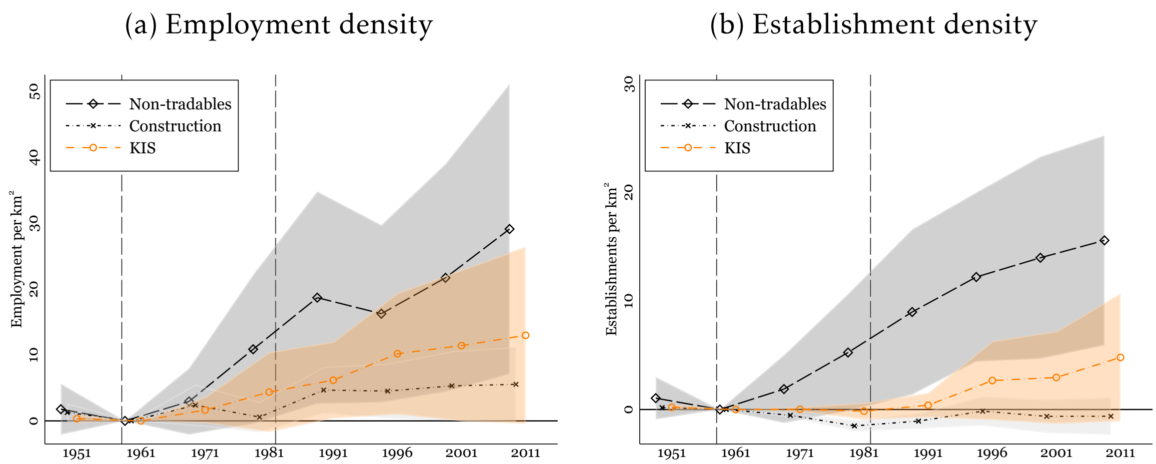
(a) Employment density

(b) Establishment density



Notes: Coefficient estimates for Equation B3.1. Sample restricted to municipalities within the minimum IDA border excluding IDA centers (treatment group) and municipalities bordering placebo centers (control group). 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. See text for details.

Appendix Figure D3. Triple differences – Services breakdown



Notes: Coefficient estimates for Equation B3.2. 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. See text for details.

Appendix Table D1. Employment and firm shares in services – Fuzzy RD estimates

	Employment		Firms	
	KIS	Other serv.	KIS	Other serv.
	Contemporaneous effect (1991)			
RD Estimate	0.08	-0.08	0.06	-0.06
	(0.06)	(0.06)	(0.03)**	(0.03)**
Mean around the border	0.17	0.83	0.11	0.89
Standard deviation	0.19	0.19	0.10	0.10
Observations	570	570	570	570
	Persistent effect (2011)			
RD Estimate	0.08	-0.08	0.06	-0.06
	(0.04)**	(0.04)**	(0.02)***	(0.02)***
Mean around the border	0.10	0.90	0.10	0.90
Standard deviation	0.10	0.10	0.06	0.06
Observations	585	585	585	585

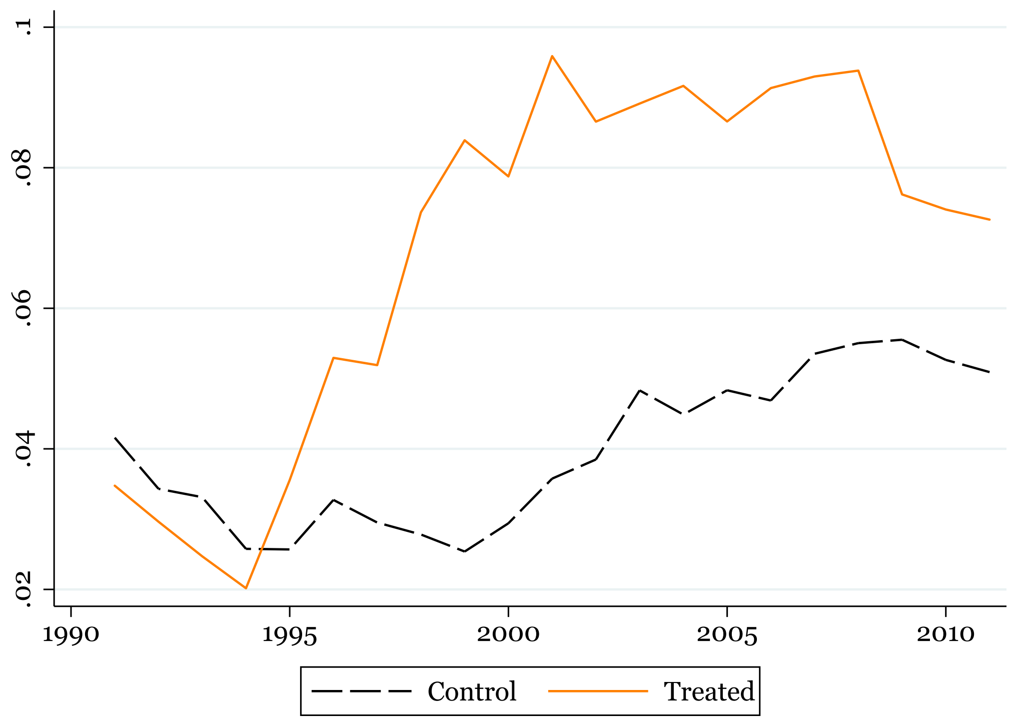
Notes: Replication of Table 3, Column (2). The outcomes are the share of employment and establishments in KIS and other services. The shares are obtained from social security data on the universe of Italian firms and the KIS classification is obtained from Eurostat/OECD. See Appendix A.3 and text for details. * p<0.10, ** p<0.05, *** p<0.01

Appendix Table D2. Employment and firm shares in manufacturing – Fuzzy RD estimates

	Employment, 1991		Establishments, 1991	
	High-tech	Low-tech	High-tech	Low-tech
RD Estimate	0.27	-0.27	0.15	-0.15
	(0.09)***	(0.09)***	(0.05)***	(0.05)***
Mean around the border	0.16	0.84	0.14	0.86
Standard deviation	0.21	0.21	0.14	0.14
Observations	566	566	566	566

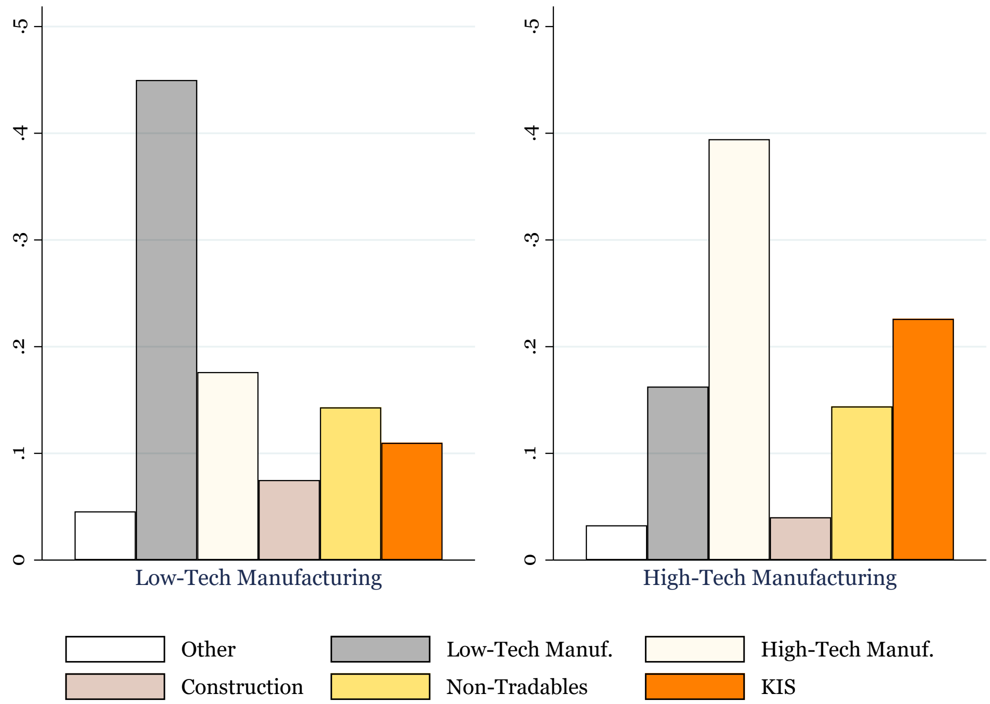
Notes: Replication of Table 3, Column (2). The outcomes are the share of employment across manufacturing sub-sectors, grouped by technological intensity. The shares are obtained from social security data on the universe of Italian firms and the technology classification is obtained from Eurostat/OECD. See Appendix A.3 and text for details. * p<0.10, ** p<0.05, *** p<0.01

Appendix Figure D4. Share of KIS new hires from high-technology manufacturing



Notes: The graph shows the cumulative share of job-to-job new hires in KIS coming from high-technology manufacturing, separately for treated and control municipalities, since 1991. The KIS classification and the manufacturing technology intensity classification are obtained from Eurostat/OECD. The shares are computed for municipalities included in the baseline estimation sample. Treated municipalities are those bordering IDA centers. See text for details.

Appendix Figure D5. Share of inputs in low- and high-technology manufacturing, 2020



Notes: The chart shows the breakdown of inputs demanded by low-technology and high-technology 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. See text for details.

Appendix Table D3. Employment shares within 3-digit services – Fuzzy RD estimates

	RD Estimate	S.E.	Mean	S.D.
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 specialised 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 and motorcycles	-0.01	(0.01)*	0.00	0.02
Retail sale in non-specialised 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 in specialised stores	-2.91	(1.06)***	3.28	4.82

Notes: Replication of Table 3, Column (2). Regressions run for employment shares within services using 3-digit sectors. We show estimates with p-value<0.11. Each outcome is in percentage units. Standard errors clustered by IDA region in parentheses. Descriptive statistics computed within the estimation sample. See text for details. * p<0.10, ** p<0.05, *** p<0.01

Appendix Table D4. Firm shares within 3-digit services – Fuzzy RD estimates

	RD Estimate	S.E.	Mean	S.D.
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 and motorcycles	-0.04	(0.02)**	0.01	0.05
Retail sale in non-specialised 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 in specialised stores	-4.15	(1.19)***	5.38	4.57

Notes: Replication of Table 3, Column (2). Regressions run for firm shares within services using 3-digit sectors. We show estimates with p-value<0.11. Each outcome is in percentage units. Standard errors clustered by IDA region in parentheses. Descriptive statistics computed within the estimation sample. See text for details. * p<0.10, ** p<0.05, *** p<0.01

Appendix Table D5. Worker AKM effects – Fuzzy RD estimates (2011)

	Total	By sector		Within services	
		Manufacturing	Services	KIS	Other serv.
RD Estimate	0.07	0.03	0.14	0.22	0.13
	(0.02)***	(0.05)	(0.05)**	(0.11)**	(0.05)**
Mean around the border	-0.17	-0.17	-0.22	-0.19	-0.22
Standard deviation	0.11	0.12	0.18	0.21	0.19
Observations	576	506	548	327	544

Notes: Replication of Table 3, Column (2). The outcomes are the worker fixed effects from an AKM model of the (log) wage (Abowd et al., 1999) estimated between 1991 and 2011. The worker effects are then averaged at the municipality level. See Appendix A.3 and text for details. * p<0.10, ** p<0.05, *** p<0.01

Appendix Table D6. Firm size and wage distribution – Fuzzy RD estimates

	Firm size			Firm wage		
	T1	T2	T3	T1	T2	T3
	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

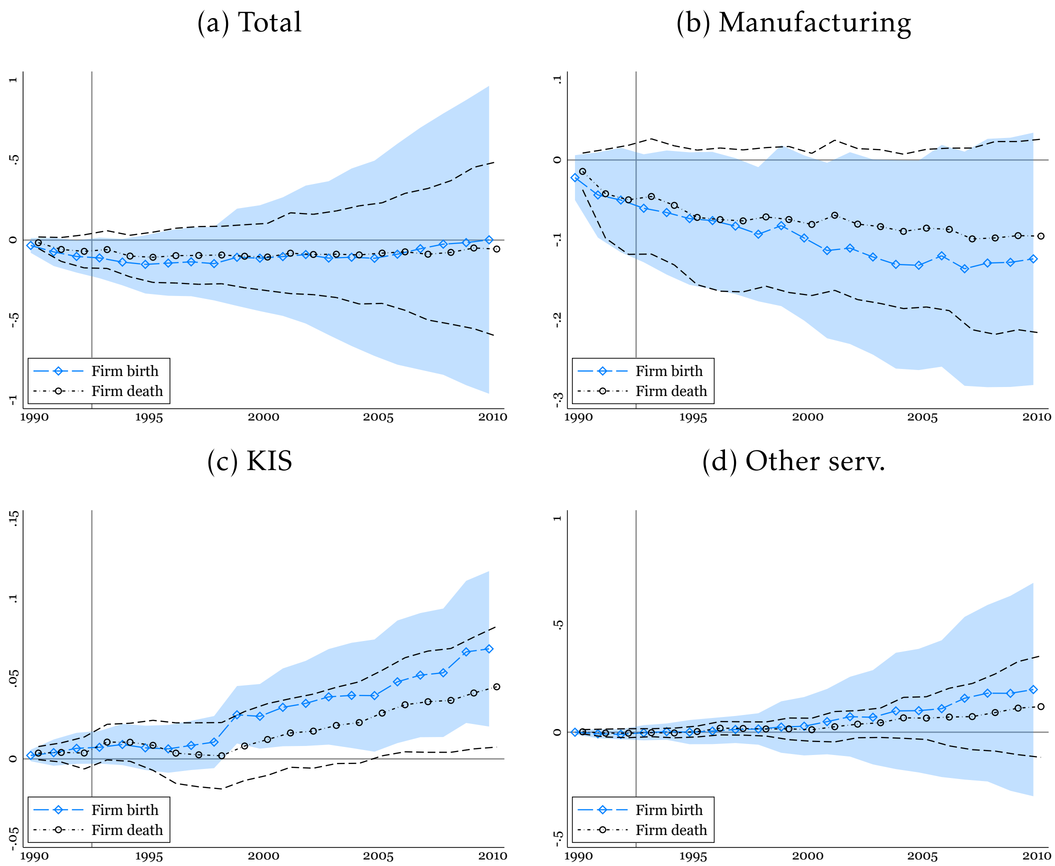
Notes: Replication of Table 3, Column (2). Outcomes are computed as the share of firms in each tertile of the distribution of firm size and wage paid. Tertiles are derived on the universe of the Italian firms each year. See Appendix A.3 and text for details. * p<0.10, ** p<0.05, *** p<0.01

Appendix Table D7. Balance sheet outcomes, 2011 – Fuzzy RD estimates

	Total	By sector		Within services	
		Manufacturing	Services	KIS	Other serv.
			Value added		
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
			Investment		
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
			Sales		
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
			Profits		
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: Replication of Table 3, Column (2). All outcomes are as of 2011 and expressed in natural logarithm, scaled by total firm workforce. See Appendix A.3 and text for details. * p<0.10, ** p<0.05, *** p<0.01

Appendix Figure D6. Firm dynamics – Fuzzy RD estimates



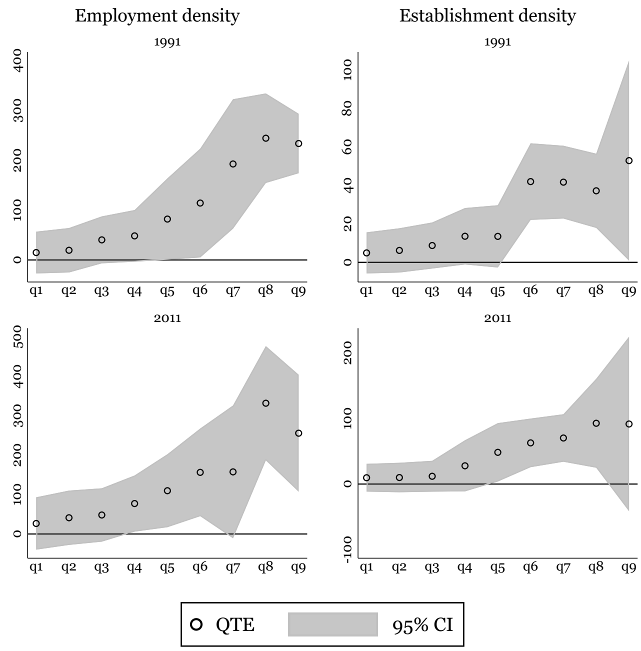
Notes: Coefficient estimates for the fuzzy RD model of Equations 1a and 1b. The shaded areas denote 95 percent confidence intervals. The vertical line marks the end of the EIM. Firm birth and death rates computed as the cumulative number of firm births and deaths every year since 1990, as a share of the total number of firms in the municipality in 1990. See text for details.

Appendix Table D8. Other outcomes – Fuzzy RD estimates

	Housing value	Rents	Tax income	Gini coeff.	Krugman Index
RD Estimate	543.97	2.01	0.33	0.03	-0.20
	(214.44)**	(0.88)**	(0.09)***	(0.01)***	(0.10)**
Mean around the border	1087.09	3.94	8.95	0.38	0.97
Standard deviation	580.83	1.97	0.23	0.03	0.32
Observations	574	537	587	587	586

Notes: Replication of Table 3, Column (2). “Housing value” 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. "Gini coeff." is the Gini coefficient as of 2011. "Krugman Index" is the Krugman Specialization Index for manufacturing in 2011 (see Appendix A.2). See text for details. * p<0.10, ** p<0.05, *** p<0.01

Appendix Figure D7. Quantile treatment effects



Notes: Quantile treatment effects for the baseline fuzzy RD estimate. The estimators are described in Frandsen et al. (2012). The algorithm calculates the propensity score using a gaussian kernel and running 100 distribution regressions. See text for details.

Appendix Table D9. Municipal expenditure – Fuzzy RD estimates

a)	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
b)	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: Replication of Table 3, Column (2). Outcomes in Panel (a) and the first three columns of Panel (b) are cumulative municipality expenditures between 2000 and 2011, sourced from municipality balance sheets. All items include both current and capital expenditure. "L. 488/1992" measures the total funds obtained through Law 488/1992. "EU Funds" are total funds received through the EU Structural Funds program between 2007 and 2013. All variables are expressed in natural logarithm of the per capita amount in € (using the 2001 population). See text for details. * p<0.10, ** p<0.05, *** p<0.01

E. Appendix E: Cost-benefit analysis

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

Cost per job. To obtain a first measure of cost per job, we consider the estimates of Table 3 Column (3). For 2011, we estimate that an increase in EIM funding of €1000 (2011 prices) per 1951 resident leads to 10.3 more workers per km^2. For municipalities in the estimation sample, the average 1951 population is 11,328.91 inhabitants and the average extension is 60.88 km^2. These numbers imply 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 using an exchange rate of 1.3924 (2011 average). The estimate rises to $37,571 assuming a deadweight loss of 50 percent.

As alternative, we use the (arguably more robust) Diff-in-Disc 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 Diff-in-Disc specification (Figure 6 Panel (a): 53.64 workers per km^2), *ii*) the design using municipalities bordering provincial capitals in the Center-North as controls (Figure C9 Panel (a): 115.44 workers per km^2) and *iii*) the triple differences (Figure C12 Panel (a): 51.20 workers per km^2). For each of the three designs, we take the average extension of municipalities in the estimation sample (57.43, 67.33 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*), 7772 for design *ii*) and 2722 for design *iii*).

To compute the costs, designs *i*) and *iii*) 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 Diff-in-Disc 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, which is very similar to the €5,720 jump reported in Table 2 Column (2) for the full sample. For design *ii*), which compares municipalities bordering IDA centers to those bordering provincial capitals in the Center-North, we simply take the average EIM funding for the former group (€11,520 per 1951 resident). We then multiply these average cost measures by the average 1951 population in the estimation sample (8287.16, 9900.70 and 7650.64) to obtain total EIM funding in the average municipality: €48,040,678 for design *i*), €114,058,387 for design *ii*) and €44,350,743 for design *iii*). Putting everything together, we estimate a cost per job of €15,596 ($21,716) for design *i*), €14,675 ($20,433) for design *ii*) and €16,294 ($22,687) for design *iii*). Assuming a 50 percent deadweight loss, the final estimates of the cost per jobs are similar to the baseline ones: \$32,575 for design *i*), \$30,650 for design *ii*) and \$34,031 for design *iii*).

Cost-benefit analysis. We now describe the cost-benefit analysis based on our estimates, which builds on the study of US Empowerment Zones in Busso et al. (2013).[50] The goal is to estimate the gains entailed by IDAs and to compare them with the total costs of the policy to assess its cost-effectiveness. In our exercise, we focus exclusively on the benefits generated by the policy *after* its termination, and assess whether any persistent effect we estimate is enough to cover the costs. We break down total surplus into three components: wage gains for workers, corporate profits for firms and rental gains for landlords.[51] 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 automatically sets to zero profits of all non-incorporated firms, thus underestimating total profits in a municipality.[52]

3. Housing rents: estimating rental gains for landowners is challenging as 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.[53] We compute annual flows in 2004 and 2011, which we then linearly interpolate for the other years.

[50] Other applications are Chaurey (2017) (India), Lu et al. (2019) (China), Lapoint and Sakabe (2022) (Japan).

[51] None of these variables are available during the policy years, which leads us to concentrate on long-run gains. We are also unable to distinguish between benefits for IDA residents and non-resident commuters, as done in Busso et al. (2013). That said, our focus on benefits in the long term makes this distinction less meaningful as we have documented no migration and commuting patterns after the end of IDAs.

[52] 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.

[53] We approximate the building area of a municipality as 1.3 percent of the 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 most likely larger in our setting as we focus on urban centers, meaning that the rental gains we estimate are a lower bound of the true value.

We then compute the effect of the policy on each of these outcomes in the post-IDA years ($\hat{\pi}_j$). 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 regression produces a unique (reduced-form) estimate of the effect of IDAs after their termination. Estimating the coefficient year by year and then 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 simple average of the two coefficients. Table E1 shows the estimation output.

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 roughly 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 transfers are enough to cover the total costs of the policy.

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 directly borne by the consortium, which are not reported in the ASET data. On the other hand, however, our estimates of the program 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 D8. 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 for in our baseline calculations. All considered, our conclusion that the gains of IDAs in the two decades after their end at least compensate for the total cost of the policy seems fairly robust. In turn, this suggests that the program entailed a net surplus assuming that it generated benefits while it was in place.

Appendix Table E1. Coefficient estimates ($\hat{\pi}_j$) for the cost-benefit analysis

	(Log) Wage bill	(Log) Firm profits	(Log) Rents	
			2004	2011
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 wage bill and firm profits, we estimate Equation 1b on the pooled sample of years 1991-2011 and control for year effects. For rents, we run Equation 1b separately for 2004 and 2011. Standard errors clustered by IDA region in parentheses. See text for details. * p<0.10, ** p<0.05, *** p<0.01

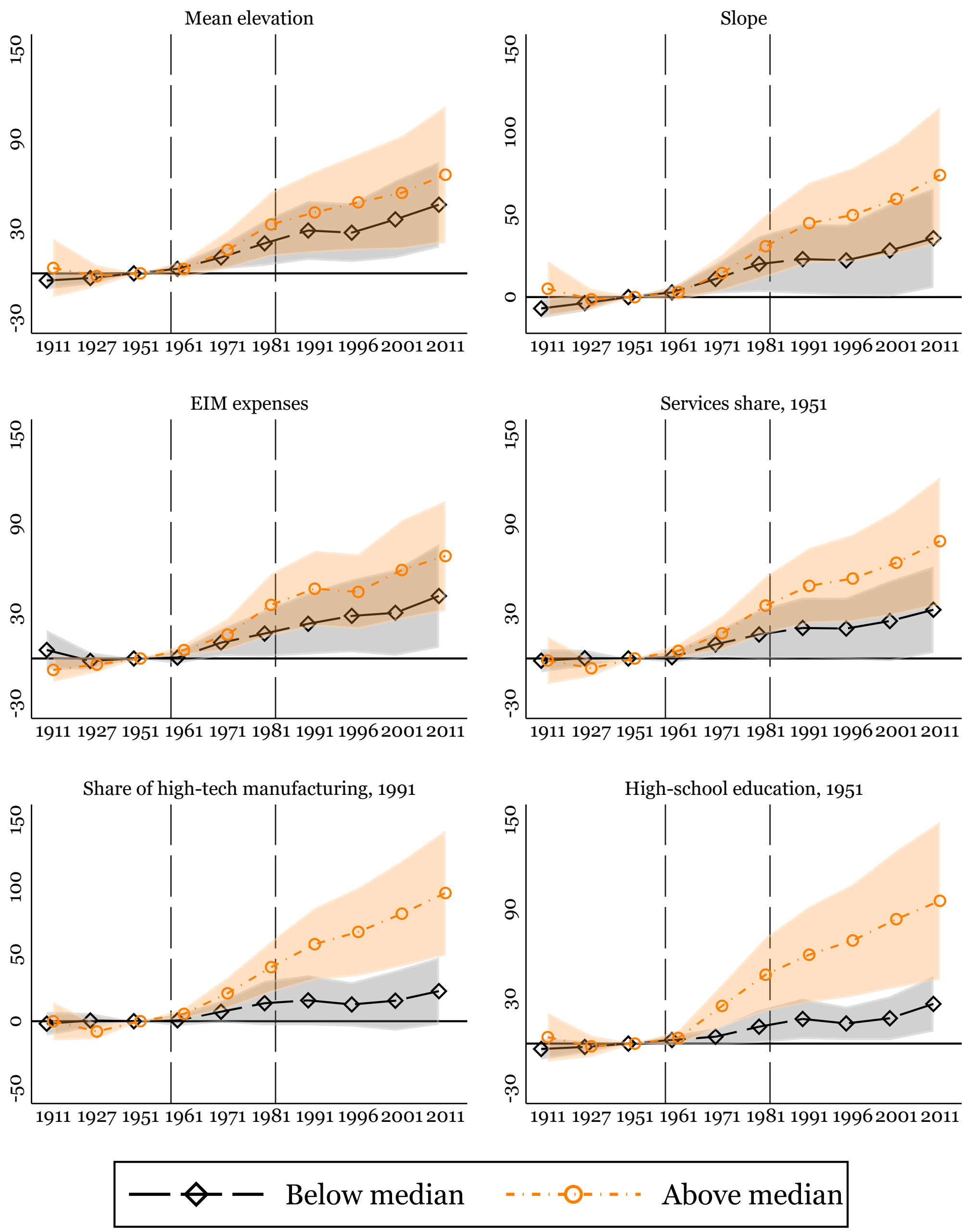
Appendix Table E2. Benefits of the IDA policy

	Observed (€bn)	$\hat{\pi}_j$	Counterfactual (€bn)	Benefit (€bn)	PDV benefits (€bn)
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). The counterfactual amount is obtained as $counterfactual_j = observed_j/(1+\hat{\pi}_j)$. We transform the coefficient using $(e^{\hat{\pi}_j} - 1)$. The presented discounted value is calculated using a 10% discount rate. The effect of the policy $\hat{\pi}_j$ is estimated using the reduced-form specification in Equation 1b. For firm profits, the actual flows refer only to incorporated firms in the Cerved data. See text for details.

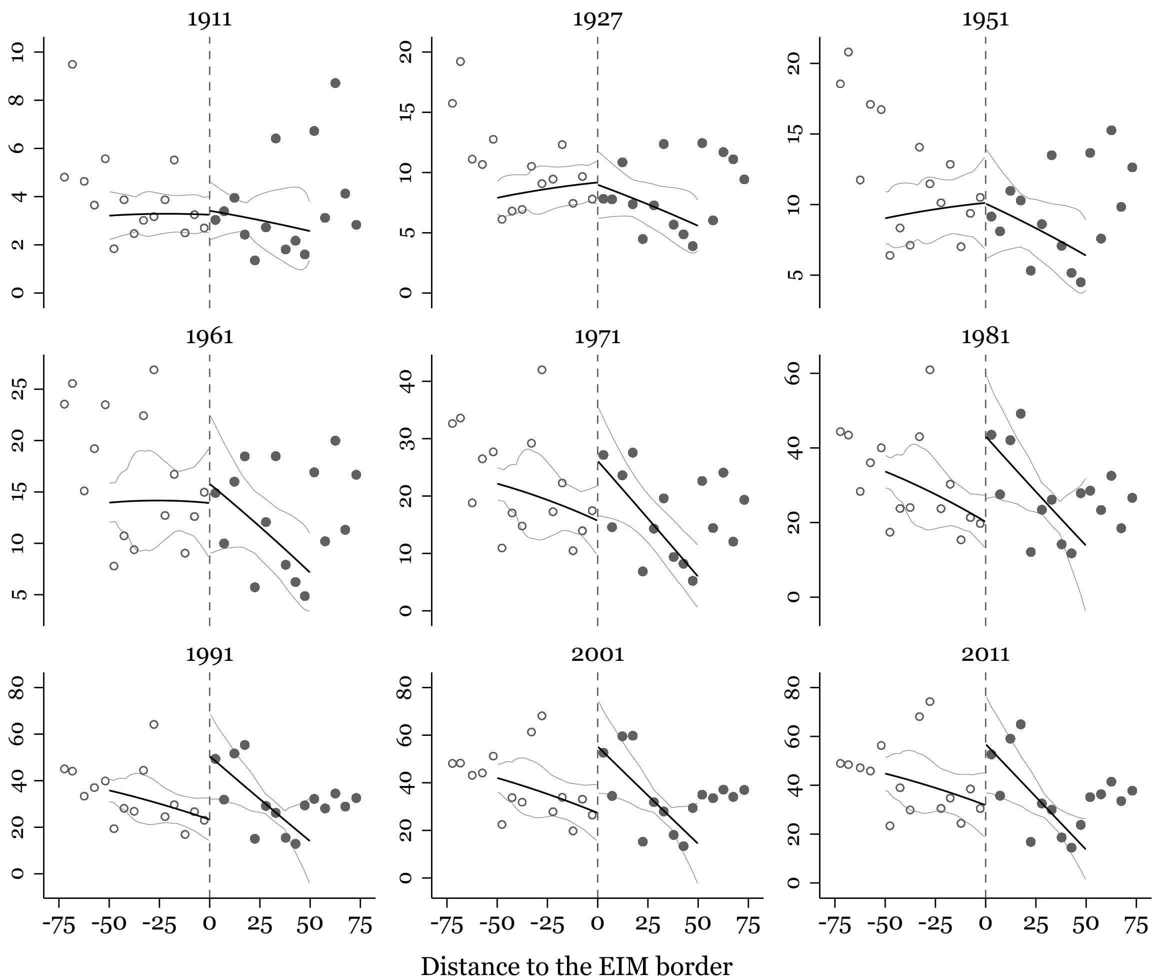
F. Appendix F

Appendix Figure F1. Employment density – Heterogeneity



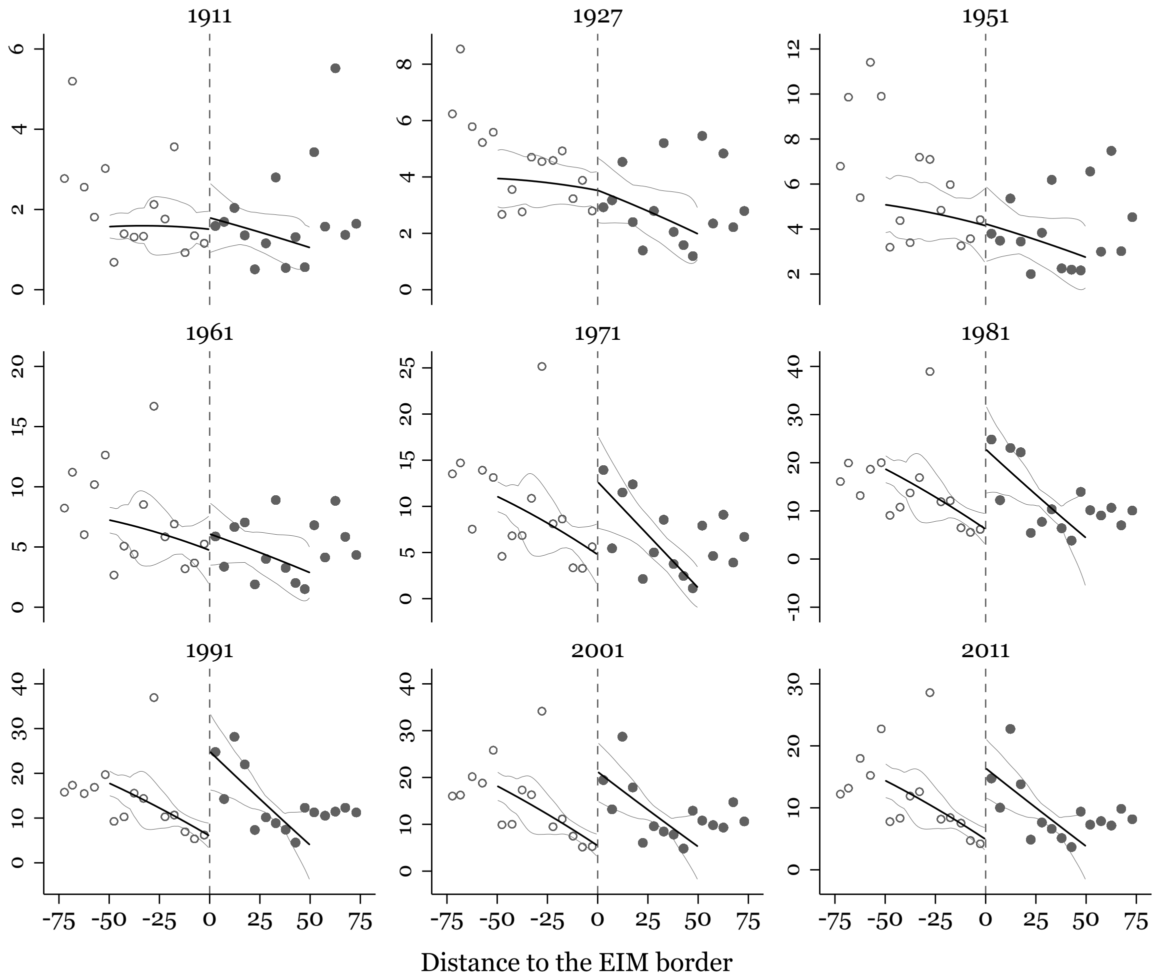
Notes: Coefficient estimates for Equation 2. EIM expenses measured in euros (2011 prices) per 1951 inhabitant, cumulated between 1950 and 1992. For each of the six variables, we compute the mean within each IDA region using only municipalities bordering the IDA center. Share of high-technology manufacturing computed according to the Eurostat/OECD classification, using administrative data on the universe of firms. For each variable we compute the median across IDA regions. Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. See text for details.

Appendix Figure F2. Employment density



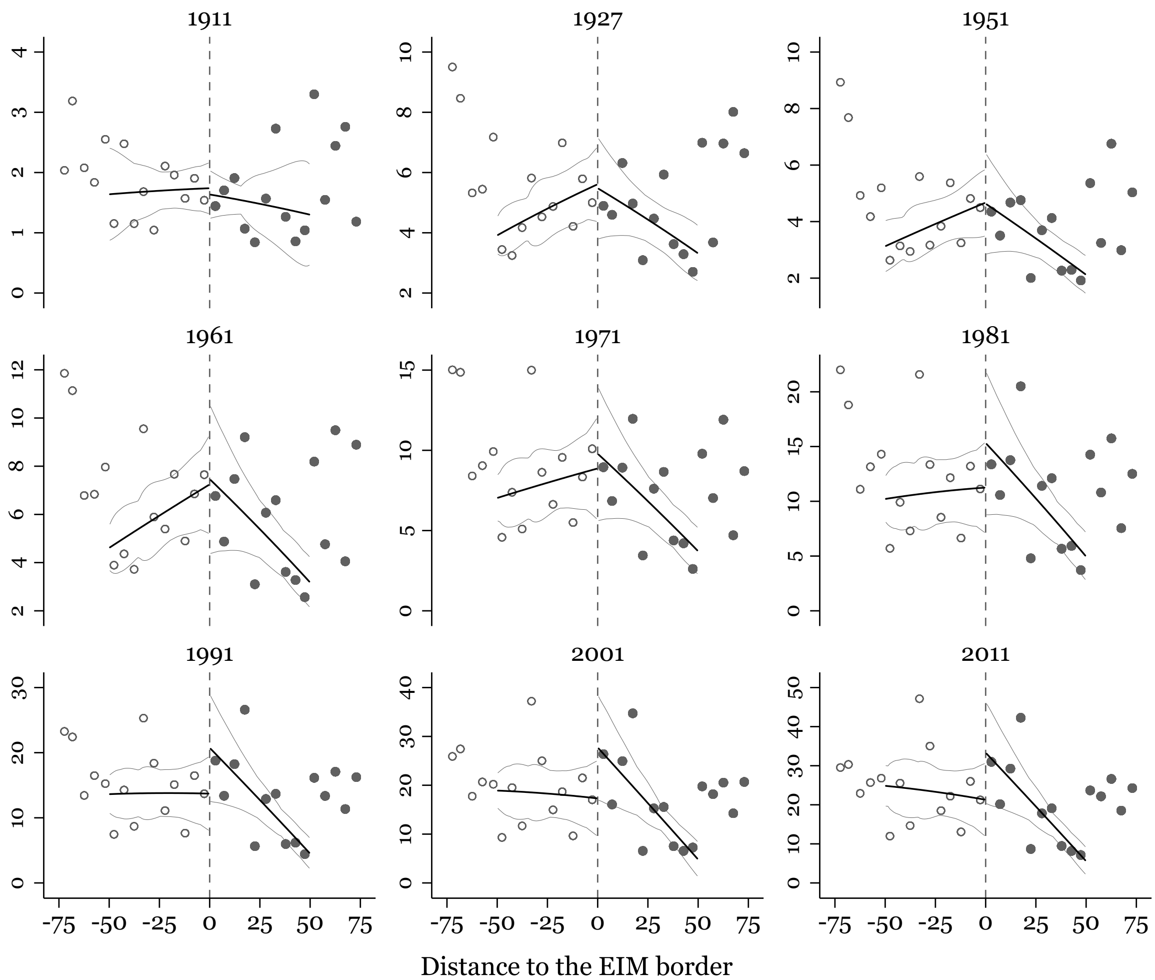
Notes: Negative distance denotes municipalities north of the EIM border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately north and south of the border using a 50-km symmetric bandwidth. The gray lines are 95 percent confidence intervals. See text for details.

Appendix Figure F3. Manufacturing employment density



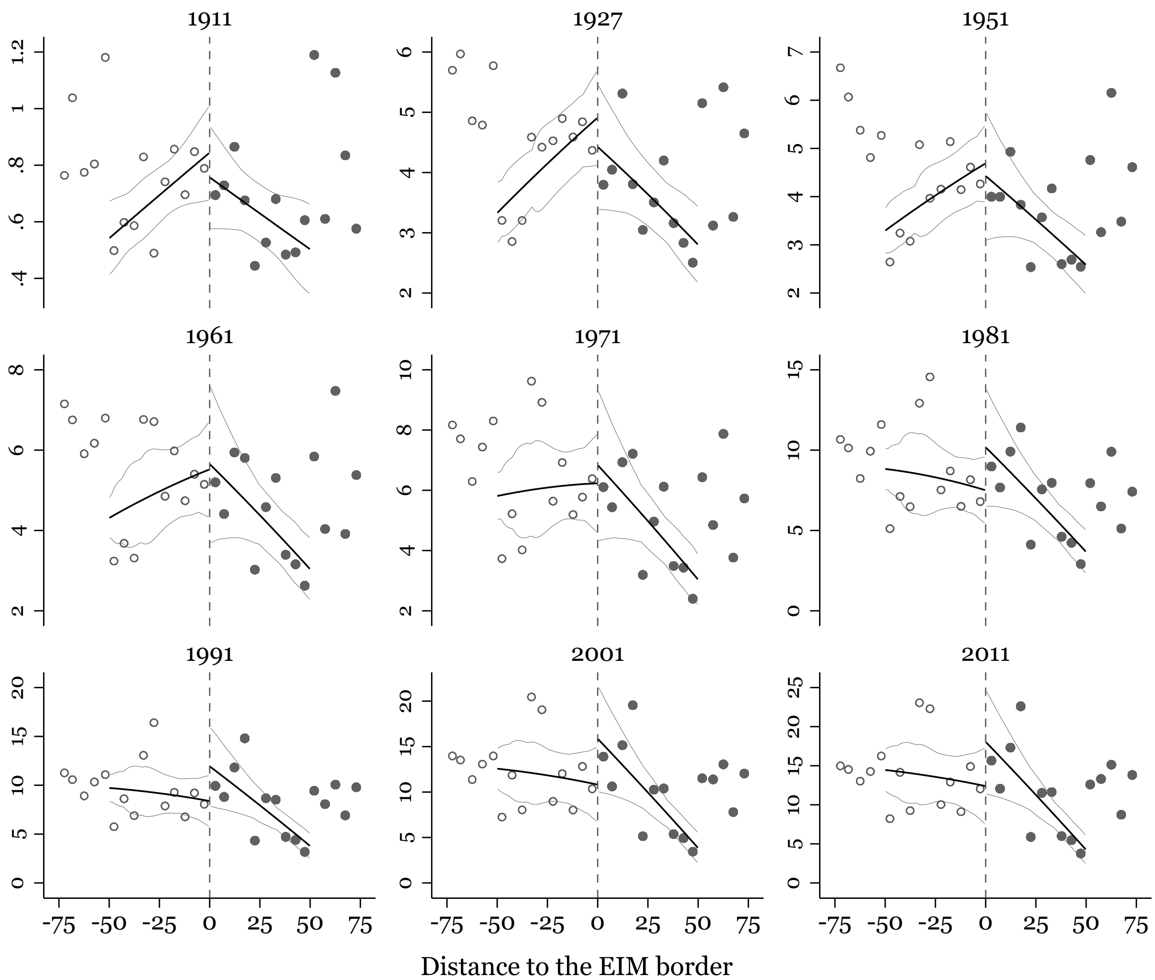
Notes: Negative distance denotes municipalities north of the EIM border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately north and south of the border using a 50-km symmetric bandwidth. The gray lines are 95 percent confidence intervals. See text for details.

Appendix Figure F4. Services employment density



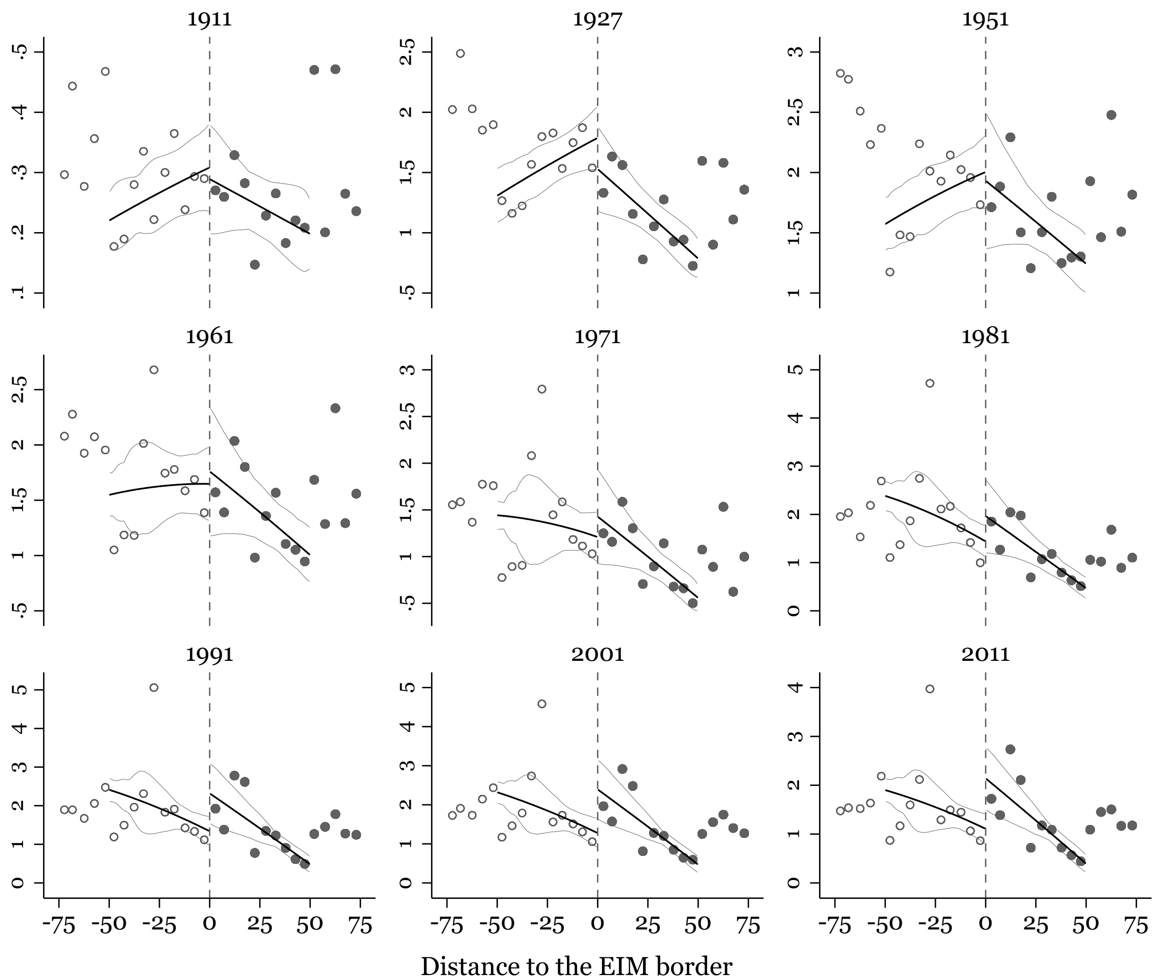
Notes: Negative distance denotes municipalities north of the EIM border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately north and south of the border using a 50-km symmetric bandwidth. The gray lines are 95 percent confidence intervals. See text for details.

Appendix Figure F5. Establishment density



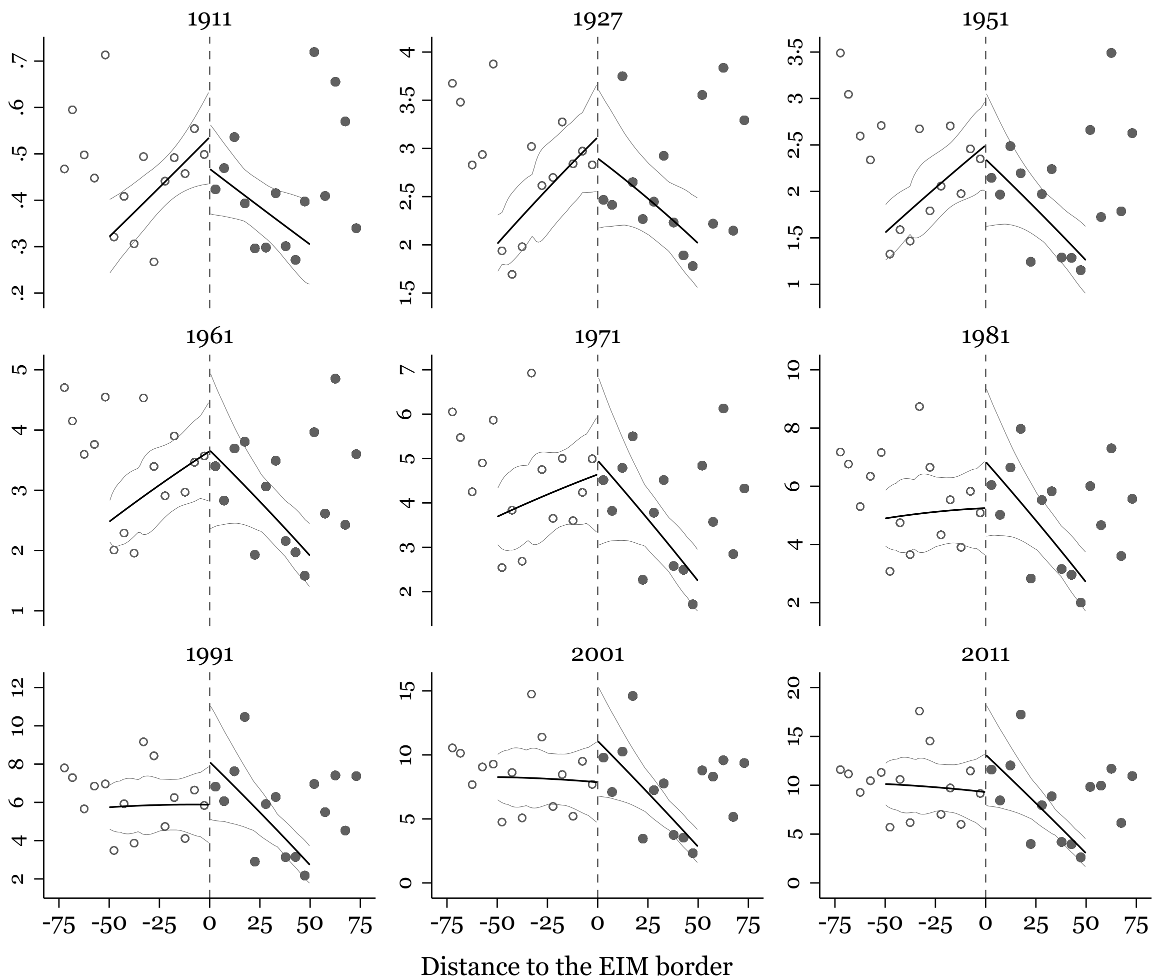
Notes: Negative distance denotes municipalities north of the EIM border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately north and south of the border using a 50-km symmetric bandwidth. The gray lines are 95 percent confidence intervals. See text for details.

Appendix Figure F6. Manufacturing establishment density



Notes: 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. See text for details.

Appendix Figure F7. Services establishment density



Notes: 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. See text for details.

Appendix Table F1. RD estimates – EIM border

	Empl., 1991	Empl., 2011	Est., 1991	Est., 2011
RD Estimate	18.59	14.95	1.94	2.77
	(9.93)*	(11.72)	(2.40)	(4.09)
Mean around the border	30.78	37.09	8.64	12.59
Standard deviation	61.14	71.38	14.74	24.01
Observations	587	587	587	587
R^2	0.29	0.30	0.34	0.29

Notes: Coefficient estimates from Equation B4.1 separately for employment density and establishment density. 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. Standard errors allow for spatial correlation (Conley, 1999). See text for details. * p<0.10, ** p<0.05, *** p<0.01

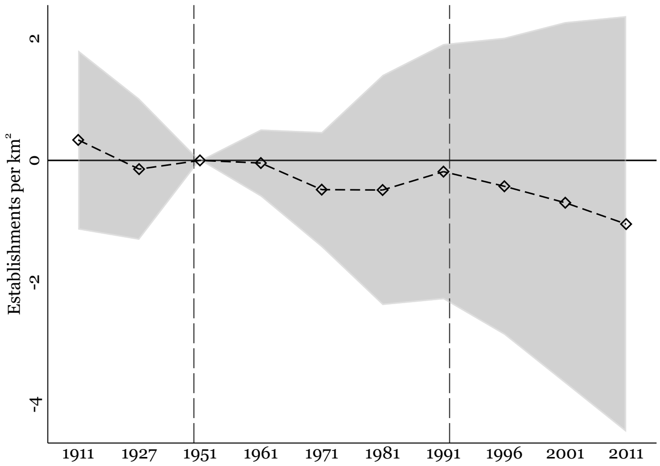
Appendix Table F2. Manufacturing and services densities – EIM border

	Employment density		Establishment density	
	Manufacturing	Services	Manufacturing	Services
	Contemporaneous effect (1991)			
RD Estimate	15.36	3.44	0.71	1.03
	(4.02)***	(5.01)	(0.42)	(1.81)
Mean around the border	12.77	13.53	1.66	5.76
Standard deviation	28.13	28.45	3.22	10.48
Observations	587	587	587	587
	Persistent effect (2011)			
RD Estimate	9.26	6.04	0.77	1.56
	(2.61)***	(7.86)	(0.35)**	(3.25)
Mean around the border	9.61	21.79	1.40	9.14
Standard deviation	19.60	46.82	2.61	18.81
Observations	587	587	587	587

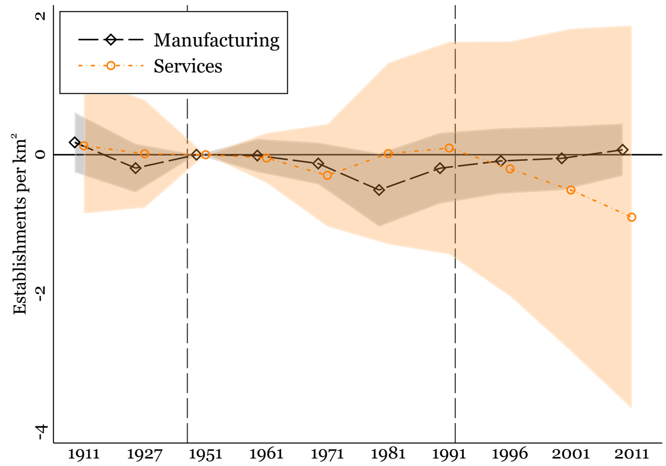
Notes: Coefficient estimates from Equation B4.1 separately for employment density and establishment density. All regressions are estimated over a 50-km symmetric bandwidth around the EIM border and control for a linear polynomial in the distance to the border and border segment effects. Standard errors allow for spatial correlation (Conley, 1999). See text for details. * p<0.10, ** p<0.05, *** p<0.01

Appendix Figure F8. The EIM border – Difference-in-discontinuities

(a) Establishment density

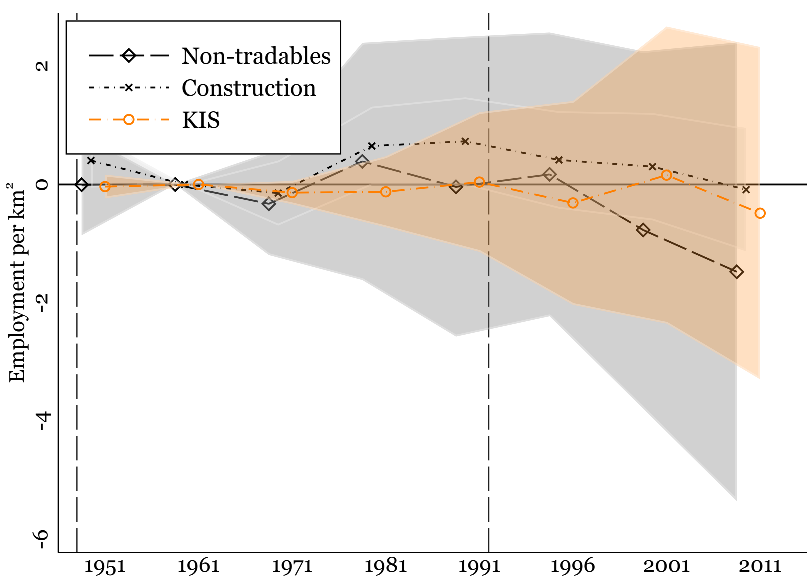


(b) Manufacturing versus services



Notes: Coefficient estimates for Equation B4.2. 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 EIM. See text for details.

Appendix Figure F9. The EIM border – Employment density, sectoral breakdown



Notes: Coefficient estimates for Equation B4.2. 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 EIM. "Non-tradables" include wholesale and retail trade, hotels and restaurants and other. KIS include communication, finance and insurance and services to firms. See text for details.

Appendix Table F3. Employment and firm shares in services – EIM border

	Employment		Establishments	
	KIS	Other serv.	KIS	Other serv.
	Contemporaneous effect (1991)			
RD Estimate	-0.02	0.02	-0.01	0.01
	(0.03)	(0.03)	(0.02)	(0.02)
Mean around the border	0.13	0.87	0.11	0.89
Standard deviation	0.20	0.20	0.14	0.14
Observations	526	526	526	526
	Persistent effect (2011)			
RD Estimate	0.00	-0.00	0.01	-0.01
	(0.02)	(0.02)	(0.01)	(0.01)
Mean around the border	0.09	0.91	0.09	0.91
Standard deviation	0.13	0.13	0.09	0.09
Observations	570	570	570	570

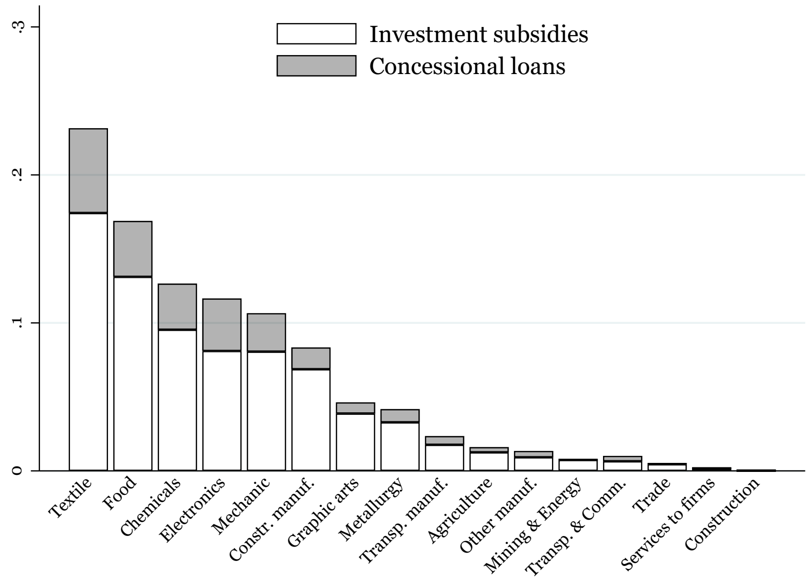
Notes: Coefficient estimates from Equation B4.1. All regressions are estimated over a 50-km symmetric bandwidth around the EIM border and control for a linear polynomial in the distance to the border and border segment effects. Standard errors allow for spatial correlation (Conley, 1999). The outcomes are the share of employment and establishments in KIS and other services. The shares are obtained from social security data on the universe of Italian firms and the KIS classification is obtained from Eurostat/OECD. See Appendix A.3 and text for details. * p<0.10, ** p<0.05, *** p<0.01

Appendix Table F4. Employment and firm shares in manufacturing – EIM border

	Employment, 1991		Establishments, 1991	
	High-tech	Low-tech	High-tech	Low-tech
RD Estimate	0.02	-0.02	-0.00	0.00
	(0.03)	(0.03)	(0.03)	(0.03)
Mean around the border	0.14	0.86	0.13	0.87
Standard deviation	0.21	0.21	0.15	0.15
Observations	509	509	509	509

Notes: Coefficient estimates from Equation B4.1. 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. Standard errors allow for spatial correlation (Conley, 1999). The outcomes are the share of employment across manufacturing sub-sectors, grouped by technological intensity. 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 and text for details. * p<0.10, ** p<0.05, *** p<0.01

Appendix Figure F10. The EIM border – Subdsidies to firms, breakdown



Notes: Sector breakdown of firm investment subsidies and concessional loans. Sample includes municipalities up to 50 km south of the EIM border.

Appendix Table F5. (Log) wages – EIM border

	Total	By sector		Within services	
		Manufacturing	Services	KIS	Other serv.
		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. 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. Standard errors allow for spatial correlation (Conley, 1999). Outcome computed as the natural logarithm of the average monthly wage paid by the firm, then averaged across firms in a municipality. See Appendix A.3 and text for details. * p<0.10, ** p<0.05, *** p<0.01

Appendix Table F6. Education and occupations – EIM border

	High school educ.	Univ. degree	Low-skill	High-skill
	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. 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. Standard errors allow for spatial correlation (Conley, 1999). "High school educ." is the share of people aged at least 6 with high school education or more. "Univ. degree" is the ratio of the resident population aged 30-34 years old with a university degree to the resident population aged 30-34 years old. "Low-skill" is the employment share of those in low-skill jobs (unskilled occupations - Isco08 code 8). "High-skill" is the employment share of those in high-skill jobs (Legislators, Entrepreneurs, High Executives, Scientific and Highly Specialized Intellectual Professions, Technical Professions - Isco08 codes 1, 2 and 3). See text for details. * p<0.10, ** p<0.05, *** p<0.01

Appendix Table F7. Firm size and wage distribution – EIM border

	Firm size			Firm wage		
	T1	T2	T3	T1	T2	T3
	Contemporaneous effect (1991)					
RD Estimate	-0.11	0.01	0.10	-0.19	0.07	0.11
	(0.03)***	(0.02)	(0.02)***	(0.03)***	(0.02)***	(0.03)***
Mean around the border	0.42	0.33	0.25	0.36	0.32	0.32
Standard deviation	0.18	0.17	0.15	0.20	0.15	0.18
Observations	580	580	580	580	580	580
	Persistent effect (2011)					
RD Estimate	-0.07	0.02	0.05	-0.03	0.01	0.03
	(0.02)***	(0.02)	(0.02)***	(0.02)	(0.02)	(0.02)
Mean around the border	0.42	0.32	0.25	0.36	0.30	0.34
Standard deviation	0.16	0.13	0.13	0.15	0.13	0.14
Observations	584	584	584	584	584	584

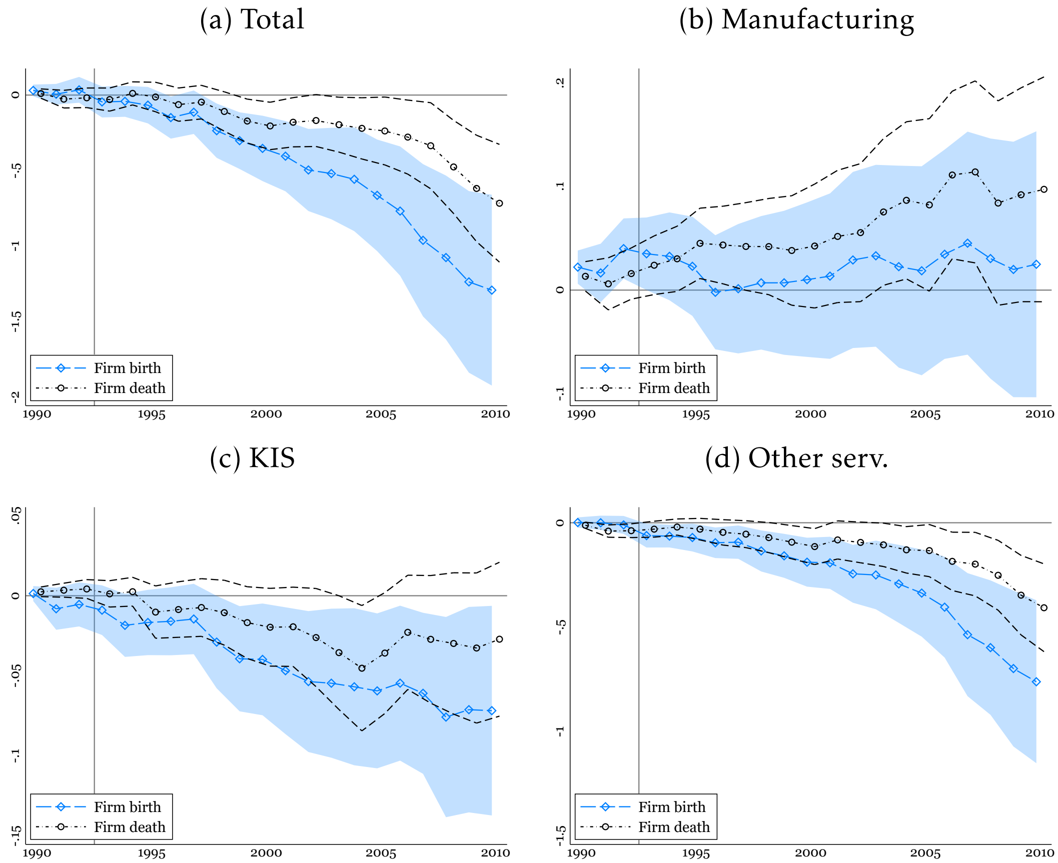
Notes: Coefficient estimates from Equation B4.1. All regressions are estimated over a 50-km symmetric bandwidth around the EIM border and control for a linear polynomial in the distance to the border and border segment effects. Standard errors allow for spatial correlation (Conley, 1999). Outcomes are computed as the share of firms in each tertile of the distribution of firm size and wage paid. Tertiles are derived on the universe of the Italian firms each year. See Appendix A.3 and text for details. * p<0.10, ** p<0.05, *** p<0.01

Appendix Table F8. Balance sheet outcomes, 2011 – EIM border

	Total	By sector		Within services	
		Manufacturing	Services	KIS	Other serv.
			Value added		
RD Estimate	0.50	0.39	0.27	0.21	0.31
	(0.15)***	(0.19)**	(0.19)	(0.25)	(0.20)
Mean around the border	4.38	4.28	4.11	3.94	4.13
Standard deviation	1.00	1.10	1.19	0.99	1.23
Observations	542	417	497	278	484
			Investment		
RD Estimate	0.85	0.50	0.79	0.47	0.81
	(0.21)***	(0.25)*	(0.25)***	(0.38)	(0.25)***
Mean around the border	2.66	2.48	2.41	2.00	2.41
Standard deviation	1.35	1.48	1.51	1.58	1.53
Observations	542	418	496	270	487
			Sales		
RD Estimate	0.74	0.35	0.49	0.37	0.48
	(0.17)***	(0.21)*	(0.20)**	(0.29)	(0.21)**
Mean around the border	5.89	5.71	5.79	5.01	5.86
Standard deviation	1.11	1.19	1.28	1.23	1.30
Observations	548	425	507	287	496
			Profits		
RD Estimate	0.93	0.28	0.09	-0.02	0.21
	(0.31)***	(0.39)	(0.36)	(0.42)	(0.37)
Mean around the border	2.21	2.27	2.18	1.80	2.21
Standard deviation	1.65	1.79	1.68	1.45	1.73
Observations	334	247	275	173	271

Notes: Coefficient estimates from Equation B4.1. 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. Standard errors allow for spatial correlation (Conley, 1999). All outcomes are as of 2011 and expressed in natural logarithm, scaled by total firm workforce. See Appendix A.3 and text for details. * p<0.10, ** p<0.05, *** p<0.01

Appendix Figure F11. Firm dynamics – EIM border



Notes: Coefficient estimates of Equation B4.1 using a symmetric 50-km bandwidth a controlling for a linear polynomial in distance to the EIM border and for border segment fixed effects. Standard errors allow for arbitrary spatial correlation (Conley, 1999). The shaded areas denote 95 percent confidence intervals. The vertical line marks the end of the EIM. Firm birth and death rates computed as the cumulative number of firm births and deaths every year since 1990, as a share of the total number of firms in the municipality in 1990. See text for details.

Appendix Table F9. Other outcomes – EIM border

	Housing value	Rents	Tax income	Gini coeff.	KSI
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 of Equation B4.1 using a symmetric 50-km bandwidth a controlling for a linear polynomial in distance to the EIM border and for border segment fixed effects. Standard errors allow for arbitrary spatial correlation (Conley, 1999). "Housing value" and "Rents" are residential real estate prices and rents as of Q1-2011, measured in euros per squared meter. "Tax income" denote (log) tax income in euros per capita in 2010. "Gini coeff." is the Gini coefficient as of 2011. "KSI" is the Krugman Specialization Index for manufacturing in 2011 (see Appendix A.2). See text for details. * p<0.10, ** p<0.05, *** p<0.01

Appendix Table F10. The IDAs versus the EIM border – descriptive statistics

	IDAs	EIM border
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: 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 euros per 1951 resident, winsorized at 1 and 99 percent. Employment and establishments (total and manufacturing) are sourced from the 1951 industrial census. "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" and "Slope" measured in meters. "Seismicity" is a categorical variable ranging from 1 "High seismicity" to 4 "Very low seismicity". Standard deviations in parentheses.

G. Appendix G: External validity

A drawback of RD designs is that external validity is limited to units close to the cutoff. This issue is exacerbated further in fuzzy RD, as the LATE estimate refers to compliers only. A series of papers have emerged assessing the external validity of RD estimates for units far from the cutoff (Angrist and Rokkanen, 2015) and, specifically for fuzzy RD, other compliance groups (Bertanha and Imbens, 2020). We briefly analyze both cases in this Appendix.

Extrapolation away from the cutoff. Do the positive effects of PBIP still hold away from IDAs? Angrist and Rokkanen (2015) propose to extrapolate RD treatment effects to inframarginal units using predictors of the outcome other than the running variable ("CIA covariates"). Conditional on such covariates, there is mean independence between the outcome and the running variable – a Conditional Independence Assumption (CIA). To identify the CIA covariates, we exploit the data-driven algorithm in Palomba (2023).[54] Specifically, we feed the following list of potential predictors of the outcome (employment density in 2011): slope, mean elevation, coastal location, seismicity, employment and population density in 1951, manufacturing and agriculture shares in 1951 and high-school education in 1951. The algorithm selects slope, mean elevation, seismicity and population density in 1951 as CIA covariates. Conditional on these, the correlation between employment density and distance to the cutoff breaks, as showed in Columns (1) and (2) of Table G1.[55] CIA covariates are then used to identify counterfactual values of the outcome away from the cutoff and in turn extrapolate the RD effects. We show in Column (3) that replacing the running variable with the CIA covariates produces treatment effects at varying bandwidths away from the cutoff that are very similar to the baseline RD estimate of 60 workers per km^2 in 2011.

Other compliance groups. Another limitation to external validity in fuzzy RD is that the LATE refers to compliers (in our case, municipalities that are included in an IDA if and only if they are contiguous to an IDA center). What about the effects for always-takers and never-takers? To this end, Bertanha and Imbens (2020) define external validity as "independence between potential outcomes and compliance types". If this holds, then the LATE for compliers equals that for always- and never-takers. This condition implies exogeneity of treatment participation, which can be falsified using a joint test of restrictions. Namely, one should

[54] We use the *ciasearch* Stata command included in the *getaway* package (Palomba, 2023).

[55] This approach additionally rests on a common support assumption that assumes variation in treatment status within cells based on the selected CIA covariates (Angrist and Rokkanen, 2015).

Appendix Table G1. IDAs – External validity

	CIA		External validity
	Distance to the minimum IDA border		Employment density, 2011
Bandwidth	(1)	(2)	(3)
20 km	-1.86	-1.07	58.15
	(0.53)***	(0.28)***	(26.44)*
30 km	-1.32	-0.21	57.04
	(0.27)***	(0.15)	(26.09)*
40 km	-1.03	-0.24	59.78
	(0.16)***	(0.09)**	(27.83)*
50 km	-0.72	-0.08	59.93
	(0.11)***	(0.06)	(27.72)*
60 km	-0.55	-0.03	59.15
	(0.09)***	(0.05)	(27.20)*
70 km	-0.49	-0.04	59.05
	(0.07)***	(0.04)	(26.98)*
80 km	-0.46	-0.04	59.00
	(0.06)***	(0.04)	(27.08)*

Notes: External validity analysis based on Angrist and Rokkanen (2015). Columns (1) and (2) show the coefficient for the running variable (distance to the minimum IDA border) in a regression of the outcome (employment density in 2011) on the running variable outside of the minimum border, within the bandwidth indicated on the left. Column (2) additionally controls for slope, mean elevation, seismicity and population density in 1951. These controls, which break the correlation between the outcome and the running variable, are obtained through the *ciasearch* algorithm in Palomba (2023). Column (3) estimates Equation 1b within the bandwidth indicated on the left, but replaces distance to the border with the above covariates. See text for details. * p<0.10, ** p<0.05, *** p<0.01

test equality of average outcomes between always-takers and treated compliers, and never-takers and control compliers. They propose a joint formal test of these restrictions, which we perform using employment density in 2011 as outcome.[56] The test delivers an F-stat of 0.226, meaning that we fail to reject equality of average outcomes across compliance types, lending support to external validity. We do not place much emphasis on this result as we lack statistical power due to the small sample size. Importantly, testing equality between never-takers and control compliers is not feasible in our set-up due to the very low number of never-takers (there are only ten municipalities bordering IDA centers and not part of an IDA). If anything, our results at the EIM border suggest that never-taker municipalities are unlikely to benefit from PBIP in the long run – see the discussion in Section 8.

[56] We use the *rdexo* Stata command introduced in Bertanha and Imbens (2020).